A Proposed Assessment and Decision-Making Framework to Inform Scaup Harvest Management

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1. Executive Summary

Pursuant to a request from the Service Regulations Committee (SRC), we synthesized existing monitoring data, developed an assessment framework, and derived a state-dependent harvest strategy to inform scaup harvest management decisions. Within this framework, the harvest strategy prescribes an optimal harvest level given an observed breeding population size and an explicit harvest management objective. In addition, we analyzed historical harvest data to develop predictive, Flyway-specific harvest models and to calculate a Flyway-specific proportional harvest allocation. The Bayesian assessment resulted in an estimate of maximum sustainable yield (MSY) for scaup of 0.389 million birds. We then used the estimates from the Bayesian assessment to generate optimal harvest strategies with stochastic dynamic programming while considering a large number of different models in the optimization. We derived state-dependent harvest strategies for a set of objective functions that ranged from 100 percent of the maximum long-term cumulative harvest to 90% MSY. Given the current status of the scaup population, contemporary scaup harvest estimates exceed the optimal harvest levels specified under each strategy regardless of the objective function used during the optimization. We then characterized possible regulatory alternatives that would be expected to achieve Flyway-specific target harvest levels in relation to a range of optimal, allowable harvest totals. For the 2007 regulations cycle, we propose that this assessment framework be used to calculate an optimal scaup harvest level under an objective to achieve 95% of MSY. The historical harvest allocation would then be used to determine Flyway-specific, allowable harvest levels, and the harvest modeling results would subsequently be used in developing a set of scaup harvest regulations for consideration during this year's regulations cycle.

2. Introduction

The continental scaup (greater *Aythya marila* and lesser *Aythya affinis* combined) population has experienced a long-term decline (Austin *et al.* 2000, Afton and Anderson 2001, Austin *et al.* 2006). As a result, waterfowl managers are challenged with the issue of how to manage the harvest of this declining population in the absence of an objective harvest strategy. In response to this dilemma, the SRC requested that a scaup harvest strategy be developed for the 2007 regulations cycle. Here, we report on the development of a proposed decision-making framework to guide scaup harvest management.

We began this work with the intent to develop a framework based on a formal derived harvest strategy that would enable managers to make an informed decision in relation to scaup harvest management. Our intent for this report is to propose a modeling framework from which

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a harvest strategy can be derived, provide a context for describing the role that scaup harvest management objectives have in structuring the harvest strategy, and to propose a decision-making framework for implementation during the 2007 regulations cycle.

3. Assessment Framework

The lack of scaup demographic information over a sufficient timeframe and at a continental scale precludes the use of a traditional balance equation to represent scaup population and harvest dynamics. As a result, we continue to use a discrete-time, stochastic, implementation of a logistic growth population model with a harvest process to represent changes in scaup according to

$$N_{\mathrm{t}} = (N_{t-1} + rN_{t-1}(1 - N_{t-1}/K) - H_{t-1})e^{\varepsilon_t}. \qquad (2.\ 1)$$

With this formulation, annual changes in population size (N) are governed by the intrinsic rate of increase (r), and the carrying capacity (K), while accounting for losses through the harvest (H) and process error (ε). We use a Bayesian approach (Meyer and Millar 1999, Millar and Meyer 2000) to estimate the population parameters, characterize the uncertainty associated with the monitoring programs (observation error), and the ability of our model to predict actual changes in the system (process error).

In response to feedback from the waterfowl management and research communities, we have incorporated several changes to our original assessment framework (Boomer et al. 2004, Boomer and Johnson 2005). Recent analyses exploring the reliability of the scaup breeding population estimates (Koneff *et al*. unpublished data) have highlighted some significant differences between prairie and bush survey protocols used by observers in the late 1960's that we believe limit the use of the scaup breeding population estimates prior to 1974. As a result, we have truncated the time series of breeding population estimates used in our assessment to only include years from 1974 through 2005. This change also allowed us to represent total scaup harvest levels based on information from both the United States and Canada.

Our initial assessment relied on the critical assumption that the data used to estimate the population parameters were measured on the same absolute scale. Research conducted to model waterfowl populations from different sources of information has provided evidence of bias in waterfowl survey programs (Martin *et al*. 1979, Runge *et al.* 2002). While the source(s) of this bias are not yet known, it is possible to estimate correction factors to reconcile predictions based on disparate sources of information (e.g., USFWS 2006). To address this issue, we chose to include an additional parameter in our assessment to function as a scaling factor that enables us to combine breeding population and harvest estimates in an expression of population change. It is important to note that this term represents the combined limitations and uncertainty of all the monitoring data and functional relationships used in our assessment framework. Although, our initial attempts to estimate a scaling parameter from population and harvest data yielded reasonable estimates, the variance estimates were large. We found that the inclusion of a limited amount of scaup banding and recovery data provided enough information to structure the harvest process and reduce the uncertainty in the scaling parameter estimate. More details regarding this parameterization and the estimation framework can be found in Appendix 1.

4. Assessment Results

The state space formulation and Bayesian analysis framework provided reasonable fits to the observed breeding population and total harvest estimates with realistic measures of variation (Figure 1 A and C). The posterior mean harvest rate estimates ranged from 0.03 to 0.08 (Figure 1 B). In general, harvest rates fluctuated over the first decade and then tracked the declining population trend until the early 1990's, when harvest rate estimates increased significantly before dropping in 1999 (Figure 1 D). The posterior mean estimate of the intrinsic rate of increase (r) is 0.110 while the posterior mean estimate of the carrying capacity (K) is 8.236 million birds (Table 1). The posterior mean estimate of the scaling parameter (q) is 0.541, ranging between 0.461 and 0.630 with 95% probability. Based on the estimated population parameters, the estimated average maximum sustainable yield (MSY) on the adjusted scale is 0.211 million scaup (0.389 million scaup on the observed scale). One of the benefits of a Bayesian approach is that we can perform an equilibrium analysis during the estimation. This results in a realistic representation of the variation in sustainable harvest levels because all forms of uncertainty are accounted for during the simulation. The resulting yield curve depicts the scaled, sustainable harvest levels with wide credibility intervals that highlights the large amount of uncertainty associated with the estimates of scaup harvest potential (Figure 2). Plotting the current observed harvest levels that have been scaled by the mean estimate of q on the yield curve suggests that recent levels of exploitation are approaching or have achieved MSY levels.

5. Derivation of a harvest strategy

The results from the Bayesian analysis provide a reasonable basis for representing scaup population and harvest dynamics. All major forms of uncertainty were considered in the estimation and the resulting population parameter values and their measures of variation can be used to model scaup population changes and responses to exploitation. Because our goal was to develop an informed decision-making framework to provide an objective basis for scaup harvest management, we believe the decision problem must be structured by a derived, state-dependent harvest strategy. With this type of strategy each year's harvest management decision would be based on the current state of the system (e.g., breeding population size). In addition, we also wanted to ensure that the harvest strategy would be adjusted each year in relation to past performance and our current understanding of the system. To meet these demands, we used discrete, stochastic dynamic programming to derive an optimal harvest strategy relative to an agreed upon management objective. This procedure is analogous to the analytical methods currently used to derive an optimal state-dependent harvest strategy for midcontinent mallards under the annual AHM process (Johnson *et al.* 1997, USFWS 2006).

