A Negative Binomial Loglinear Model with Application for the Estimation of Bycatch of Blacknose Shark in the Gulf of Mexico Penaeid Shrimp Fishery

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Abstract

Bycatch estimation of blacknose shark (*Carcharchinus acronotus*) by the penaeid shrimp trawl fishery in the Gulf of Mexico currently uses a model developed for the bycatch of red snapper (*Lutjanus campechanus*) run under the computer program WinBUGS. Alternative models for the estimation of blacknose bycatch were not considered possibly because the extreme execution time (up to 70 hours) discouraged exploration of alternative models. The impact of Turtle Exclusion Devices (TEDs), which have been in widespread use since 1990, was not considered despite an expected ability to exclude fish the size of blacknose shark. To address these problems we developed a bycatch estimation model under the program AD Model Builder that mimics the WinBUGS version but runs much faster (less than a minute). The model was extended to include the impact of TEDs. Bycatch estimates using six alternative models (combinations of with and without year effects, a pre-post 1990 time trend effect as a replacement for the year effect, and with and without TED effects) were made from 30,548 tows made in the Gulf of Mexico. We recommend the pre-post 1990 time trend with a TED model option based on fit to the data. There is a critical need for additional shrimp trawl observer information on the capture of blacknose shark to enable better definition of the TED effect and subsequent bycatch estimates.

Introduction

Bycatch estimation of blacknose shark (*Carcharchinus acronotus*) by the penaeid shrimp trawl fishery in the Gulf of Mexico is described by Nichols (2007). The methodology was developed for the bycatch of red snapper (*Lutjanus campechanus*) by shrimp trawls (Nichols 2005a, Nichols 2005b) and applied to blacknose shark with only minor adjustments (Nichols 2007). In essence, the bycatch estimates are a product of shrimp trawl catch rate and effort predictions. Because catch rates from observers onboard shrimp vessels were not sufficiently complete to form a time series, fishery independent research trawl catch rates were scaled to form the catch rate used for the bycatch estimates. Predictions for the catch rates were accomplished through the application of a log-linear (effects were year, season, area, depth and trawl data source without interactions) negative binomial Bayesian mixed model. Computations were made with the program WinBUGS (Spiegelhalter et al. 2003) with execution times up to 70 hours. Alternative models for the estimation of blacknose bycatch were not considered possibly because the extreme execution time discouraged exploration of alternative models.

The impact of Turtle Exclusion Devices (TEDs), which have been in widespread use since 1990, on the bycatch of blacknose shark was not considered by Nichols (2007). A TED consists of a metal grid that is installed in the shrimp trawl to divert sea turtles to pass through a trap door. Because the spacing of the grid bars can not exceed 10 cm, other species wider than this spacing, such as blacknose shark, can also be excluded. In an accompanying paper, Rayborn et al. (2009) used a negative binomial regression model in a before-after-control-impact design to show that TEDs reduced substantially the catch rate for blacknose shark. Raborn (2009) also found that year effect was not important for the prediction of catch rate. They conclude that the current blacknose model requires review and revision to include the potential for TED effects.

Our objectives here are: (1) to develop a bycatch estimation program in AD Model Builder (ADMB, ADMB Foundation 2008) that mimics the Nichols (2007)

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Bayesian version such that execution times will not be an impediment to model development and evaluation; (2) to extend the model to accommodate with and without year effects, a pre-post 1990 time trend effect, and with and without TED effects; and (3) to recommend a bycatch model and suitable estimates for blacknose shark. In the text that follows we describe the catch rate data obtained from research and commercial shrimp trawls and effort from commercial shrimp trawls. Next, the bycatch estimation model is described and the fundamental parameters are estimated using the ADMB program under six model alternatives. Finally, the models are assessed and bycatch estimates for blacknose shark are recommended.

Methods

The notation used for the strata and data variables as well as parameters introduced for model development described below are provided by Table 1. In Table 1, the variables are organized into indices, data and associated descriptors (any combinations of same), fundamental parameters to be estimated, logged probability density functions and interim variables (some combination of data and fundamental parameters) used to clarify model description or of interest to the user.

Bycatch Observations and Effort Estimation

The catch rate (number of blacknose shark captured per trawl net hour) data and effort information used in this analysis were provided by National Marine Fisheries Service (NMFS). The catch rate data came from both fishery independent and dependent sources. The fisheries independent sampling programs (Southeast Area Monitoring and Assessment Program [SEAMAP]), henceforth referred to as “research data”, used standard 40-ft commercial shrimp trawls without bycatch reduction devices or TEDs. The fishery dependent observer programs, henceforth referred to as “observer data”, were obtained from observers placed on commercial shrimp trawl vessels. By 1990 TEDs were in widespread use by the offshore commercial penaeid shrimping fleet. There were three studies (Historical, Characterization, and Modern) of multiple year duration with substantial periods of time between the studies without sampling (see Table 2).

For each trawl tow the duration of the tow and the number of blacknose shark caught were recorded. For some of the tows, a sub-sample of the catch was identified to species and the number of blacknose shark taken by the tow estimated. The trawl information was categorized into temporal and spatial strata consistent to that used by Nichols (2007); namely, 35 years (1972 – 2006), three trimesters (Jan-Apr, May-Aug, Sep-Dec), 4 areas (statistical reporting areas 1-9, 10-12, 13-17, 18-21), 2 depth zones (inside ten fathom, outside ten fathom), and three trawl data sources (observer without a TED, observer with a TED and research).

The number of vessel hours and associated precision estimates were made available by NMFS for all strata described above and are the same as used by Nichlos (2007). The number of nets per vessel and the associated precision were available by year only. Therefore, we have assumed, as did Nichols (2007), that the number of nets per vessel is consistent across trimester, area and depth zone within a year.

Global Model Definition

The prediction of catch rate as a function of the fundamental parameters of interest is an important task for the model. The assumption used here and by Nichols (2007) is that the logarithm of catch rate for year *i*, trimester *j*, area *k*, depth zone *l* and dataset *m* (U_{ijklm}) is a simple (no interactions) linear function of fixed and random effects, i.e.,

$$U_{ijklm} = \mu + y_i + s_j + a_k + d_l + w_m + \xi_{ijklm} \quad , \qquad (1)$$

where μ is the overall mean, y_i is the coefficient for year *i*, s_j is the coefficient for trimester *j*, a_k is the coefficient for area *k*, d_l is the coefficient for depth zone *l*, w_m is the coefficient for dataset *m* (observer trawl without a TED, observer trawl with a TED or research trawl) and ξ_{ijklm} is a random effect for every strata and dataset combination. The random effect ξ creates an additional correlation structure, not directly observed, which asserts that the catch rate observations are "clumped" together within a stratum and trawl type.

