ABSTRACT

A principle U.S. fisheries management concern is ensuring compliance with Endangered Species Act requirements to limit incidental takes of listed species to levels which do not result in potential jeopardy to existing population stocks. Part of the risk assessment process involves an analysis of historic takes (bycatch) of ESA-listed species relative to fishing effort. Sample bycatch per unit of effort (BPUE) ratios are used to gauge the take risk to ESA-listed species posed by future fishing effort. The rare-event nature of protected species takes complicates the interpretation of sample BPUE ratios. For illustration, a total of 23 leatherback turtles were incidentally taken by fishermen in the California-Oregon drift gillnet fishery from the 1990 through 2006 fishing seasons in 7733 sets of fishing effort, with from 0 to 5 leatherback takes per season over the entire period. Should one conclude the incidental take risk was significantly higher during the season with 5 leatherback turtle takes than in seasons with 0 takes? To address this and related inference problems, we specify a state space model which describes the pattern of observed takes as a Poisson process conditional on the level of fishing effort. A time-varying Poisson rate parameter, expressed as BPUE, measures the time-varying level of take risk. A Kalman filter for Poisson processes is used to estimate the intertemporal variation in take risk from California-Oregon drift gillnet fishery observer data. A key question regards attributing the observed pattern of takes to randomness which drives fluctuations in observed takes versus intertemporal variation in the level of take risk.

JEL Classification: Q22, Q28, Q57, Q58.

Keywords: Kalman filter, Poisson process, government conservation policy, endangered species, biodiversity conservation.

INTRODUCTION

The U.S. Federal Endangered Species Act (ESA) requires U.S. fisheries management agencies to regulate the incidental take of species which are determined to be threatened or endangered. Section 7(a)(2) of the ESA requires that each federal agency “shall ensure that any action authorized, funded, or carried out by such agency is not likely to jeopardize the continued existence of any endangered or threatened species or result in the destruction or adverse modification of critical habitat of such species.” The question of what actions jeopardize the continued existence of an endangered or threatened (protected) species is a difficult one to answer. Clearly if no incidental takes of protected species ever occur, then there is no question of jeopardy. But so long as any incidental takes occur in connection with a federal action at even a very infrequent rate, a question of potential jeopardy must be addressed through a Section 7 consultation. Part of the Section 7 consultation includes conducting an analysis to support a biological opinion (BIOP) about how the action may affect the protected species of concern.

One example of incidental take of endangered species in U.S. federally managed fisheries is that of leatherback turtle take in the California-Oregon drift gillnet (CA-OR DGN) fishery. A drift gillnet fishing trip consists of a number of sets, typically on the range from 1 to 20, where each set involves lowering a net into the water at dusk then pulling it back up in the morning to retrieve the catch, following a soak duration of 12-14 hours, depending on the length of the night (Barlow [1]). The sets which target
swordfish are roughly homogenous with respect to duration and gear type, so that each set may be regarded as one nominal unit of fishing effort. Since marine turtles are oxygen-breathing reptiles, a turtle which is entrapped more than one hour before the end of a set is likely to die of suffocation.

Incidental take of leatherback turtles in the CA-OR DGN fishery is a rare event: There were a total of twenty-three leatherback takes in 7733 observed CA-OR DGN sets over the seasons from 1990-2006. However, dwindling stocks of Pacific leatherback turtles have raised concerns that even a seemingly low number of incidental takes coupled with a significant post-capture mortality rate could result in potential jeopardy to the Pacific leatherback turtle’s continued existence. Because the Endangered Species Act requires limiting the capture or killing of endangered species such as the leatherback turtle to a level that does create jeopardy of extinction, a small number of takes can have large economic implications for the commercial fisheries which are responsible for the incidental catch. For example, in 2001 a time-and-area closure was established for a large portion of the CA-OR DGN fishery for the period from August 15 through November 15 to protect leatherback turtles. There was a substantial loss in average annual CA-OR DGN fishery revenues in subsequent years.