We modeled the state dynamics with the discrete logistic population growth model (equation 3.1), but with the harvest scaled by q, and we included multiplicative random process error that was assumed to be normally distributed with a mean equal to 0 and variance specified with the posterior mean estimate of $\sigma^2_{Process}$. The population parameters r, K, and the scaling factor q were allowed to vary but not independently. To include a correlation structure for these parameters within the optimization, we defined a joint distribution representing 3 discrete outcomes for each of the 3 parameters. This distribution was specified by first calculating the frequency of occurrence of each of the 27 possible combinations of each parameter value based on the simulation results from the Bayesian analysis and then assigning each parameter a discrete

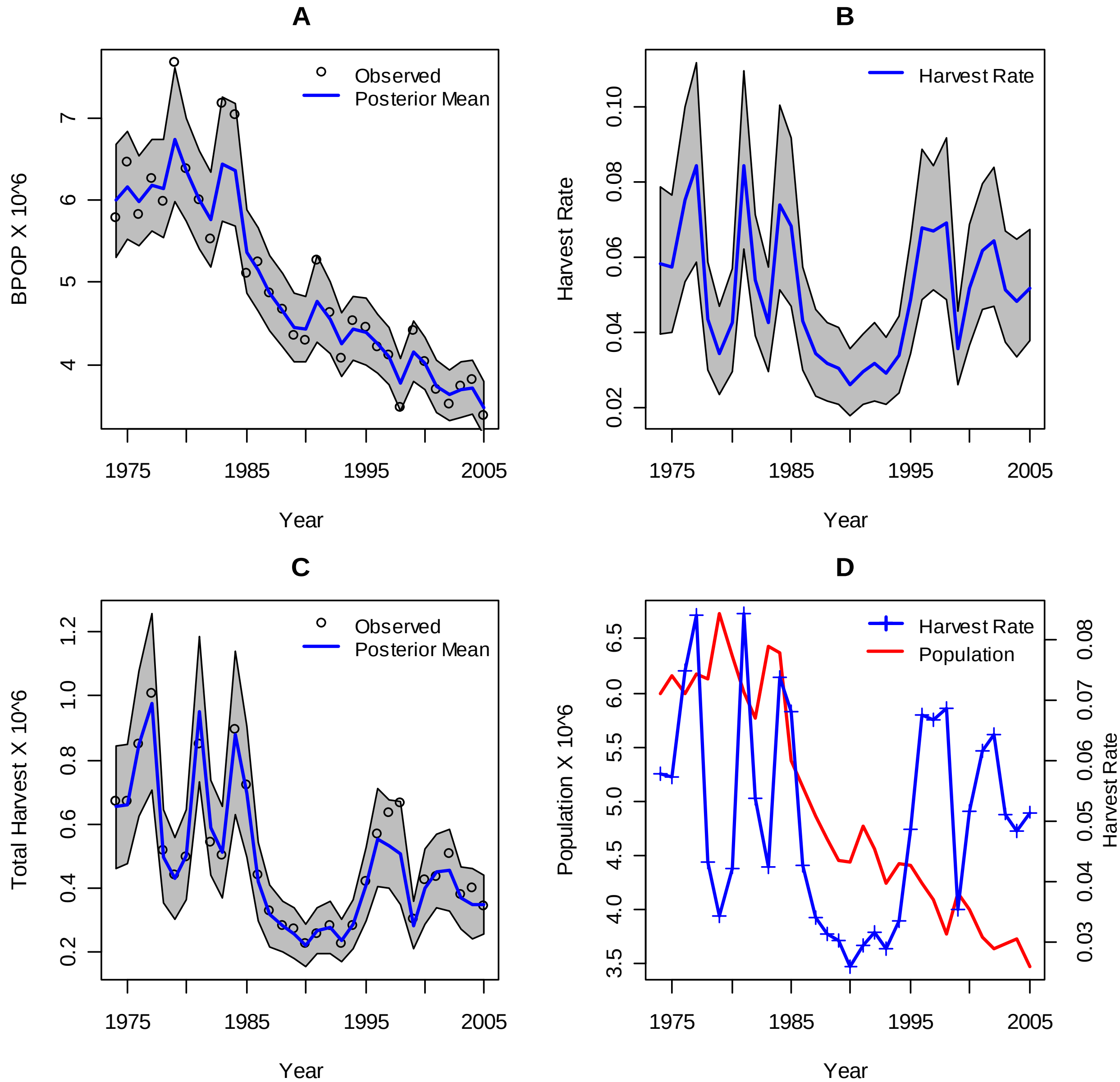

Figure 1 A-D. Population assessment results based on a Bayesian analysis and scaup population and harvest data from 1974-2005. A. The posterior mean population estimates and 95% credibility intervals (gray shading) plotted with the observed breeding population sizes. B. The posterior mean harvest rate estimates and 95% credibility intervals. C. The posterior mean estimates of the U.S. harvest plotted on the observed scale with 95% credibility intervals and observed harvest levels. D. The posterior mean scaup population and harvest rate estimates resulting from the Bayesian analysis.

Table 1. Summary statistics (mean, standard deviation, median and 95% credibility intervals) of the posterior distribution of each population and management parameter resulting from a Bayesian assessment of scaup population and harvest dynamics based on data from 1974 to 2005.					
Parameter	**mean**	**Sd**	**2.50%**	**50%**	**97.50%**
r	0.110	0.063	0.022	0.097	0.271
K (millions)	8.236	1.773	5.727	7.880	12.210
MSY (millions)	0.212	0.097	0.048	0.201	0.437
$\sigma^2_{Process}$	0.008	0.004	0.002	0.007	0.018
PopMSY	4.118	0.886	2.863	3.940	6.105
q	0.541	0.043	0.461	0.539	0.630
MSY (millions)*	0.389	0.171	0.093	0.372	0.784
Deviance	90.926	12.370	68.089	90.415	117.000

*Observed scale.

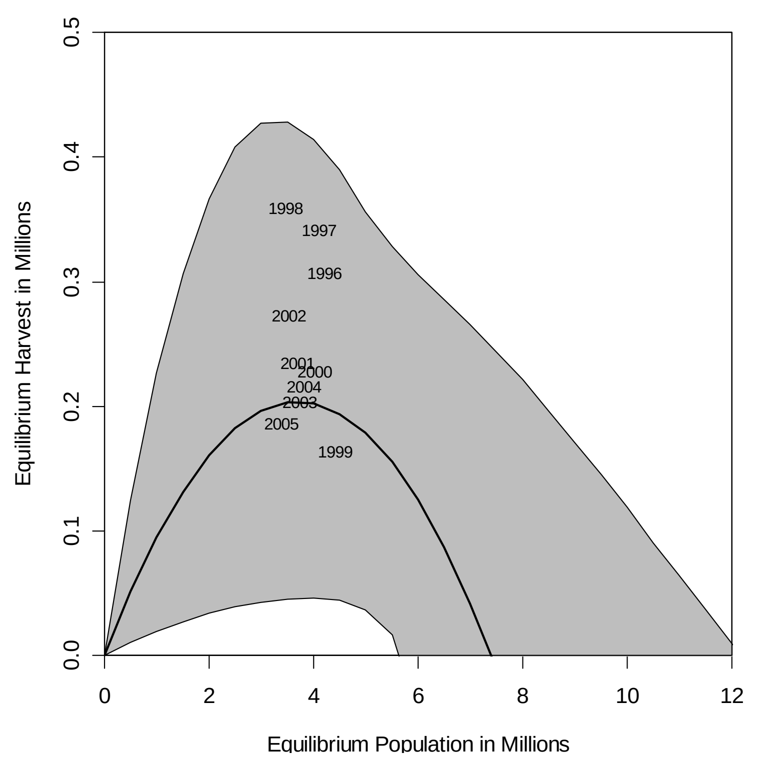

Figure 2. Average sustainable scaup harvest levels and 95% credibility intervals (gray shading) and corresponding equilibrium population sizes estimated with the Bayesian analysis. The years represent the observed breeding population sizes and total harvest levels that have been adjusted with the scaling parameter (*q*).

value for each event. We used the 30 and 70 percent quantiles for each parameter as the cutoff ranges from which to define the three values of each parameter. The midpoint of each of these ranges (15, 50, 85 percent quantiles) were then used as the actual parameter values in the optimization. It is important to note that the use of this joint distribution allowed us to represent multiple models during the optimization with each model weighted by the available evidence resulting from the Bayesian estimation.