We term equation (1) the global model because all alternative models considered here are simplifications. With and without year effect model options are obtained by including or not the year coefficient, y_i. A less severe option is to replace the year coefficient with a time trend before and after 1990, i.e.,

$$y_i = \begin{cases} p_1 i & \text{if } i < 19 \\ p_2 i & \text{otherwise} \end{cases}, \tag{2}$$

where p_1 is the time trend coefficient for 1972 – 1989 and p_2 is the coefficient for 1990 - 2006. With and without TED effect model options are obtained by number of trawl type levels defined. The without TED effect has two (observer and research) and with TED effect has three (observer without a TED, observer with a TED, and research).

Model Objective Function

The objective of the analysis is to minimize the sum of the negative log-probability density functions (*L)*. In this model we consider nine sources,

$$L = L_C + L_\xi + L_\tau + L_\mu + L_y + L_s + L_a + L_d + L_w, \tag{3}$$

where L_C is associated with the tow catches, L_ξ with the random effect, L_τ with a hyper parameter τ associated with the random effect (see equation 4), L_μ with the overall mean catch rate, L_y with the year coefficient, L_s with the trimester coefficient, L_a with the area coefficient, L_d with the depth zone coefficient and L_w with the dataset coefficient. The observed tow catch and duration data contribute to the objective function through the L_C

likelihood. All other sources serve to constrain L_C. The constraints can be viewed through a Bayesian perspective with L_τ, L_μ, L_y, L_s, L_a, L_d and L_w priors with their distributions as defined below and L the posterior. An alternative viewpoint is to consider equation (2) a constrained negative log-likelihood with the attendant likelihood theory applicable.

The trawl catch data are assumed to be distributed as a varying element size negative binomial distribution following Power and Moser (1999). Ignoring constant terms the log-likelihood is expressed as:

$$L_c = \sum_i \sum_j \sum_k \sum_l \sum_m \sum_h \begin{bmatrix} \log_e\left\{\Gamma(r)\right\} - \log_e\left\{\Gamma(\tilde{C}_{ijklm(h)} + r)\right\} - r\log_e\left\{r\right\} \\ -\tilde{C}_{ijklm(h)} \log_e\left\{\theta_{ijklm(h)}\right\} + (r + \tilde{C}_{ijklm(h)}) \log_e\left\{\tilde{C}_{ijklm(h)} + \theta_{ijklbm(h)}\right\} \end{bmatrix}, \quad (4)$$

where

$$\theta_{ijklm(h)} = \exp\left\{U_{ijklm}\right\} \cdot \tilde{T}_{ijklm(h)},$$

and where $\log_e \Gamma(z)$ is the log-gamma function (see Press et al. 1992:214), $\tilde{C}_{ijklm(h)}$ is the observed tow catch of blacknose shark in tow h taken from year i, trimester j, area k, depth l, and dataset m, r is the negative binomial dispersal coefficient (a fundamental parameter that requires estimation), $\theta_{ijklh(h)}$ is the predicted catch in tow h and $\tilde{T}_{ijklm(h)}$ is the duration for tow h. Note that the predicted log catch rate (U_{ijklm}) comes from equation (1) and the tow duration defines the element size of the negative binomial distribution.

The random effect ξ is assumed to have a normal distribution with precision (reciprocal of the variance) τ (a fundamental parameter that requires estimation). Ignoring constant terms the log-likelihood is expressed as:

$$L_\xi = 0.5 \sum_i \sum_j \sum_k \sum_l \sum_m \left\{\tau \xi_{ijklm}^2 - \log_e(\tau)\right\}. \quad (5)$$

The contribution to the objective function from the prior of the precision is given by

$$L_\tau = b_\tau \left(\log_e \tau\right)^2 - \log_e \tau \text{ ,} \qquad (6)$$

where b_τ is a penalty or weighting factor to be supplied (i.e., not estimated). We assume that τ is log-normally distributed with a known variance V_τ; such that

$$V_\tau = \frac{1}{2b_\tau} .$$

We set the penalty weight default to 1.75 and thus the variance is approximately 0.29 with a coefficient of variation (CV) of approximately 0.5 (in log-space the standard deviation and CV are approximately equal). In other words, prior knowledge of τ was assumed to be weak.

The overall mean, μ, was assumed to be normally distributed with a mean of 1.0 with a default penalty weight of 0.5 (CV = 0.7, approximately), thus

$$L_\mu = b_\mu (\mu - 1)^2 . \qquad (7)$$

The contributions to the objective function for priors of the remaining fixed effects were assumed to be normally distributed with a mean of 0. The contribution from year coefficient is given by

$$L_y = b_y \sum_i y_i^2 \text{ ,} \qquad (8)$$

where the default penalty weight, b_y, is set to 0.5. The contribution of the trimester coefficient is given by

$$L_s = b_s \sum_j s_j^2 \,, \tag{9}$$

where the default penalty weight, b_s, is set to 0.5. The contribution of the area coefficient is given by

$$L_a = b_a \sum_k a_k^2 \,, \tag{10}$$

where the default penalty weight, b_a, is set to 0.1. The contribution of the depth zone coefficient is given by

$$L_d = b_d \sum_l d_l^2 \,, \tag{11}$$

where the default penalty weight, b_d, is set to 0.1. Finally, the contribution of the dataset coefficient is given by

$$L_w = b_w \sum_m w_m^2 \,, \tag{12}$$

where the default penalty weight, b_w, is set to 0.5.

The prior distributions for the time trend coefficients are assumed to be uniform and thus add a constant value to the negative log posterior distribution that can be ignored for the purpose of minimization.

Parameter and Bycatch Estimation

Parameter estimation is accomplished through calculating the mode of the posterior distribution. Bard (1974) showed that this is equivalent to finding the minimum of the negative log-likelihood function plus the negative log-probability density functions of the associated priors, i.e., find the fundamental parameter values that minimize equation (2).

The model definition and minimization of the model objective function were implemented through the software package ADMB (ADMB Foundation 2008). The package allows for the restriction or bounding of parameter values, stepwise optimization, the estimation of user defined variables, report production of standard errors and correlation between all estimated variables. The random effects package application we used (ABMB-RE) integrated the random effects out of the objective function using Laplace approximation and estimated the hyper parameter (τ) by maximum likelihood. ADMB Foundation (2008) points out that with random effects it often happens that the maximum likelihood estimate of the variance component becomes small (i.e., τ becomes large) if the data do not support a random effect. The implication is that our model would revert to a Bayesian negative binomial regression without the random effect term.

The sensitivity of the parameter estimates to using alternative default weights b_τ, b_μ, b_y, b_s, b_a, b_d, and b_w (equations 6 to 12) multiplied by 0.5 - 2.0 was explored. Also, the impact of alternative years (e.g., 1989, 1991) for partitioning the log-linear time trend segments was investigated.