A key challenge for fisheries managers is to analyze the available data on rare protected turtle interactions as a basis for managing the future interaction risk without eliminating the economic viability of managed fisheries. We first describe the current approach to predicting unobserved leatherback turtle interactions in the CA-OR DGN fishery, and the way this analysis informs the policy process. We then present an alternative analysis strategy based on a Kalman filter for count data models. The analysis strategy has the attractive feature that it avoids the strong assumptions implicit in the current inference methodology that (1) the current season’s observed turtle bycatch per unit of effort is independent of past seasons’ interactions and (2) the bycatch per unit of unobserved effort is adequately predicted as equal to the current season’s observed bycatch per unit of effort.

Two versions of the Kalman filter are estimated and compared; the first version only includes a stochastic time trend for incidental take risk, while the second version introduces explanatory variables. A hypothesis test of a restriction to constant incidental take risk after controlling for relevant explanatory variables is conducted on the second version of the model. The best fitting model is used to produce prediction intervals for marine turtle takes as a function of the observed and unobserved shares of the effort, under the assumption that the number of unobserved takes follows a Poisson process which is statistically independent from the number of observed takes, after conditioning on relevant explanatory variables and the inferred rate parameter. Comparison with the predictions from the current methodology suggests that the “worst case scenario” estimate used to justify the 2001 leatherback turtle closure may overstate the ongoing DGN leatherback turtle interaction risk, potentially resulting in excessively stringent leatherback turtle conservation regulatory measures.

DRIFT GILLNET OBSERVER DATA

The U.S. National Marine Fisheries Service (NMFS) established an observer program as mandated by the 1988 amendments to the Marine Mammal Protection Act. Since 1990, DGN fishing effort has been observed in the U.S. exclusive economic zone (EEZ) from the waters off San Diego to the waters off Oregon. Observers record catch and bycatch by taxon for fish, marine mammals, and sea turtles, collect specimens, and record data on environmental conditions and over 10 different net characteristics (NMFS, 1997 [2]).

Vessels are selected on an opportunistic basis, with the hope that the observed sample will be representative of all the effort that occurred in a given year. Vessels are required to carry an observer about 20 percent of the time on a rotating basis; thus a vessel which just took an observer would not be
required to carry another observer until it would approach their 20 percent requirement. Observer coverage averaged approximately 16 percent from 1991-99.

An important question regarding the CA-OR DGN observer data is the degree of independence between incidental takes of leatherback turtles in the (approximate) 20 percent of effort which is observed versus in the 80 percent of effort which is unobserved. A related question is the degree of independence in leatherback takes across seasons. The present approach to predicting leatherback takes in the unobserved portion of CA-OR DGN effort relies upon three implicit assumptions: (1) the stochastic process governing leatherback take fluctuations is a case of pure uncertainty (Pearce [3]), implying that no probability distribution can be used to explain the counts; (2) only the current season’s observed leatherback takes are used to predict the unobserved takes, implying an assumption that the unobserved takes in the current season are completely independent from the past history of observed leatherback takes; (3) the current season take rate in the unobserved share of effort is predicted to equal the leatherback take rate per set (nominal effort unit) in the observed share of effort, implying an assumption of 100 percent correlation between current season leatherback take counts in the unobserved and observed portions of effort.

The sample of observed effort is not a true simple random sample of overall effort for the CA-OR DGN fishery in a given season, as the selection of vessels to be observed is by nonrandom choice, and the observed sets of effort are spatially and temporally clustered according to which vessels’ trips are selected. Nonetheless, it is conceivable that given the rare and unpredictable nature of leatherback turtle bycatch, the pattern of takes which occurs over time in the observed portion of CA-OR DGN effort is highly similar to what would be seen in a true random sample. It is useful to conduct the thought experiment regarding the relationship between leatherback takes in the observed and unobserved portions of effort if the observed share of effort were chosen as a simple random sample of overall effort. In this case, after conditioning on factors which affect the mean leatherback take risk for the fishery as a whole, the number of takes in the observed and unobserved portions of effort would be independent by design of the sampling method.