We used ASDP software (Lubow 1995) to derive a state-dependent harvest strategy under an objective to maximize long-term cumulative harvest (MSY) and an objective to attain a shoulder point (calculated as percentage of MSY) on the yield curve. We evaluated harvest levels from 0 to 5 million (in increments of 50,000) for population sizes of 1 to 10 million (in increments of 50,000) and harvest objectives ranging from 90 to 100% MSY (in 2 % increments). For each optimization we assumed perfect control over the harvest decision variable. We then simulated each strategy for 5000 iterations to characterize the management performance expected if the harvest strategy was followed and the system remained static.

Under an objective to maximize long-term cumulative harvest (MSY) the resulting strategy is extremely knife-edged (Figure 3). This strategy prescribes zero harvests for population sizes less than 3.2 million and seeks to hold the population size at maximum productivity (one half the carrying capacity). In contrast to the MSY strategy, the harvest strategies necessary to achieve a shoulder point are considerably less knife-edged and would allow for harvest at lower population sizes (see Figure 3). However, current scaup harvest levels (317,000) exceed the prescribed harvests resulting from optimizations with each of the objective functions we evaluated. The simulated management performance of each harvest strategy demonstrates the tradeoffs that arise when a shoulder point objective is used to derive an optimal harvest strategy. As the desired shoulder point moves away from MSY, average harvest levels decrease while the average population increases (Table 2).

6. Scaup Harvest Prediction and Allocation

A predictive relationship between regulations and scaup harvest is required to determine a set of possible regulatory alternatives necessary to achieve the target harvest levels specified under the derived harvest strategy. As a result, we used historical information and simple linear regression to model scaup harvest as a function of Flyway-specific regulations. The details of this analysis, our model selections, and an exemplar set of harvest predictions are presented in Appendix 2. The regression analyses resulted in a set of Flyway-specific models to predict scaup harvest as a function of season length and bag limits (Table 3). The prediction errors associated with these models are large (e.g., see Figure 2.2) due to the limited contrast in the data sets and relatively short time series. Moreover, harvest predictions over combinations of season lengths and bag limits for which we have no experience should be evaluated with extreme caution. The resulting harvest models provide a means to predict the expected scaup harvest as a function of Flyway-specific regulations. However, these predictions must be evaluated in relation to the target harvest levels specified by the harvest strategy and the distribution of the expected harvest across each Flyway. A proportion of the allowable harvest specified under the state dependent harvest strategy must be allocated to each Flyway. These allocations would then be compared to the harvest levels predicted from the harvest models to determine the set of Flyway-specific regulatory alternatives that would be necessary to achieve the total allowable scaup harvest for

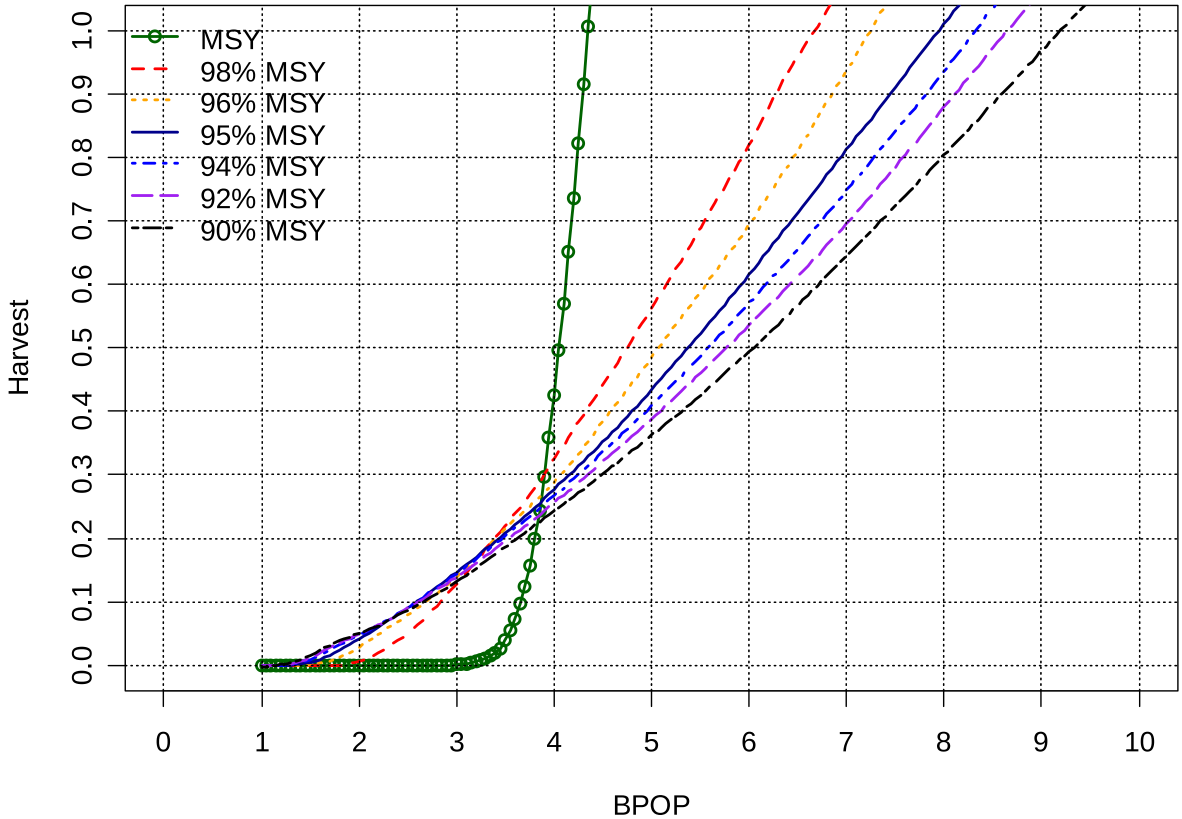

Figure 3. Optimal scaup harvest levels (observed scale in millions) as a function of the observed breeding population size derived under objective functions ranging from 100 to 90 percent of MSY.

Table 2. Summary statistics of simulated harvest strategies derived under objective functions chosen as a percentage of MSY. The average of the simulated population and harvest levels are displayed along with the frequency of prescribed optimal harvest levels (in millions).

	Average		Expected frequency of harvest levels			
% MSY	N	H	H = 0	H ≤ 0.1	0.1 < H ≤ 0.3	H >0.3
100	3.893	0.388	22.98	21.55	14.82	40.65
98	4.219	0.380	0.04	2.90	40.41	56.65
96	4.404	0.374	0.00	1.94	42.80	55.27
95	4.559	0.367	0.00	1.47	44.65	53.88
94	4.648	0.363	0.00	1.35	45.67	52.98
92	4.746	0.358	0.00	1.18	44.57	54.24
90	4.866	0.351	0.00	1.27	47.57	51.16

Table 3. Flyway-specific proportional allocation of allowable harvest in the U.S. (excluding Alaska) and regression models to predict scaup harvest levels (H in millions) as a function of Flyway-specific regulations (e.g., *Days, Bag, and HIP*).