We considered six alternative models based on with and without year, a pre-post 1990 time trend and TED effects. For notational and computational convenience concerning the catch rate predictions, we treated trimester, area and depth zone as a single index t. The catch rate predictions (u_{it}) at the posterior mode (i.e., when equation 2 is at a minimum) to be used for bycatch computation are:

$$u_{it} = \exp\left\{U_{ijklm}\right\} \quad \text{where } t = l + 2[k - 1 + 3(j - 1)]. \qquad (13)$$

The dataset (m) used for the catch rate estimates depends on the model alternative. For models without a TED effect, dataset had only two levels (observer and research) and the catch rate predictions were based on the observer strata (m = 1). For models with a TED effect, dataset had three levels (observer without TEDs, observer with TEDs, research) and the catch rate predictions were based on the observer without TEDs strata (m =1) for 1972 – 1989 and with TEDs strata (m = 2) for 1990 -2006. For models with a full year effect and pre-post 1990 time trends, predictions were made for every year. For models without a year effect, the predictions were the same for each year.

The bycatch estimate for year i (C_i) was computed as

$$C_i = \tilde{v}_i \sum_t \tilde{f}_{it} u_{it} \tag{14}$$

where $\tilde{v}_i$ is the nets-per-shrimp-boat in year i and $\tilde{f}_{it}$ is the shrimp boat-hours during year i in strata t (as defined in equation 13). Assuming that the nets-per-shrimp-boat, boat-hours and catch rate are stochastically independent then by definition the variance of the bycatch estimate is

$$\begin{aligned} Var(C_i) = \tilde{v}_i^2 \left\{ \sum_t \left[\tilde{f}_{it}^2 Var(u_{it}) + u_{it}^2 Var(\tilde{f}_{it}) \right] + 2 \sum_{t<x} \sum \tilde{f}_{it} \tilde{f}_{ix} Cov(u_{it}, u_{ix}) \right\} \\ + \left(\sum_t \tilde{f}_{it} u_{it} \right)^2 Var(\tilde{v}_i) \end{aligned} \tag{15}$$

where $Var(u_{it})$ and $Cov(u_{it}, u_{ix})$ are obtained from the ADMB output.

The model with a year effect and without a TED effect is consistent to that used by Nichols (2007). However, a direct blacknose shark bycatch comparison could not be made because we were not certain that the assembled data would exactly match that used by Nichols (2007). Furthermore, the priors used for blacknose shark by Nichols are unknown. Our calibration to the WinBUGS estimates was produced by using WinBUGS and ADMB on the data used for this study and with the prior values implied by Nichols (2007, Appendix red snapper listing).

The alternative models were evaluated through Akaike Information Criteria (AIC) following Burnham and Anderson (2002). Corrections for lack of fit and effective sample were not used in the comparison of models.

Results

Overall, our analyses included data from 30,548 tows made in the Gulf of Mexico (Table 2). About 89% of the tows were designated as research tows. The duration of the observer tows (mean of 6.0 hours) was substantially longer than the research tows (mean of 0.3 hours) with few of the tows capturing one or more blacknose shark (< 0.4%, see Table 2). The total number of tows and mean catch rate by year in the observer and research data are plotted in Figures 1 and 2, respectively. Note that during the 1983 – 1991, 1995 – 2000, and 2003 – 2006 periods no observer tows were gathered because either observer's were not onboard the vessels or sharks were not identified to species. A summary of shrimp trawl effort (nets-per-boat, boat-hours, and net-hours) is provided in Table 3 and a plot of the cumulative effort (net-hours) by year is shown in Figure 3. The standard deviation (SD) values were calculated assuming that nets-per-boat and boat-hours were measured independently.

All model runs with a random effect resulted in estimates of τ (the precision of the random effect) becoming large. As discussed above, this implies that the data do not support a random effect (i.e., the fixed effects explain the variation equally well). Therefore, the results of model runs presented below were computed without a random effect (i.e., equations 4 and 5 removed or set to 0).

The negative binomial distribution can be difficult to optimize because the response surface is flat for parameter values not close to optimal (the problem is said to be "stiff") which results in large steps in trial parameter values that may cause numerical problems. For example, the large number of tows without a blacknose shark implies a dispersal coefficient $r << 1$; however, negative values in r will generate an error. A strategy to deal with this problem is to restrict or bound the parameter values. We used $\log_e(r)$ for the fundamental parameter instead of r directly which ensures $r > 0$. Furthermore, broad bounds were placed on all parameter values. Different initial or starting values were tried within these bounds and the same minimum for the objective function was found regardless of alternative initial values.

Alteration of penalty weights (equations 6 to 12) had little impact (<1%) on the parameter estimates. Similarly, alternative years for partitioning the log-linear time trend segments (1989 orb 1991 instead of 1990) resulted in little change to the bycath estimates.

Comparison between the WinBUGS and ADMB programs (calibration runs) for the estimation of blacknose shark bycatch estimates by year are plotted in Figure 4. The WinBUGS program was run for 16,000 iterations (the standard run length used by Nichols 2007); however, the program reported convergence would require more than 100,000 iterations. Therefore, some change in the WinBUGS results would be expected for further runs of 16,000 iterations. Nevertheless, there is good agreement between the WinBUGS and ADMB results. With the exception of 2004, these series also agree with Nichols (2007). Recently, a single research tow of 23 minutes in 2004 that reported 11 blacknose sharks captured was corrected to one shark captured. After these analyses were completed an additional 78 observer tows in the Modern era (2001-2002) were located and added to our data. For reference, the results (labeled “ADMB – Amended”) using the amended data are also plotted in Figure 4. The amended data were used in all results presented below and produced little change in the bycatch estimates under the calibration setup (with year and without TED effects).

Parameter estimates and the associated SDs for the six alternative models (with and without year, pre-post 1990 time trends, and TED effects) are listed in Table 4. Model comparisons using AIC are provided in Table 5. The criteria selected the pre-post 1990 time trends with a TED model as the best fit to the catch rate data. This model accounts for about 94% of the AIC weighting. The year effect adds almost nothing to fitting the data, i.e., the models with a year effect are less than 1 in 50 million as likely as the time trend models.

Blacknose shark bycatch estimates and the associated SDs by year for the alternative models are listed in Table 6. Plots of the bycatch by year for the models with a year effect are provided by Figure 5, without a year effect by Figure 6 and with the pre-post 1990 time trends in Figure 7. Note that the TED effect increases the bycatch in comparison to the without TED model for the years when TEDs were not used (1972 – 1989) and decreases the bycatch for the years when TEDs were used (1990 – 2006). Shrimp trawl effort (million net-hours) is overlaid in Figure 6 to illustrate that the bycatch estimates are directly proportional to shrimp trawl effort when the model does not contain a year effect. Also, note that the post 1990 bycatch estimates are similar for the without year and time trend models.