Departure from full independence could arise if unobserved fishermen faced a systematically different risk of leatherback takes, or if the variance of within-trip leatherback take risk was smaller than the variance of leatherback take risk between trips. The second potential departure from independence could, in principle, be tested empirically by comparing between-trip variation in leatherback takes to within-trip variation. The first potential departure from independence is more problematic to assess, as unobserved effort is, by its very nature, not available for empirical investigation. On the grounds that DGN fishermen have little to gain and much to lose from catching leatherback turtles, we see no prior reason to assume an elevated take risk in the unobserved portion of effort. We adopt a working hypothesis for the balance of this paper that the observer sample may be reasonably treated as observationally equivalent to a simple random sample of all effort for the season, recognizing that whether this is the case is an open question.

USING THE KALMAN FILTER TO MEASURE DYNAMIC LEATHERBACK TAKE RISK

We consider the possibility that after conditioning on known factors which affect the risk of leatherback takes, the take rates in a given season are conditionally independent between the unobserved and observed shares of CA-OR DGN effort. Adopting a working hypothesis that the stochastic process governing leatherback takes is a Poisson process with the rate parameter being conditionally dependent on the amount of nominal fishing effort and other factors which affect the take risk, we describe a structural model of leatherback take risk and use the Kalman filter for count data models (Harvey [4]) to estimate it. Our hope is to obtain a more realistic model of the stochastic process governing leatherback turtle takes by separating the random factors which account for fluctuations in take counts across observed sets from the effect of relevant covariates on the level of leatherback take risk.
STATE SPACE MODEL OF LEATHERBACK TAKE RISK

There is no way to use the available fishery-dependent observer data to separately identify the stock density from factors which affect catchability. Hence we specify a reduced form approach which makes no attempt to separately identify the stock density and catchability. Let $x_t$ denote a row vector of covariates which are believed to affect leatherback take risk, and let $\delta$ denote a conforming column vector of parameters. Leatherback take risk is specified as the product of a base level of leatherback take risk $\mu_t$, multiplied by an exponential factor $\exp(x_t, \delta)$ which can adjust to account for covariates which are believed to affect take risk.

$$\mu_t(x_t) = \exp(x_t, \delta) \mu_t$$  \hspace{1cm} \text{(Eq. 1)}

The prior predictive distribution of the base level of leatherback take risk is specified as conditionally dependent on all past observations on the covariates, $X_{t-1}$, and leatherback takes, $Y_{t-1}$, as of the time when set $t-1$ of effort occurred:

$$\left(\mu_t \mid X_{t-1}, Y_{t-1}\right) \sim \Gamma(a_{t|t-1}, b_{t|t-1})$$ \hspace{1cm} \text{(Eq. 2)}

Dependence of the gamma distribution parameters $a_{t|t-1}$ and $b_{t|t-1}$ on available data through observer set $t-1$ is described below in Equations 4 through 7.

The conditional distribution for the number of leatherback takes $y_t$ is a Poisson distribution with rate parameter given by the product of current effort effort $Z_t$ multiplied by the take risk for covariates $x_t$:

$$\left(y_t \mid x_t\right) \sim \text{Poisson}(Z_t, \mu_t(x_t))$$ \hspace{1cm} \text{(Eq. 3)}

A single set of drift gillnet fishing effort occurs each time a fisherman soaks his net in the water at dusk and pulls it up again at dawn to remove the catch. A natural unit of fishing effort is given by the number of sets included in observation $t$, which we denote $Z_t$. The CA-OR DGN observer data are disaggregated to the set-level, implying that $Z_t = 1$ for each set $t$. However, the method may be extended to inference and prediction when the data include multiple sets of effort per observation.

MAXIMUM LIKELIHOOD ESTIMATION

Methodology to estimate the Kalman filter model for maximum likelihood estimation and inference of count data model presented above is developed in Harvey [4], with methodology for a count data model without regressors given in section 6.6, and for a model with regressors in section 7.9. We present a few essential details here and refer the interested reader to Harvey for the complete development.