Flyway	Allocation	Harvest Model
Atlantic	0.19	$H = -0.0308336 + 0.0017935\ Days$
Mississippi	0.52	$H = -0.1663336 + 0.0025277\ Days + 0.0612130\ Bag$
Central	0.17	$H = -0.0767054 + 0.0013297\ Days + 0.0157356\ Bag$
Pacific	0.12	$H = -2.165e{-}02 + 3.544e{-}04\ Days + 4.776e{-}03\ Bag + 1.698e{-}02\ HIP$

each Flyway's allocation. We chose to use the same data from the harvest modeling analyses (see Appendix 3), to calculate the average percentage of the total scaup harvest in the US (excluding Alaska) taken from each Flyway (AF = 0.19, MF = 0.52, CF = 0.17, PF = 0.12; see Table 3). For the purposes of determining Flyway-specific regulatory alternatives to achieve an allowable, US, scaup harvest, we chose to use a constant value of 0.04 million to represent scaup harvested in Canada and Alaska. Due to the decreasing trend in Canadian scaup harvest levels, we based this value on the latest 5 year mean.

7. Proposed Implementation

The implementation of this framework requires a clearly articulated objective for scaup harvest management. We propose that this objective should seek to achieve 95% of MSY. This point on the right hand shoulder of the yield curve represents a small tradeoff between lower allowable harvest levels with the expectation of larger population sizes (see Table 2). This objective also limits the knife-edge behavior associated with an objective of MSY, allowing harvest opportunity when breeding populations are smaller than K/2. Given this objective function and an observed breeding population size of 3.25 million, the optimal harvest level is 0.150 million birds (Table 4).

We used the Flyway-specific harvest models with different combinations of season lengths and bag limits to predict a set of Flyway-specific harvests. We then compared these expected results to Flyway-specific harvest allocations for a range of allowable, total harvests (Table 5). For this year's regulations cycle, we propose that these results be used as a guide as the Service works with the Flyways to consider appropriate regulatory alternatives in relation to the allowable harvest specified under the optimal harvest strategy. From an operational standpoint, we acknowledge that this process is not ideal because it would possibly require the consideration of a different set of regulations each year. In addition, we fully recognize that the regulatory alternatives suggested by this analysis are based on harvest predictions that include large amounts of uncertainty and in some cases represent extrapolation beyond the range of the historical data. For example, because we have no experience with a one bird bag, it may be appropriate to consider the possibility of allowing Flyways the option of a one-bird bag and a restricted season length, when the models predict harvests that exceed the allowable harvest levels. This would allow some harvest opportunity and the ability to gain experience with a one bird bag limit.

Table 4. Optimal scaup harvest levels (observed scale in millions) and corresponding breeding population sizes (in millions) derived under an objective to achieve 95% of maximum long term cumulative harvest.

Breeding Population	Optimal Harvest
1.0	0
1.25	0
1.5	0
1.75	0
2.0	0.05
2.25	0.05
2.5	0.10
2.75	0.10
3.0	0.15
3.25	0.15
3.5	0.20
3.75	0.25
4.0	0.25
4.25	0.30
4.5	0.35
4.75	0.40
5.0	0.40

Table 5. Possible regulatory alternatives that would approach Flyway-specific target harvest levels for total allowable harvests of 0.100, 0.200, and 0.300 million. The harvest predictions (H_{pred}, in millions) were calculated with the Flyway-specific harvest models.

Total Allowable Harvest = 0.100 million birds

Atlantic			Mississippi			Central			Pacific		
Target Harvest: 0.0186			Target Harvest: 0.052			Target Harvest: 0.0173			Target Harvest: 0.012		
SL	Bag	H_{pred}	SL	Bag	H_{pred}	SL	Bag	H_{pred}	SL	Bag	H_{pred}
20	3	0.005	60	1	0.047	60	1	0.019	38	1	0.014
			30	2	0.032	39	2	0.007			

Total Allowable Harvest = 0.200 million birds

Atlantic			Mississippi			Central			Pacific		
Target Harvest: 0.037			Target Harvest: 0.104			Target Harvest: 0.035			Target Harvest: 0.024		
SL	Bag	H_{pred}	SL	Bag	H_{pred}	SL	Bag	H_{pred}	SL	Bag	H_{pred}
30	3	0.023	30	3	0.093	60	2	0.035	38	3	0.023
			60	1	0.047	39	3	0.022	60	1	0.021

Total Allowable Harvest = 0.300 million birds

Atlantic			Mississippi			Central			Pacific		
Target Harvest: 0.056			Target Harvest: 0.156			Target Harvest: 0.052			Target Harvest: 0.036		
SL	Bag	H_{pred}	SL	Bag	H_{pred}	SL	Bag	H_{pred}	SL	Bag	H_{pred}
45	3	0.050	45	3	0.131	60	3	0.050	107	1	0.038
			60	2	0.108	74	1	0.037	86	2	0.035

SL = season length;
Bag = bag limit;

The Service plans to continue to work with the Flyways to determine an acceptable set of regulatory alternatives that would be used as a decision variable in the optimization that is used to derive an optimal harvest strategy. Under this scenario, the derived, state-dependent harvest strategy would specify an optimal set of regulatory alternatives. Considerable feedback from the Flyways will be required to develop these packages in relation to the results from the harvest models.

We suggest that the proposed estimation and optimization framework be used to derive a state-dependent harvest strategy to determine the optimal harvest level for scaup for the 2007 regulations cycle. The harvest models would then be used as a guide to determine a set of scaup harvest regulations for this year's hunting season. This would serve as a stopgap procedure until an agreed upon set of regulatory alternatives can be used as the decision variable in the formal derivation of a scaup harvest strategy. We also believe that a harvest strategy should be derived on an annual basis with updated parameter estimates and harvest models as information and experience accrues over time. This annual process would ensure that the harvest strategy is consistent in relation to current observations from the monitoring programs and that all available information has been used to update the model of the system.

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Appendix 1. Modeling and Estimation Framework
We use a state-space formulation of scaup population and harvest dynamics within a Bayesian estimation framework (Meyer and Millar 1999, Millar and Meyer 2000). This analytical framework allows us to represent uncertainty associated with the monitoring programs (observation error) and the ability of our model formulation to predict actual changes in the system (process error).

8.1 Process Model

Given a logistic growth population model that includes harvest (Schaefer 1954), scaup population and harvest dynamics are calculated as a function of the intrinsic rate of increase (*r*), the carrying capacity (*K*), along with the harvest (H_t). Following Meyer and Millar (1999), we scaled population sizes by *K* (i.e., $P_t = N_t/K$) and assumed that process errors (ε_t) are lognormally distributed with a mean of 0 and variance $\sigma^2_{Process}$. The state dynamics can be expressed as

$$P_{1974} = P_0 \, e^{\varepsilon_{1974}} \tag{8.1.1}$$

$$P_t = \left(P_{t-1} + rP_{t-1}(1 - P_{t-1}) - H_{t-1} / K\right)e^{\varepsilon_t}, \mathrm{t} = 1975,...,2005, \tag{8.1.2}$$

where P_0 is the initial ratio of population size to carrying capacity. To predict total scaup harvest levels, we modeled scaup harvest rates (h_t) as a function of the pooled direct recovery rate (f_t) observed each year with

$$h_t = f_t / \lambda_t. \tag{8.1.3}$$

We specified reporting rate (λ_t) distributions based on estimates for mallards (*Anas platyrhynchos*) from large scale historical and existing reward banding studies (Henny and Burham 1972, Nichols *et. al*. 1995, Garrettson et al. *unpublished data*). We accounted for increases in reporting rate believed to be associated with changes in band type (e.g., from AVISE and new address bands to 1-800 toll free bands) by specifying year specific reporting rates according to

$$\lambda_t \sim Normal(0.38, 0.04) \quad t = 1974,...,1996 \tag{8.1.4}$$

$$\lambda_t \sim Normal(0.70, 0.04) \quad t = 1997,...,2005. \tag{8.1.5}$$

We then predicted total scaup harvest (H_t) with

$$H_t = h_t\left[P_t + rP_t(1 - P)\right]K, \mathrm{t} = 1974,...,2005. \tag{8.1.6}$$