Discussion

The primary structural difference between the models operated under WinBUGS and ADMB environments is that the ABMB models lack a random effect to account for the "clumping" of observations within a strata (year, trimester, area, depth and trawl data type) combination. Given that 99.6% of the tows have the same number of blacknose sharks (i.e., 0 catch), it is not surprising that ADMB could not distinguish variance differences within the strata combinations. The similarity of the bycatch estimates from the two environments infers that the random effect is not an important component of the WinBUGS model. We conclude that the blacknose shark bycatch estimation in the ADMB environment can duplicate the results obtained using the WinBUGS program.

The foremost advantage of the ADMB approach is the speed of execution. The ADMB models take less than a minute to run in contrast to a minimum of 12 hours for WinBUGS (time for 16,000 iterations that, while not fully converged, confers an approximate estimate of the bycatch). The mission for ADMB is to find the fundamental parameter values that minimize the objective function, whereas WinBUGS simulates more than 60,000 distributions (two for every tow plus the priors) per iteration. Therefore, the ADMB approach is not an impediment to model development and evaluation.

There are some disadvantages to using ADMB. The user must code the distributional log-densities in C++ and follow some very arcane model structure to allow ADMB to successfully integrate out random effects, whereas WinBUGS only requires specification of the distributions and definition of the model structure is straightforward. More importantly, we calculate the bycatch estimates and the associated SDs outside of ADMB (see equations 14, 15), whereas WinBUGS generates the marginal posterior profile for any quantity of interest.

Corrections for lack of fit and effective sample size were not used in the comparison of models. Since the negative binomial distribution is overdispersed, particularly when r becomes small (Power and Moser 1999), corrections for lark of fit are not required. In our case $r \approx 0.001$ and the distribution is termed hyper-inflated. The effective sample size correction promotes the importance of the difference in the number of parameter values for the purpose of model selection. For the blacknose shark data, the effective sample size is unknown because the observer tows were not a random sample and the research tows are likely correlated because few vessels were used. However, as a rule of thumb, the corrections to AIC are required when the ratio of sample size to the number of parameters is less than 40 (Anderson and Burnham 2002). With over 30,000 tows the sample size can be reduced by a factor of 17 to account for any sampling problems. Other methods for model selection such as Bayesian Information Criteria (BIC) require that the sample size be well defined (Link and Barker 2006). Burnham and Anderson (2004) argue for the application of AIC in this situation and we follow their advice.

The models with a full year effect were shown here and by Rayborn et al. (2009) to be highly over-parameterized for the blacknose shark catch rate data. Alterative models removed the year effect entirely and a less severe option used log-linear time trends pre-post 1990. These year effect modifications provided substantially better fits to the data. Additional improvement may be feasible by the application of higher order spline functions for a piecewise characterization of the catch rate. However, research and observer catch rates may not have a tight year-to-year coincidence and may only share broad trends after corrections for TEDs have been made. The sparseness of the observer data precludes detailed investigation of research and observer correlation. Also consistent with Rayborn at al. (2009), models with TED effects were shown to fit the catch rate data better and to reduce sharpnose shark bycatch estimates.

Of the models evaluated here, only the without year and TED effect model and the pre-post 1990 time trends with a TED effect model are reasonable candidates. Both models yield similar bycatch estimates post 1990 with about a 50% reduction in bycatch over the 1999 – 2005 base period (see Table 6). This occurs because the post 1990 time trend model estimates a slope not significantly different than zero (p_2 = -0.016, SD = 0.014, see Table 4), whereas the without year effect model assumes the line to be horizontal (0 slope). The pre 1990 bycatch estimates, however, are significantly different because the time trend model estimates a decreasing trend (p_1 = -0.133, SD = 0.038). We prefer the pre-post 1990 time trends model because it fits the data better by a 1000:1 margin (see Table 5). The recommended bycatch estimates and associated SDs are plotted in Figure 8.

There is a critical need for additional observer data to be collected concurrent with research data. Our characterization of the TED effect depends upon 1,716 nonrandom observer tows taken in 5 of 17 years since 1990. The last observer tow was made in 2002.

Acknowledgments

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Table 1. Notation used in the negative binomial log-linear model developed to estimate the bycatch of blacknose shark.

Indices:	
h	Tow within a year, trimester, area, depth and dataset
i	Year (i = 1, 2, …, 35)
j	Trimester (j = 1, 2, 3)
k	Area (k = 1, 2, 3, 4)
l	Depth (l = 1, 2)
m	Dataset (m = 1, 2, 3)
t, x	Stratum {$t, x = l + 2[k - 1 + 3(j - 1)]$ } composed of trimester, area and depth
Data and input variables:	
b_τ	Penalty weight (default = 1.75) for the prior precision of the cell random effect
b_μ	Penalty weight (default = 0.5) for the prior mean CPUE
b_y	Penalty weight (default = 0.5) for the prior year coefficient
b_s	Penalty weight (default = 0.5) for the prior trimester coefficient
b_a	Penalty weight (default = 0.1) for the prior area coefficient
b_d	Penalty weight (default = 0.1) for the prior depth coefficient
b_w	Penalty weight (default = 0.5) for the prior dataset coefficient
$\tilde{C}_{ijklm(h)}$	Catch of blacknose shark in tow h taken from year i, trimester j, area k, depth l, and dataset m
$\tilde{f}_{it}$	Shrimp boat-hours during year i in strata t
$Var(\tilde{f}_{it})$	Variance of shrimp boat-hours during year i in strata t
$\tilde{T}_{ijklm(h)}$	Length (hours) of tow h taken from year i, trimester j, area k, depth l, and dataset m
$\tilde{v}_i$	Nets per shrimp boat in year i
$Var(\tilde{v}_i)$	Variance of nets per shrimp boat in year i
Fundamental parameters to be estimated:	
a_k	Coefficient for area k (statistical areas 1-9, 10-12, 13-17, 18-21)
d_l	Coefficient for depth l (inside 10 fathom, outside 10 fathom)
p_1	Coefficient for the time trend 1972 – 1989
p_2	Coefficient for the time trend 1990 – 2006
r	Negative binomial dispersal coefficient
s_j	Coefficient for trimester j (Jan-Apr, May-Aug, Sep-Dec)
w_m	Coefficient for dataset m (observer without TED, observer with TED, research)
y_i	Coefficient for year i (35 years: 1972-2006)
ξ_{ijklm}	Local cluster for year i, trimester j, area k, depth l and dataset m
τ	Precision of the random effect ξ

μ	Mean of log catch rate

Negative log-probability densities:

L	Total joint posterior
L_C	Likelihood of tow catch
L_a	Prior for area
L_d	Prior for depth zone
L_s	Prior for trimester (season)
L_w	Prior for dataset
L_y	Prior for year
L_ξ	Likelihood of local cluster for year *i*, trimester *j*, area *k*, depth *l* and dataset *m*
L_τ	Prior for precision of random effect ξ
L_μ	Prior for mean log of catch rate

Interim variables:

C_i	Predicted bycatch for year i
U_{ijklm}	Predicted log catch rate for year *i*, trimester *j*, area *k*, depth zone *l* and dataset *m*
u_{it}	Predicted catch rate for year *i* and strata *t* used for bycatch of blacknose shark
$Cov(u_{it,}u_{ix})$	Covariance of predicted catch rate for year *i* between strata *t* and *x*
$Var(u_{it})$	Variance of predicted catch rate for year *i* and strata *t*
θ	Predicted catch for tow *h* taken from year *i*, trimester *j*, area *k*, depth zone *l* and dataset *m*

Table 2. Elementary statistics for the catch rate data.