The approach we took follows Harvey exactly (see development in section 6.6.1 beginning on page 350), except that we combined the two approaches to exploit the insight that the section 6.6 model without regressors may be described as a restricted version of the section 7.9 model with regressors, and we adjusted the definitions of $a_t$ and $b_t$ to reflect irregularly spaced time intervals between observed sets of CA-OR DGN effort. Letting $s_t$ denote the exact date on which set $t$ was fished and $\omega$ denote a rate of time discount with $0 < \omega \leq 1$, the gamma distribution parameters for the predictive distribution of leatherback take risk based on observations through set $t-1$ are defined recursively as follows:

$$a_{t|t-1} = \omega^{s_t-s_{t-1}} a_{t-1}$$ \hspace{1cm} \text{(Eq. 4)}
\[ b_{t_{i-1}} = \omega^{y_{t_{i-1}}} b_{i-1}. \]  
(Eq. 5)

Once set \( t \) information becomes available, the gamma distribution parameters may be updated to those of the posterior predictive distribution of leatherback take risk:

\[
a_t = \omega^{y_{t_{i-1}}} a_{t_{i-1}} + y_t = \sum_{j=1}^{t_{i}} \omega^{y_{j}} y_j = EWMA(y)
\]  
(Eq. 6)

\[
b_t = \omega^{y_{t_{i-1}}} a_{t_{i-1}} + \exp(x_t) = \sum_{j=1}^{t_{i}} \omega^{y_{j}} \exp(x_t) = EWMA(\exp(x_t)).
\]  
(Eq. 7)

These formulas demonstrate that the parameters of the posterior predictive (gamma) distribution of leatherback take risk, \( a_t \) and \( b_t \), may respectively be expressed as exponentially-weighted moving averages of the entire history of leatherback takes \( y_j \) and risk-adjusted exposures \( \exp(x_t) \) for all past sets of fishing effort \( j = 1, 2, ..., t \).

Harvey’s development leads to a log likelihood function of form:

\[
\log L(\omega) = \sum_{t=\tau}^{T} \{ \log \Gamma(a_{t_{i-1}} + y_t) - \log \Gamma(a_{t_{i-1}}) + a_{t_{i-1}} \log b_{t_{i-1}} - (a_{t_{i-1}} + y_t) \log(b_{t_{i-1}} + 1) \},
\]  
(Eq. 8)

where \( \tau \) is the first period in the data with \( y_t > 0 \) and \( T \) is the last period in the data. We used the Nelder-Mead simplex algorithm (Matlab’s \texttt{fminsearch} function) to solve for the optimal values of \( \omega \) and \( \delta \) for several alternative specifications of the explanatory variables in the model.

The exponential weighted moving average formula which describes the parameters of the posterior distribution of leatherback take risk lends itself to a useful interpretation of the time discount parameter \( \omega \). For \( \omega = 1 \), the mean of the posterior predictive distribution of leatherback take risk is given by

\[
E(\mu_t | Y_t) = a_t / b_t = \sum_{j=1}^{t_{i}} y_j / \sum_{j=1}^{t_{i}} \exp(x_t),
\]  
(Eq. 9)

a formula which shows the expected take risk conditional on time \( t \) information is based upon an equally weighted average of the entire history of leatherback takes, with the denominator adjusted for factors which influence leatherback take risk. By contrast, for \( \omega \to 0^+ \), the posterior predictive mean level of the risk approaches a limiting value of

\[
\lim_{\omega \to 0^+} E(\mu_t | Y_t) = \lim_{\omega \to 0^+} a_t / \lim_{\omega \to 0^+} b_t = y_t / \exp(x_t),
\]  
(Eq. 10)

which is closer to the current practice of estimating the present year’s leatherback take rate in the unobserved portion of CA-OR DGN effort by the current year’s bycatch rate in the observed portion of DGN effort.