8.2 Observation Model

We compared our predictions of population and harvest numbers from our process model to the observations collected by the Waterfowl and Breeding Habitat Survey (WBPHS) and the Harvest Survey programs with the following relationships, assuming that the population and harvest observation errors were additive and normally distributed. May breeding population estimates were related to model predictions by

$$
\begin{aligned}
&N_t^{Observed} - P_t K = \varepsilon_t^{BPOP}, \text{where} \\
&\varepsilon_t^{BPOP} \sim N(0, \sigma_{t,BPOP}^2), t = 1974,...,2005,
\end{aligned}
\tag{8.2.1}
$$

where $\sigma_{t,BPOP}^2$ is specified for each year with the variance estimates resulting from the WBPHS.

We adjusted our harvest predictions to the observed harvest data estimates with a scaling parameter (q) according to

$$
\begin{aligned}
&H_t^{Observed} - \left(h_t\left[P_t + rP_t(1-P)\right]K\right)/q = \varepsilon_t^H, \mathrm{t} = 1974,...,2005, \text{ where} \\
&\varepsilon_t^H \sim N(0, \sigma_{t,Harvest}^2).
\end{aligned}
\tag{8.2.2}
$$

We assumed that appropriate measures of the harvest observation error $\sigma_{t,Harvest}^2$ could be approximated by assuming a coefficient of variation for each annual harvest estimate equal to 0.15 (Paul Padding *pers. comm.*). The final component of the likelihood included the year specific direct recovery rates that were represented by the rate parameter (f_t) of a Binomial distribution indexed by the total number of birds banded preseason and estimated with.

$$
\begin{aligned}
&f_t = m_t / M_t, \\
&m_t \sim Binomial(M_t, f_t)
\end{aligned}
\tag{8.2.3}
$$

where m_t is the total number of scaup banded preseason in year t and recovered during the hunting season in year t and M_t is the total number of scaup banded preseason in year t.

8.3 Bayesian Analysis

Following Meyer and Millar (1999), we developed a fully conditional joint probability model, by first proposing prior distributions for all model parameters and unobserved system states and secondly by developing a fully conditional likelihood for each sampling distribution.

Prior Distributions

For this analysis, a joint prior distribution is required because the unknown system states P are assumed to be conditionally independent (Meyer and Millar 1999). This leads to the following joint prior distribution for the model parameters and unobserved system states

$$
\begin{aligned}
&P(r, K, q, f_t, \lambda_t, \sigma_{process}^2, P_0, P_{1,...,T}) \\
&= p(r)p(K)p(q)p(f_t)p(\lambda_t)p(\sigma_{\text{Process}}^2)p(P_0)p(P_1 \mid P_0, \sigma_{\text{Process}}^2) \times \prod_{t=2}^{n} p(P_t \mid P_{t-1}, r, K, f_{t-1}, \lambda_{t-1}, \sigma_{\text{Process}}^2).
\end{aligned}
\tag{8.3.1}
$$

In general, we chose non-informative priors to represent the uncertainty we have in specifying the value of the parameters used in our assessment. However, we were required to use existing information to specify informative priors for the initial ratio of population size to carrying capacity (P_0) as well as the reporting rate values (λ_t) specified above that were used to adjust the direct recovery rates estimates to harvest rates.

We specified that the value of P_0, ranged from the population size at maximum sustained yield ($P_0 = N_{MSY}/K = (K/2)/K = 0.5$) to the carrying capacity ($P_0 = N/K = 1$), using a uniform distribution on the log scale to represent this range of values. We assumed that the exploitation experienced at this population state was somewhere on the right-hand shoulder of a sustained yield curve (i.e., between MSY and *K*). Given that we have very little evidence to suggest that historical scaup harvest levels were limiting scaup population growth, this seems like a reasonable prior distribution.

We used non-informative prior distributions to represent the variance and scaling terms, while the priors for the population parameters *r* and *K* were chosen to be vague but within biological bounds. These distributions were specified according to

$$P_0 \sim Uniform(\ln(0.5),0), \tag{8.3.2}$$

$$K \sim Lognormal\,(2.17,\, 0.667), \tag{8.3.3}$$

$$r \sim Uniform\,(0.00001,\, 2), \tag{8.3.4}$$

$$f_t \sim Beta(0.5,0.5), \tag{8.3.5}$$

$$q \sim Uniform(0.0,\, 2), \tag{8.3.6}$$

$$\sigma^2_{Process} \sim Inverse\ Gamma\,(0.001,\, 0.001). \tag{8.3.7}$$

Likelihood

We related the observed population, total harvest estimates, and observed direct recoveries to the model parameters and unobserved system states with the following likelihood function:

$$\begin{aligned} &P(N_{1,\dots,T}, H_{1,\dots,T}, m_{1,\dots,T}, M_{1,\dots,T} \mid r, K, f_t, \lambda_t, q, \sigma^2_{process}, \sigma^2_{Harvest}, P_{1,\dots,T}) \\ &= \prod_{t=1}^{T} p(N_t \mid P_t, K, \sigma^2_{BPOP}) \times \prod_{t=1}^{T} p(H_t \mid P_t, r, K, f_t, \lambda_t, q, \sigma^2_{Harvest}) \times \prod_{t=1}^{T} p(m_t \mid M_t, f_t). \end{aligned} \tag{8.3.8}$$

Posterior Evaluation

Using Bayes theorem we then specified a posterior distribution for the fully conditional joint probability distribution of the parameters given the observed information according to

$$P(r,K,q,f_t,\lambda_t,\sigma^2_{process},P_0,P_{1,\dots,T}\mid N_{1,\dots,T},H_{1,\dots,T},m_{1,\dots,T},M_{1,\dots,T})$$

$$\propto p(r)p(K)p(q)p(f_t)p(\lambda_t)p(\sigma^2_{\text{Process}})p(P_0)p(P_1\mid P_0,\sigma^2_{\text{Process}})\times\prod_{t=2}^{n}p(P_t\mid P_{t-1},r,K,f_{t-1},\lambda_{t-1},\sigma^2_{\text{Process}}) \quad (8.3.9)$$

$$\times\prod_{t=1}^{T}p(N_t\mid P_t,K,\sigma^2_{BPOP})\times\prod_{t=1}^{T}p(H_t\mid P_t,r,K,q,f_t,\lambda_t,\sigma^2_{Harvest})\times\prod_{t=1}^{T}p(m_t\mid M_t,f_t,).$$

We used Markov Chain Monte Carlo (MCMC) methods to evaluate the posterior distribution using WinBUGS (Spiegelhalter et al. 2003). We randomly generated initial values and simulated 5 independent chains each with 1,000,000 iterations. We discarded the first half of the simulation and thinned each chain by 250, yielding a sample of 10,000 points. We calculated Gelman-Rubin statistics (Brooks and Gelman 1998) to monitor for lack of convergence.