Data Source	Hours Towed	Number of Tows	Number of Tows with blacknose	Blacknose Caught
Research	8,550.3	27,096	97	134.0
Observer				
Historical (1972-82)	11,627.1	1,736	11	68.0
Characterization (1992-94)	7,466.7	1,336	11	13.0
Modern (2001-2002)	1,530.8	380	1	3.6
Total	29,174.9	30,548	120	218.6

Table 3. Shrimp trawl effort by year (millions of boat-hours and net-hours) in the Gulf of Mexico.

Year	Nets·Boat^{-1}	SD(Nets·Boat^{-1})	Boat-hours (millions)	SD(Boat-hrs)	Net-hours (millions)	SD(Net-hrs)
1972	1.870	0.076	4.050	0.068	7.572	0.334
1973	1.882	0.076	3.503	0.060	6.593	0.290
1974	1.873	0.081	3.560	0.056	6.668	0.307
1975	1.884	0.086	2.918	0.049	5.499	0.268
1976	1.955	0.112	3.712	0.061	7.255	0.434
1977	2.141	0.130	4.179	0.074	8.948	0.564
1978	2.263	0.156	4.940	0.085	11.181	0.796
1979	2.373	0.187	5.327	0.100	12.640	1.022
1980	2.436	0.213	4.457	0.085	10.855	0.973
1981	2.471	0.238	4.241	0.009	10.482	1.008
1982	2.489	0.250	4.173	0.010	10.388	1.044
1983	2.460	0.247	4.111	0.014	10.115	1.014
1984	2.425	0.267	4.602	0.014	11.160	1.230
1985	2.423	0.265	4.719	0.012	11.433	1.250
1986	2.416	0.263	5.443	0.015	13.148	1.433
1987	2.507	0.252	5.806	0.019	14.553	1.465
1988	2.521	0.258	4.939	0.016	12.451	1.274
1989	2.549	0.231	5.308	0.020	13.527	1.228
1990	2.611	0.258	5.085	0.019	13.277	1.315
1991	2.767	0.242	5.361	0.019	14.832	1.301
1992	2.670	0.218	5.200	0.019	13.885	1.135
1993	2.668	0.231	4.908	0.019	13.091	1.133
1994	2.668	0.237	4.698	0.023	12.534	1.117
1995	2.847	0.236	4.238	0.015	12.067	1.002
1996	2.961	0.224	4.552	0.016	13.475	1.021
1997	2.954	0.211	4.990	0.017	14.742	1.055
1998	2.838	0.122	5.208	0.020	14.781	0.636
1999	2.973	0.224	4.811	0.018	14.304	1.078
2000	2.994	0.246	4.610	0.017	13.801	1.135
2001	2.991	0.221	4.743	0.020	14.186	1.051
2002	3.100	0.165	4.959	0.024	15.375	0.823
2003	3.100	0.232	4.035	0.015	12.509	0.938
2004	3.100	0.267	3.519	0.012	10.909	0.941
2005	3.100	0.316	2.468	0.009	7.651	0.781
2006	3.100	0.316	2.114	0.007	6.553	0.669

Table 4. Parameter estimates and associated standard deviation by model (parameters defined in Table 1).

	Year & No TED		Year & TED		No Year & No TED		No Year & TED		Time Trnd & No TED		Time Trnd & TED	
Parameter	Est.	SD	Est.	SD	Est.	SD	Est.	SD	Est.	SD	Est.	SD
$\log_e(r)$	-4.519	0.175	-4.507	0.176	-4.933	0.163	-4.870	0.165	-4.880	0.163	-4.782	0.166
μ	-0.087	0.907	-0.174	0.904	-0.041	0.906	-0.130	0.904	0.108	0.908	-0.007	0.905
p_1									-0.132	0.037	-0.133	0.038
p_2									-0.029	0.013	-0.016	0.014
y_1	0.157	0.662	0.138	0.662								
y_2	0.482	0.497	0.454	0.496								
y_3	-0.604	0.534	-0.604	0.534								
y_4	0.765	0.391	0.685	0.399								
y_5	0.042	0.471	-0.016	0.473								
y_6	1.501	0.374	1.382	0.388								
y_7	0.338	0.479	0.184	0.505								
y_8	-0.739	0.782	-0.745	0.780								
y_9	-0.958	0.586	-1.039	0.592								
y_{10}	-0.500	0.560	-0.564	0.565								
y_{11}	-0.857	0.636	-0.888	0.635								
y_{12}	-0.702	0.654	-0.726	0.652								
y_{13}	-1.156	0.708	-1.175	0.705								
y_{14}	-0.837	0.769	-0.846	0.767								
y_{15}	-0.154	0.740	-0.154	0.740								
y_{16}	-0.802	0.792	-0.797	0.792								
y_{17}	-0.824	0.788	-0.818	0.788								
y_{18}	0.272	0.601	0.281	0.601								
y_{19}	-0.195	0.651	-0.193	0.651								
y_{20}	0.222	0.560	0.223	0.559								
y_{21}	0.118	0.485	0.288	0.515								
y_{22}	-0.384	0.492	-0.259	0.508								
y_{23}	-0.161	0.521	-0.063	0.527								
y_{24}	0.572	0.558	0.572	0.558								
y_{25}	0.185	0.592	0.189	0.591								
y_{26}	0.915	0.502	0.928	0.501								
y_{27}	0.005	0.611	0.010	0.611								
y_{28}	0.026	0.611	0.030	0.611								
y_{29}	0.270	0.588	0.281	0.588								
y_{30}	0.461	0.613	0.477	0.614								
y_{31}	-0.144	0.530	-0.049	0.535								
y_{32}	0.965	0.517	0.968	0.516								
y_{33}	0.460	0.583	0.476	0.583								
y_{34}	-0.029	0.718	-0.020	0.717								
y_{35}	0.203	0.640	0.216	0.640								
s_1	-0.373	0.597	-0.344	0.599	-0.438	0.597	-0.401	0.595	-0.309	0.600	-0.185	0.600
s_2	-0.169	0.582	-0.242	0.583	-0.095	0.582	-0.180	0.582	-0.059	0.584	-0.218	0.584
s_3	-0.545	0.581	-0.588	0.581	-0.508	0.581	-0.549	0.580	-0.524	0.581	-0.604	0.581
a_1	-0.755	1.062	-0.799	1.060	-0.806	1.051	-0.782	1.046	-0.599	1.052	-0.631	1.046
a_2	-0.957	1.012	-1.078	1.010	-1.014	1.007	-1.182	1.004	-0.925	1.008	-1.030	1.006
a_3	-1.672	1.004	-1.783	1.001	-1.580	1.003	-1.678	0.999	-1.388	1.005	-1.517	1.001
a_4	-2.050	1.012	-2.211	1.010	-1.804	1.010	-2.008	1.007	-1.549	1.013	-1.857	1.012
d_1	-2.742	1.190	-2.972	1.176	-2.665	1.187	-2.899	1.173	-2.302	1.192	-2.599	1.178
d_2	-2.692	1.185	-2.899	1.172	-2.540	1.182	-2.751	1.168	-2.159	1.188	-2.436	1.174
w_1	-1.443	0.695	-0.689	0.632	-1.249	0.693	-0.316	0.615	-1.262	0.693	-0.096	0.626
w_2	0.356	0.692	-1.314	0.656	0.208	0.691	-1.499	0.631	0.370	0.693	-1.744	0.641
w_3			0.829	0.598			0.685	0.594			0.834	0.595