**COMPARISON OF ALTERNATIVE MODEL SPECIFICATIONS**

The binary variables we used were based on the area closed to CA-OR DGN fishing from August 15 through November 15 in 2001 and subsequent years. We defined an area variable \( (x_{j,t}) \) which equals 1 for
effort within the time-and-area closure boundary and 0 for effort outside the boundary. Similarly, we defined a seasonal variable \((x_{j2})\) which equals 1 for effort during the closed season and equals 0 for effort that occurred during the rest of the year. Finally, the interaction variable is defined as the product of the other two binary variables \((x_{j3} = x_{j1} \times x_{j2})\). Based on these explanatory variables, we estimated and compared the following specifications:

1. Unrestricted model including all three binary regressors;
2. Restricted model with all regressors excluded \((\delta = [\delta_1, \delta_2, \delta_3] = 0)\);
3. Restricted model only including binary explanatory variable for area fished \((\delta_2 = \delta_3 = 0)\).

A side-by-side comparison of estimation results for alternative specifications is given below in Table I. The left column shows parameter estimates for the unrestricted regression specification with time discount parameter \((\omega)\) and binary variables for the closed area \((\delta_1)\), for the closed season \((\delta_2)\), and for the seasonal closure interaction \((\delta_3)\). The middle specification excludes the time and area regressors, while the right column includes the closed area variable.

The specifications were compared by likelihood ratio tests. The unrestricted model necessarily has the highest likelihood, and a restriction to the model without regressors \((\delta = 0)\) produced a likelihood ratio \((LR)\) statistic which leads to a strong rejection of the exclusion restrictions \((p-value < 1\% )\). By contrast, the model with only the seasonally-closed area binary variable included as an explanatory variable produced a \(LR\) statistic \(p-value\) of 31.36 percent, which does not lead to rejection at customary significance levels of the null hypothesis that the seasonal binary variable can be excluded.

Harvey suggests checking specifications by computing the variance of the Pearson residual (Harvey [4]). The Pearson residual is obtained by applying a standard unit transformation to the data \(y_t\), where the standardization uses the mean and standard deviation of the predictive distribution given time \(t-1\) information:

\[
v_t = \frac{y_t - E(y_t | \mu_{t-1})}{\sqrt{\text{Var}(y_t | \mu_{t-1})}}
\]

(Eq. 11)

A correctly specified model has a (theoretical) Pearson residual variance equal to 1; hence values of the sample Pearson residual close to 1 are indicative of good fit. Out of the three specifications under comparison, the unrestricted model had the closest Pearson residual variance to 1, while the other models had smaller values, indicating under-dispersion relative to the variance predicted by the fitted time series model. While the \(LR\) test results are inconclusive, consideration of the Pearson residual variance suggests the unrestricted model fits the data better than the two models with exclusion restrictions. This comparison suggests that failing to account for the effect of variation in leatherback take risk due to the location of effort results in an overestimate of the effect of the recent leatherback take rate on the current level of the risk.
Table I: Comparison of Alternative Model Specifications.