Literature Cited in Appendix 1.

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Appendix 2. Harvest Model Development

An evaluation of historical scaup harvest regulations is complicated by the annual variation in individual state selections of scaup regulatory options from the late 1960s through the late 1980's. Over this time period, individual states had a range of regulatory alternatives to manage scaup harvest opportunity, including bonus bag limits, bonus seasons, or a range of point values under the Point System. Because individual state selections of these regulatory alternatives were not consistent over time or across Flyways, the development of models that predict scaup harvest at the Flyway scale is problematic. As a result, harvest data observed under these regulatory options were not considered during model development. The availability of scaup bonus bag limits or bonus season lengths was suspended during the regulations cycle in 1988. Therefore, harvest information from 1988 through 2005 formed the basis for the development of scaup harvest models as a function of Flyway-specific, historical scaup harvest regulations. Scaup harvest from each Flyway was modeled as a function of season length and bag limit information. Indicator variables were used to distinguish harvest data collected under the Mail Questionnaire Survey (MQS) and the Harvest Information Program (HIP).

Atlantic Flyway

The addition of bag limit information in a model that already included season length was not significant. As a result, scaup harvest in the Atlantic Flyway was modeled as a linear function of season length (Table 1). This model explains 59% of the variation in historical scaup harvests. The resulting model to predict scaup harvest (H) in the Atlantic Flyway is:

$$H = -0.0308336 + 0.0017935\ Days \qquad (2.2)$$

where Days is the season length. Predictions with this model based on a range of season lengths are depicted in Figure 1.

Table 2.1. The results from fitting a linear model that predicts the scaup harvest in the Atlantic Flyway as a function of season length (Days).

Atlantic Flyway: Harvest ~ Days

```
lm(formula = Harvest ~ Days, data = af)
Residuals:
      Min        1Q    Median        3Q       Max
-0.031596 -0.011388 -0.002530  0.006568  0.042965

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0308336  0.0168122  -1.834   0.0824 .
Days         0.0017935  0.0003279   5.469 2.82e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.01993 on 19 degrees of freedom
Multiple R-Squared: 0.6116,     Adjusted R-squared: 0.5911
F-statistic: 29.91 on 1 and 19 DF,  p-value: 2.817e-05

Analysis of Variance Table
Response: Harvest
          Df    Sum Sq   Mean Sq F value    Pr(>F)
Days       1 0.0118863 0.0118863  29.914 2.817e-05 ***
Residuals 19 0.0075496 0.0003973
```

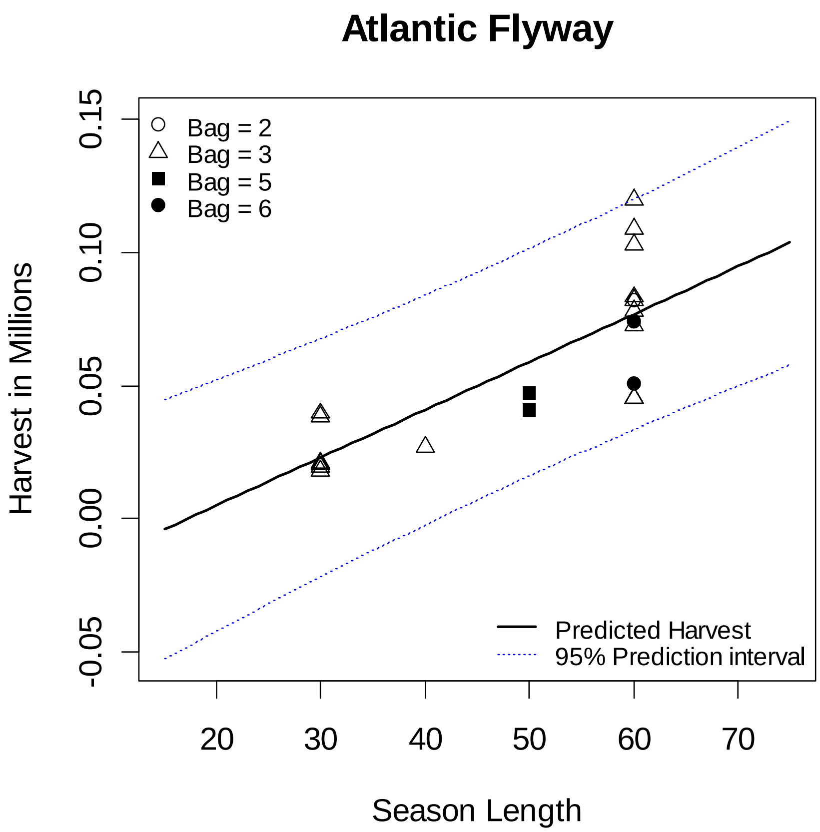

Figure 2.1. Observed Atlantic Flyway scaup harvest (1988-2005) and predicted harvest calculated as a function of season length.

Mississippi Flyway

A plot of Mississippi harvest data as a function of historical regulations suggests a direct relationship between large harvests with longer season lengths and higher bag limits (Figure 2.2). The full model that included an interaction term between season length and bag limit was not significant. As a result, the model used to predict Mississippi harvest included a linear effect of season length and bag limit information. This model explains 78% of the variation in scaup harvest (Table 2). The resulting model to predict scaup harvest in the Mississippi Flyway is:

$$H = -0.1663336 + 0.0025277\ Days + 0.0612130\ Bag \qquad (2.3)$$

where Days is the season length and Bag is the bag limit. Predictions calculated with this model evaluated over a range of season lengths and bag limits are shown in Figure 2.2.

Table 2.2. The results from fitting a linear model that predicts the scaup harvest in the Mississippi Flyway as a function of season length (Days) and bag limit (Bag).

Mississippi Flyway: Harvest ~ Days + Bag

```
lm(formula = Harvest ~ Days + Bag, data = mf)
Residuals:
      Min        1Q    Median        3Q       Max
-0.079013 -0.018086 -0.001584  0.032055  0.053650

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.1663336  0.0426653  -3.899  0.00105 **
Days         0.0025277  0.0007011   3.605  0.00202 **
Bag          0.0612130  0.0088597   6.909 1.85e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04188 on 18 degrees of freedom
Multiple R-Squared: 0.8011,     Adjusted R-squared: 0.779
F-statistic: 36.24 on 2 and 18 DF,  p-value: 4.881e-07

Analysis of Variance Table
Response: Harvest
          Df   Sum Sq  Mean Sq F value    Pr(>F)
Days       1 0.043398 0.043398  24.743 9.818e-05 ***
Bag        1 0.083729 0.083729  47.737 1.850e-06 ***
Residuals 18 0.031572 0.001754
```

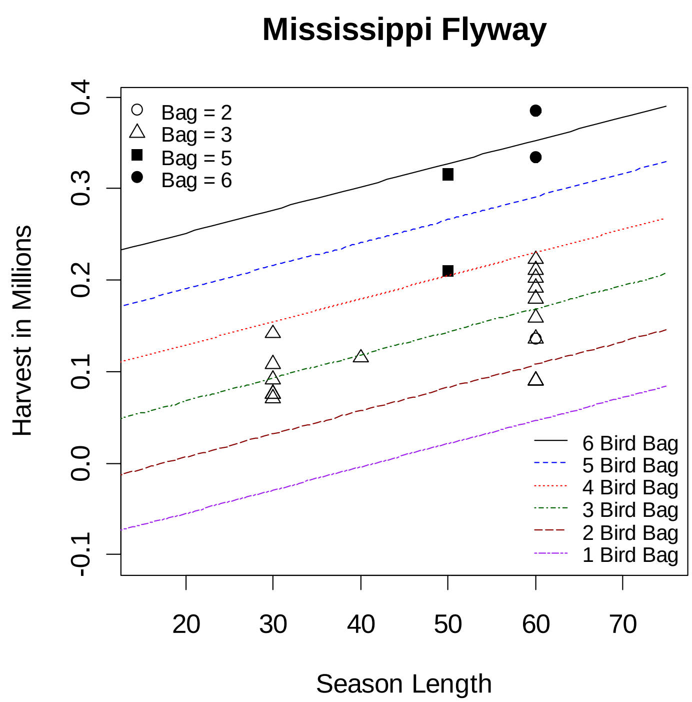

Figure 2.2. Observed Mississippi scaup harvest (1988-2005) and predictions calculated as a function of season length and bag limit based on the Mississippi harvest model.