Table 5. Model comparisons using Akaike information content.
AIC = Akaike Information Criteria, AIF = Akaike Information Factor.

Model	Function	Parameters	AIC	ΔAIC	AIC Weight	AIF
1. Time Trend & TED	860.2	11	1742.3	0.0	0.942	1.000
2. Time Trend & NO TED	864.0	10	1747.9	5.6	0.057	0.061
3. No Year & TED	869.0	9	1756.0	13.7	0.001	0.001
4. No Year & No TED	871.2	8	1758.4	16.1	0.000	<0.001
5. Year & No TED	847.0	42	1778.1	35.8	0.000	<0.001
6. Year & TED	846.9	43	1779.8	37.5	0.000	<0.001

Table 6. Blacknose shark bycatch estimates and associated SDs by year for the alternative models.

	NMFS			WithYear Effect				No Year Effect			Tre
Year	Nichols (2007)	No TED	SD(No TED)	With TED	SD(With TED)	No TED	SD(No TED)	With TED	SD(With TED)	No TED	SD(N
1972	14,921	18,948	13,421	25,320	18,937	25,960	6,447	41,647	13,589	48,419	
1973	15,177	24,130	13,109	32,176	19,118	23,702	5,903	38,596	12,895	38,802	
1974	7,743	8,321	4,897	11,479	7,463	24,034	6,024	39,431	13,328	34,822	
1975	20,404	28,566	11,967	36,562	17,491	20,694	5,323	34,330	11,921	26,046	
1976	13,287	17,458	8,880	22,636	12,548	26,555	6,759	43,396	14,686	29,292	
1977	100,259	91,185	32,832	110,204	44,387	32,309	8,264	52,334	17,581	30,847	
1978	21,472	34,911	16,812	40,808	20,249	39,280	10,145	63,618	21,454	32,917	
1979	13,168	13,111	10,928	17,775	15,473	43,554	11,576	70,893	24,311	32,064	
1980	8,669	9,177	5,659	11,572	7,521	37,728	10,006	61,530	21,236	24,318	
1981	10,194	14,386	8,628	18,385	11,740	37,555	10,051	60,933	21,115	21,233	
1982	7,963	9,634	6,600	12,686	9,150	36,091	9,631	58,167	19,926	17,862	
1983	9,533	11,560	8,176	15,381	11,452	36,373	9,802	59,077	20,521	15,717	
1984	7,285	8,269	6,297	11,043	8,804	40,998	11,118	66,240	23,031	15,461	
1985	9,794	11,224	9,251	15,190	13,071	40,434	11,027	65,624	22,875	13,478	
1986	20,222	24,791	19,787	33,826	28,370	45,774	12,521	74,318	25,892	13,450	
1987	12,131	13,682	11,594	18,592	16,458	48,901	13,277	78,489	26,931	12,591	
1988	10,900	11,825	9,965	16,058	14,143	43,204	11,587	69,048	23,491	9,693	
1989	26,649	39,217	25,793	53,418	37,636	47,310	12,641	75,355	25,433	9,273	
1990	20,081	23,398	16,555	16,871	13,279	45,426	12,240	22,017	8,861	54,837	
1991	37,291	38,886	24,019	28,050	19,848	50,199	13,462	24,403	9,783	59,101	
1992	38,197	33,511	15,902	28,846	14,455	47,879	12,509	23,596	9,239	54,983	
1993	15,514	18,552	9,050	15,281	8,063	43,917	11,622	21,609	8,521	49,174	
1994	27,351	23,287	12,403	18,690	10,763	43,459	11,488	21,481	8,422	47,213	
1995	40,316	50,343	30,881	36,958	25,685	44,431	11,691	22,259	8,612	46,833	
1996	35,295	38,589	25,006	28,580	20,632	50,164	13,258	25,396	9,771	51,635	
1997	58,309	85,555	47,762	63,714	40,852	53,999	14,073	27,126	10,428	53,783	
1998	34,082	36,586	24,292	27,015	19,928	56,848	14,616	28,656	10,922	54,858	
1999	27,461	32,717	21,803	23,940	17,818	50,256	13,213	24,877	9,713	47,134	
2000	31,556	38,935	25,133	28,468	20,687	47,564	12,593	23,269	9,217	43,208	
2001	45,593	48,298	32,300	35,690	26,523	48,604	12,741	23,995	9,389	42,908	
2002	25,400	30,271	16,155	24,315	14,035	55,766	14,465	27,723	10,722	47,778	
2003	54,258	76,850	43,910	55,978	37,088	47,070	12,543	23,287	9,161	39,080	
2004	65,546	39,820	25,546	29,625	21,205	40,288	10,695	20,075	7,833	32,815	
2005	20,568	17,985	13,899	13,303	11,133	29,560	8,094	14,740	5,831	23,362	
2006		18,607	13,017	13,723	10,590	24,152	6,636	11,955	4,763	18,486	
Mean (1999-2005)	38,626	40,697		30,188		45,587		22,567		39,469	
Reduction				25.8%				50.5%			

Figure Legends

Figure 1. Total number of tows by year for shrimp trawls vessels with observers and for research vessels.

Figure 2. Observer and research blacknose shark mean catch rate by shrimp trawls by year.