<table>
<thead>
<tr>
<th></th>
<th>Unrestricted</th>
<th>$\delta = 0$</th>
<th>Area, Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Discount ($\omega$)</td>
<td>1.0000</td>
<td>0.4580</td>
<td>1.0000</td>
</tr>
<tr>
<td>Closed Area ($\delta_1$)</td>
<td>1.3856</td>
<td>2.4456</td>
<td></td>
</tr>
<tr>
<td>Closed Season ($\delta_2$)</td>
<td>0.1752</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction ($\delta_3$)</td>
<td>1.1011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\log L$</td>
<td>-138.1979</td>
<td>-149.1102</td>
<td>-139.3577</td>
</tr>
<tr>
<td>Var(Pearson Residual)</td>
<td>0.9671</td>
<td>0.8736</td>
<td>0.9431</td>
</tr>
<tr>
<td>LR Statistic</td>
<td>21.8245</td>
<td>2.3196</td>
<td></td>
</tr>
<tr>
<td>Degrees of Freedom</td>
<td>3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>$p$-value</td>
<td></td>
<td>0.0001</td>
<td>0.3136</td>
</tr>
<tr>
<td>$\exp(\delta_1)$</td>
<td>3.9971</td>
<td>11.5377</td>
<td></td>
</tr>
<tr>
<td>$\exp(\delta_2)$</td>
<td>1.1915</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\exp(\delta_1 + \delta_2 + \delta_3)$</td>
<td>14.3236</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3 provides a graphic depiction of the estimated level of the take rate per 1000 sets, a rescaled version of the estimated value of $\mu_0$, for the model without regressors. After an initial adjustment period, the range of the estimated take rate per 1000 sets stays consistently within a range between 2 and 8 takes per 1000 sets. For effort levels around $750 \times 5 = 3,750$ sets realized at the peak years of the CA-OR DGN fishery (observed sets were 757 sets in 1993 and 748 sets in 1997, representing approximately 20 percent of all effort in each of those years) and predicted takes at the high end of the range of 8 takes per 1000 sets, the expected number of takes for all effort would approach the level of 27 suggested in the 2000 BIOP, but it is important to note that effort has been lower in subsequent years. Further, the MSE calculation suggests that the extremes of the range of risk estimates for the model without regressors may overstate the current risk, due to omitted variable bias.
By contrast, Figure 4 shows the estimated take rates per 1000 sets of effort for the different time-and-area combinations for the model with regressors. The most striking contrast between the graphs is the extent to which the estimated take rate levels off over time when the time and error where effort occurred are taken into consideration. The estimated value of $\omega = 1$ for the unrestricted model suggests that the entire history of effort should be equally weighted in estimating the current level of the take rate, rather than only relying on observed takes in the most recent season.
PREDICTION

Harvey’s methodology demonstrates that the posterior predictive distribution based on data available as of a given point in time has a negative binomial distribution with parameters $a_t$ and $b_t$. Figure 5 displays the posterior predictive distribution for the observed number of takes in 1995 – i.e., the probabilities for different observed numbers of leatherback takes during the 1995 fishing season, based on the entire history of effort through that season. The graph and a supporting calculation show the probability of observing a value as extreme as the actual observed number of 5 leatherback takes for the 1995 season was about 10 percent, a value which though unlikely, is not rare.
Figure 5: Posterior predictive distribution for number of observed 1995 leatherback takes.

Figure 6 displays the 1995 posterior predictive distribution for all takes during the 1995 season (observed plus unobserved). The graph and a supporting calculation demonstrate the probability of achieving a level of 27 or more takes is quite low – 1.25 percent. This result suggests the probability of maintaining this level of takes on average is vanishingly small.
CONCLUSIONS

We used a Kalman filter approach to estimate the level of leatherback take risk over time based on CA-OR DGN observer data on fishing effort and leatherback takes. We represented take risk as a time-varying state variable that describes the rate parameter for a Poisson process, where the Poisson arrivals are incidental takes of leatherbacks. Our results confirm the earlier finding by Carretta et al. [5] that historically there was a significantly higher leatherback take risk in the area that was closed to CA-OR DGN fleet fishing after 2001 during the period from August 15 through November 15.

The best fitting model appears to be one which includes explanatory variables for the time and area where fishing effort occurred, and which weights all past observations on DGN leatherback takes and fishing effort equally. Our results suggest consideration of whether a longer time series of observations should be used for estimating the number of leatherback takes which occurred in the unobserved portion of each season’s effort. Any such predictions should, if possible, reflect variation in leatherback take risk over the times and areas where effort occurred.

REFERENCES


ENDNOTES

a There are potential scenarios where leatherback take risk could be systematically higher in the unobserved portion of CA-OR DGN effort. For example, if swordfish CPUE and leatherback BPUE exhibited a high degree of spatial-temporal correlation, it is possible that fishermen carrying an observer would accept a lower swordfish CPUE to reduce the risk of observed leatherback bycatch. Due to the extremely rare incidence of leatherback bycatch, we are skeptical that fishermen can assess leatherback take risk with a sufficient degree of precision for this scenario to be viable.

b Note that the interaction variable could legally assume a value of 1 only for effort before the time-and-area closure became effective, as the closure prohibits fishing in the closed area during the closed season.