Central Flyway

A plot of Central Flyway harvest data and historical regulations also suggests a direct relationship between increases in harvest levels with longer season lengths and higher bag limits (Figure 2.3). The full model that included an interaction term between season length and bag limit was not significant. As a result, the model used to predict Central Flyway harvest included a linear effect of season length and bag limit information. This model explains 67% of the variation in scaup harvest (Table 2.3). The resulting model to predict scaup harvest in the Central Flyway is:

$$H = -0.0767054 + 0.0013297\ Days + 0.0157356\ Bag \qquad (2.4)$$

where Days is the season length and Bag is the bag limit. Predictions based on this model evaluated over a range of season lengths and bag limits are shown in Figure 3.

Table 2.3. The results from fitting a linear model that predicts the scaup harvest in the Central Flyway as a function of season length (Days) and bag limit (Bag).

Central Flyway: Harvest ~ Days + Bag

```
lm(formula = Harvest ~ Days + Bag, data = cf)
Residuals:
      Min        1Q    Median        3Q       Max
-0.038246 -0.005688  0.002054  0.011902  0.038659
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0767054  0.0214515  -3.576 0.002161 **
Days         0.0013297  0.0002877   4.621 0.000212 ***
Bag          0.0157356  0.0042602   3.694 0.001662 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02021 on 18 degrees of freedom
Multiple R-Squared: 0.699,      Adjusted R-squared: 0.6655
F-statistic:  20.9 on 2 and 18 DF,  p-value: 2.030e-05

Analysis of Variance Table
Response: Harvest
          Df    Sum Sq   Mean Sq F value    Pr(>F)
Days       1 0.0115001 0.0115001  28.151 4.813e-05 ***
Bag        1 0.0055734 0.0055734  13.643  0.001662 **
Residuals 18 0.0073533 0.0004085
```

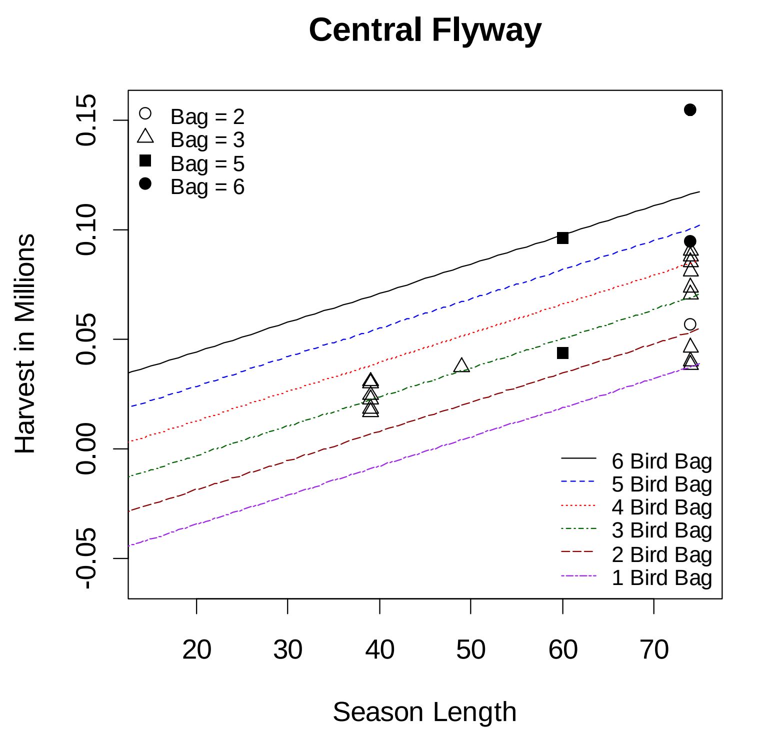

Figure 2.3. Observed Central Flyway scaup harvest (1988-2005) and predictions calculated as a function of season length and bag limit based on the Central Flyway harvest model.

Pacific Flyway

The results from an initial model that included season length, bag limit, a HIP effect, and the interaction between season length and bag limit was significant. However, this model was not considered because predictions calculated with high bag limits showed a decreasing trend in the harvest as the season lengths increased. As a result, a reduced model was used to predict Pacific Flyway harvest as a function of season length, bag limit, and a HIP effect. This model explains 81% of the variation in scaup harvest (Table 2.4). The resulting model to predict scaup harvest in the Pacific Flyway is:

$$H = -2.165\text{e-}02 + 3.544\text{e-}04\ Days + 4.776\text{e-}03\ \text{Bag} + 1.698\text{e-}02\ HIP \quad (2.5)$$

where Days is the season length, Bag is the bag limit, and HIP is an indicator variable (0 or 1) used to model the HIP effect. Predictions based on this model evaluated over a range of season lengths and bag limits are shown in Figure 2.4.

Table 2.4. The results from fitting a linear model that predicts the scaup harvest in the Pacific Flyway as a function of season length (Days), bag limit (Bag) and a HIP effect.

Pacific Flyway: Harvest ~ Days + Bag + HIP

```
lm(formula = Harvest ~ Days + Bag + HIP, data = pf)

Residuals:
       Min         1Q     Median         3Q        Max 
-0.0078350 -0.0042014 -0.0008804  0.0018886  0.0212046 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.165e-02  8.115e-03  -2.668  0.01621 *
Days         3.544e-04  9.966e-05   3.556  0.00243 **
Bag          4.776e-03  1.694e-03   2.819  0.01182 *
HIP          1.698e-02  4.828e-03   3.517  0.00264 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.006935 on 17 degrees of freedom
Multiple R-Squared: 0.8382,     Adjusted R-squared: 0.8097 
F-statistic: 29.36 on 3 and 17 DF,  p-value: 5.993e-07 

Analysis of Variance Table
Response: Harvest
          Df    Sum Sq   Mean Sq F value    Pr(>F)
Days       1 0.0036039 0.0036039  74.927 1.228e-07 ***
Bag        1 0.0000374 0.0000374   0.778  0.390051
HIP        1 0.0005951 0.0005951  12.373  0.002642 **
Residuals 17 0.0008177 0.0000481
```

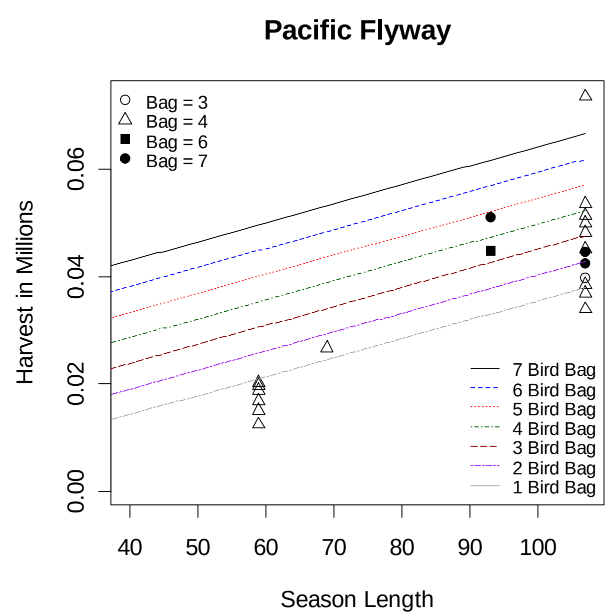

Figure 2.4. Observed Pacific Flyway scaup harvest (1988-2005) and predictions calculated as a function of season length, bag limit, and a HIP effect (i.e., HIP = 1) based on the Pacific Flyway harvest model.