Figure 3. Shrimp trawl effort (million of net-hours) by year in the Gulf of Mexico. The error bars are plus/minus one standard deviation.

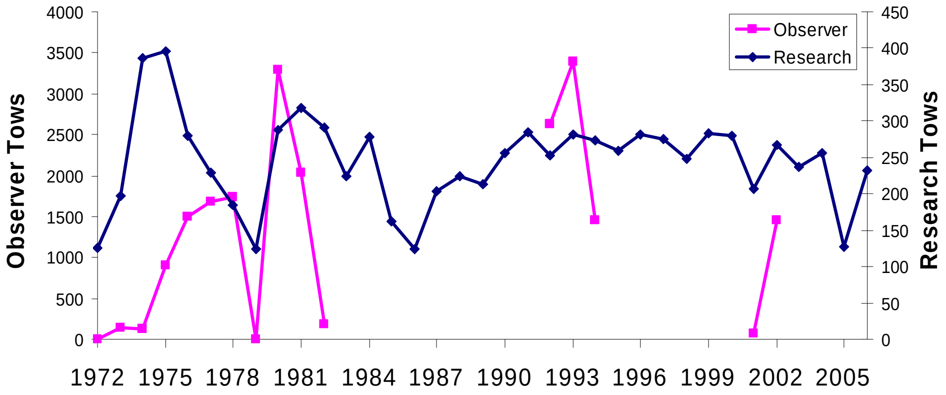
Figure 4. Blacknose shark bycatch estimation using alternative estimation methodologies and data. The Nichols (2007) series is the bycatch used for the SEDAR13 stock assessment. The "WinBUGS" series uses the WinBUGS program on a data series compiled to duplicate that used by Nichols (2007). The "ADMB" series uses the same data with the ADMB program. The "ADMB – Amended" series is the data used for this study with the ADMB program.

Figure 5. Blacknose shark bycatch estimates with a year effect.

Figure 6. Blacknose shark bycatch estimates without a year effect. Annual shrimp trawl effort (million net-hours) is overlaid.

Figure 7. Blacknose shark bycatch estimates with a pre-post 1990 time trends in replacement of the year effect .

Figure 8. Recommended blacknose shark bycatch estimates using the model with pre-post 1990 time trends with a TED effect. The error bars represent plus/minus one standard deviation.



4000
3500
3000
2500
2000
1500
1000
500
0
Observer Tows
450
400
350
300
250
200
150
100
50
0
Research Tows
Observer
Research
1972 1975 1978 1981 1984 1987 1990 1993 1996 1999 2002 2005

Figure 1.

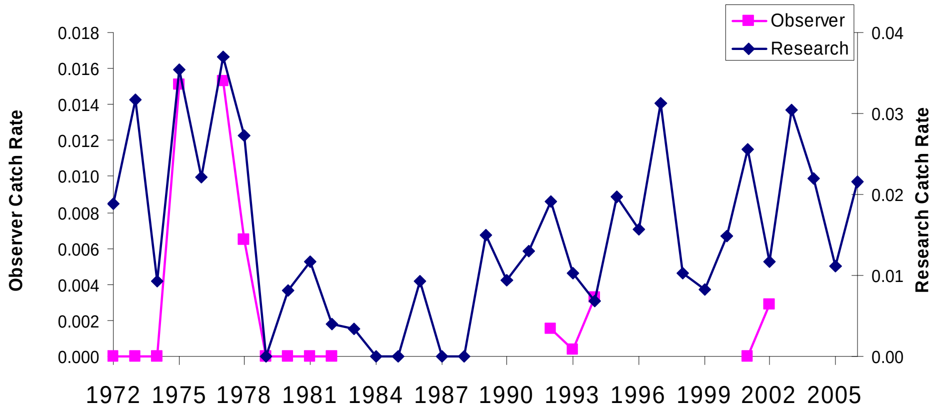

Observer
Research
Observer Catch Rate
Research Catch Rate
0.018
0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0.04
0.03
0.02
0.01
0.00
1972 1975 1978 1981 1984 1987 1990 1993 1996 1999 2002 2005

Figure 2.

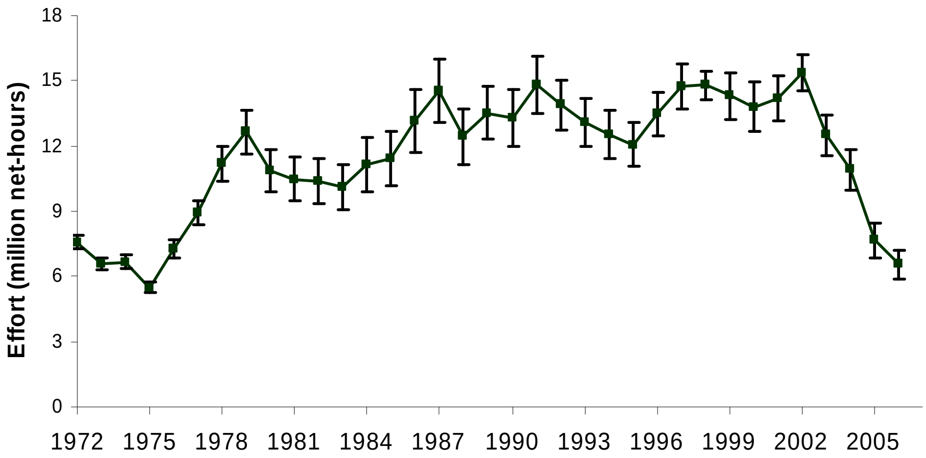
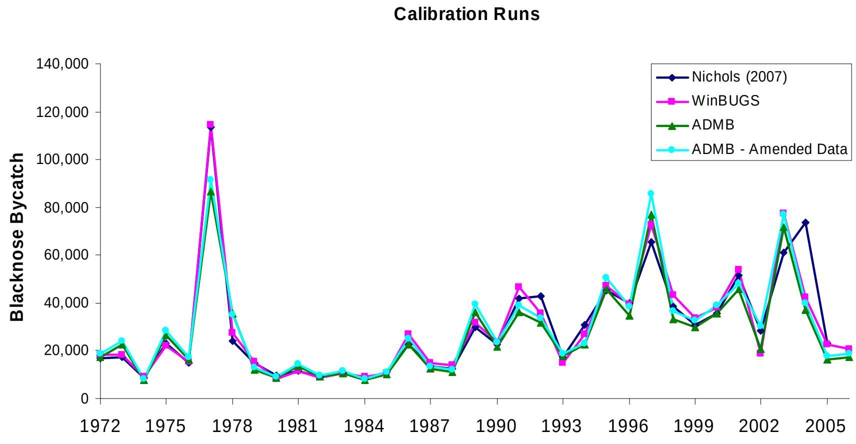

Effort (million net-hours)
0
3
6
9
12
15
18
1972 1975 1978 1981 1984 1987 1990 1993 1996 1999 2002 2005

Figure 3.