Table 2.5 Flyway-specific scaup harvest predictions (in millions) calculated as a function of different combinations of season lengths (SL), and bag limits (Bag). The predictions for the Pacific Flyway include a HIP effect.

Atlantic Flyway			Mississippi Flyway			Central Flyway			Pacific Flyway		
SL	**Bag**	**Harvest**	**SL**	**Bag**	**Harvest**	**SL**	**Bag**	**Harvest**	**SL**	**Bag**	**Harvest**
60	1	0.077	60	3	0.169	74	3	0.069	107	3	0.048
60	2	0.077	45	3	0.131	74	2	0.053	107	2	0.043
60	3	0.077	60	2	0.108	60	3	0.050	86	3	0.040
45	1	0.050	30	3	0.093	74	1	0.037	107	1	0.038
45	2	0.050	45	2	0.070	60	2	0.035	86	2	0.035
45	3	0.050	20	3	0.068	39	3	0.022	60	3	0.031
30	1	0.023	60	1	0.047	60	1	0.019	86	1	0.031
30	2	0.023	30	2	0.032	39	2	0.007	60	2	0.026
30	3	0.023	45	1	0.009	25	3	0.004	38	3	0.023
20	1	0.005	20	2	0.007	25	1	0.000	60	1	0.021
20	2	0.005	20	1	0.000	25	2	0.000	38	2	0.018
20	3	0.005	30	1	0.000	39	1	0.000	38	1	0.014

Appendix 3. Harvest data and regulation information used to develop Flyway-specific scaup harvest models.

Atlantic Flyway

Table 3.1 Total scaup harvest, season information, and population data[1] collected in the Atlantic Flyway from 1988 to 2005.

Year	Harvest	HIP	Days	Bag	BPOP
1988	0.038263	0	30	3	4.671351
1989	0.039628	0	30	3	4.34205
1990	0.020442	0	30	3	4.293141
1991	0.017867	0	30	3	5.254899
1992	0.019536	0	30	3	4.639232
1993	0.021152	0	30	3	4.080145
1994	0.026921	0	40	3	4.529044
1995	0.041026	0	50	5	4.446443
1996	0.047453	0	50	5	4.217405
1997	0.051004	0	60	6	4.112349
1998	0.074242	0	60	6	3.471916
1999	0.08197	0	60	3	4.411724
2000	0.045234	0	60	3	4.026323
2001	0.108851	0	60	3	3.69401
1999	0.072568	1	60	3	4.411724
2000	0.045181	1	60	3	4.026323
2001	0.119742	1	60	3	3.69401
2002	0.103096	1	60	3	3.524142
2003	0.078283	1	60	3	3.734444
2004	0.083345	1	60	3	3.807192
2005	0.081935	1	60	2	3.386893

[1] Harvest data in millions; HIP = data collected under the HIP program, BPOP is the May breeding population from the traditional survey strata in millions.

Mississippi Flyway

Table 3.2 Total scaup harvest, season information, and population data[1] collected in the Mississippi Flyway from 1988 to 2005.

Year	Harvest	HIP	Days	Bag	BPOP
1988	0.091553	0	30	3	4.671351
1989	0.075748	0	30	3	4.34205
1990	0.071045	0	30	3	4.293141
1991	0.108141	0	30	3	5.254899
1992	0.141492	0	30	3	4.639232
1993	0.075314	0	30	3	4.080145
1994	0.115083	0	40	3	4.529044
1995	0.209867	0	50	5	4.446443
1996	0.315621	0	50	5	4.217405
1997	0.384663	0	60	6	4.112349
1998	0.334523	0	60	6	3.471916
1999	0.089956	0	60	3	4.411724
2000	0.222619	0	60	3	4.026323
2001	0.192185	0	60	3	3.69401
1999	0.09008	1	60	3	4.411724
2000	0.203093	1	60	3	4.026323
2001	0.179427	1	60	3	3.69401
2002	0.21136	1	60	3	3.524142
2003	0.158639	1	60	3	3.734444
2004	0.13659	1	60	3	3.807192
2005	0.136169	1	60	2	3.386893

[1] Harvest data in millions; HIP = data collected under the HIP program, BPOP is the May breeding population from the traditional survey strata in millions.

Central Flyway

Table 3.3 Total scaup harvest, season information, and population data[1] collected in the Central Flyway from 1988 to 2005.

Year	Harvest	HIP	Days	Bag	BPOP
1988	0.029797	0	39	3	4.671351
1989	0.024413	0	39	3	4.34205
1990	0.018342	0	39	3	4.293141
1991	0.022569	0	39	3	5.254899
1992	0.03074	0	39	3	4.639232
1993	0.016671	0	39	3	4.080145
1994	0.037325	0	49	3	4.529044
1995	0.043507	0	60	5	4.446443
1996	0.096076	0	60	5	4.217405
1997	0.094648	0	74	6	4.112349
1998	0.154763	0	74	6	3.471916
1999	0.038375	0	74	3	4.411724
2000	0.087755	0	74	3	4.026323
2001	0.0808	0	74	3	3.69401
1999	0.039966	1	74	3	4.411724
2000	0.085201	1	74	3	4.026323
2001	0.073639	1	74	3	3.69401
2002	0.090488	1	74	3	3.524142
2003	0.046265	1	74	3	3.734444
2004	0.070509	1	74	3	3.807192
2005	0.056922	1	74	2	3.386893

[1] Harvest data in millions; HIP = data collected under the HIP program, BPOP is the May breeding population from the traditional survey strata in millions.

Pacific Flyway

Table 3.4 Total scaup harvest, season information, and population data[1] collected in the Pacific Flyway from 1988 to 2005.

Year	Harvest	HIP	Days	Bag	BPOP
1988	0.015044	0	59	4	4.671351
1989	0.01248	0	59	4	4.34205
1990	0.018835	0	59	4	4.293141
1991	0.020253	0	59	4	5.254899
1992	0.016848	0	59	4	4.639232
1993	0.01969	0	59	4	4.080145
1994	0.026689	0	69	4	4.529044
1995	0.04483	0	93	6	4.446443
1996	0.051047	0	93	7	4.217405
1997	0.044705	0	107	7	4.112349
1998	0.042552	0	107	7	3.471916
1999	0.033986	0	107	4	4.411724
2000	0.036894	0	107	4	4.026323
2001	0.038505	0	107	4	3.69401
1999	0.04816	1	107	4	4.411724
2000	0.050004	1	107	4	4.026323
2001	0.045204	1	107	4	3.69401
2002	0.051481	1	107	4	3.524142
2003	0.053588	1	107	4	3.734444
2004	0.073566	1	107	4	3.807192
2005	0.03975	1	107	3	3.386893

[1] Harvest data in millions; HIP = data collected under the HIP program, BPOP is the May breeding population from the traditional survey strata in millions.