Calibration Runs
Blacknose Bycatch
140,000
120,000
100,000
80,000
60,000
40,000
20,000
0
1972
1975
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005
Nichols (2007)
WinBUGS
ADMB
ADMB - Amended Data

Figure 4.

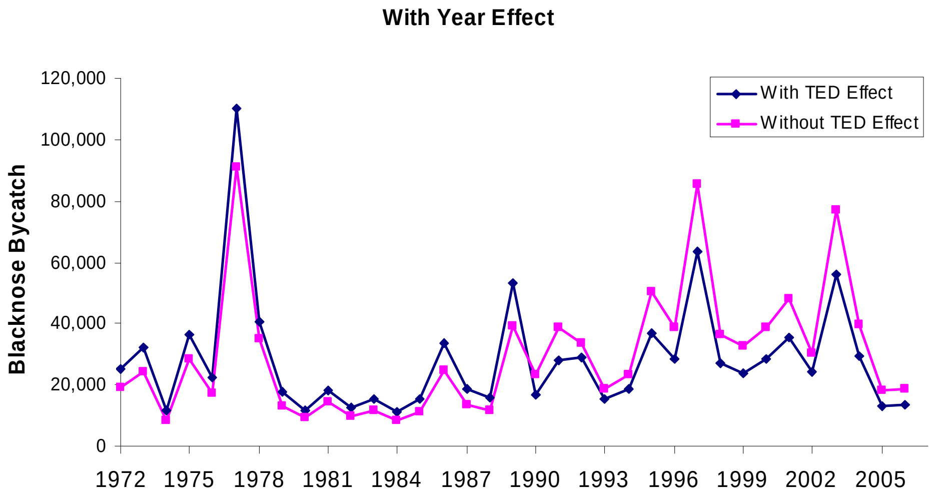

With Year Effect
Blacknose Bycatch
120,000
100,000
80,000
60,000
40,000
20,000
0
1972
1975
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005
With TED Effect
Without TED Effect

Figure 5.

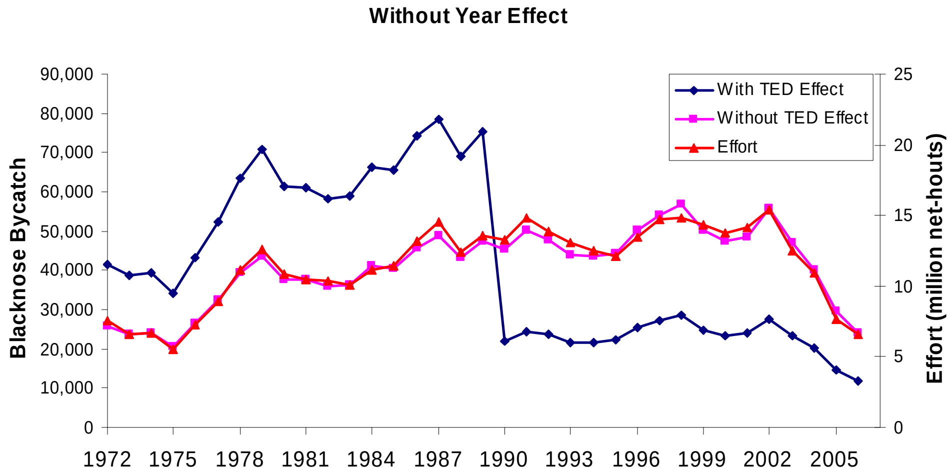

Without Year Effect
Blacknose Bycatch
Effort (million net-houts)
With TED Effect
Without TED Effect
Effort
90,000
80,000
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
25
20
15
10
5
0
1972
1975
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005

Figure 6.

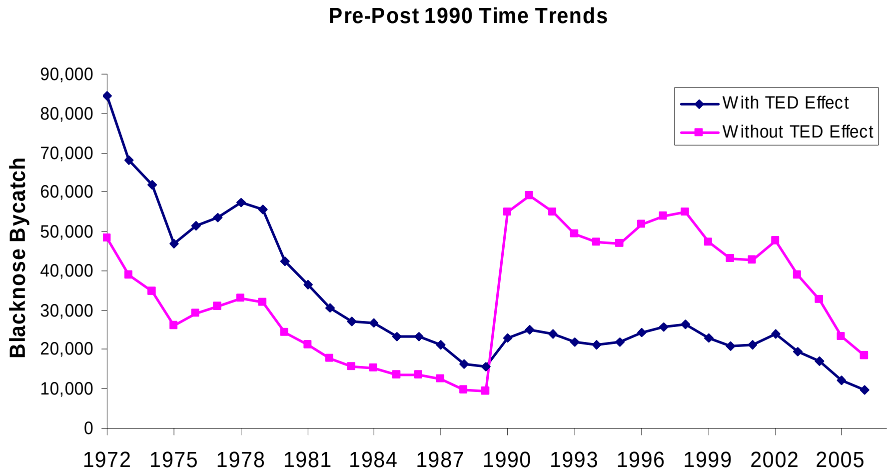

Pre-Post 1990 Time Trends
Blacknose Bycatch
90,000
80,000
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
1972
1975
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005
With TED Effect
Without TED Effect

Figure 7.

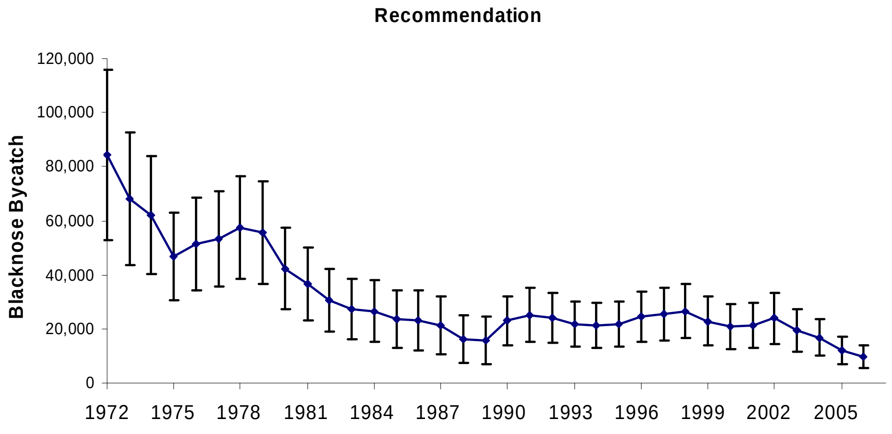

Recommendation
Blacknose Bycatch
120,000
100,000
80,000
60,000
40,000
20,000
0
1972
1975
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005

Figure 8.