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Tag Reporting Rate Estimation: 2. Use of High-Reward Tagging and Observers in Multiple-Component Fisheries

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Abstract.—Tag return models can be used to estimate survival and tag recovery rates. The additional knowledge of an estimated tag reporting rate allows separation of the total mortality rate into fishing and natural mortality components. We briefly review two methods for estimating tag reporting rates: high-reward tags with a 100% reporting rate, and catch from multiple-component fisheries with a 100% reporting rate in one component (e.g., due to the presence of observers in a boat-based commercial fishery). The assumptions of each method are presented and discussed. We simulated the effects of combining the two methods to obtain more robust estimates of the tag reporting rate and other important parameters, such as the exploitation rate. When high-reward tags did not produce a 100% reporting rate or when the observer component in a multiple-component fishery did not have a 100% reporting rate, the combination of methods provided better estimates. It is still necessary to assume that the high-reward tags in the observer component of the fishery have 100% reporting rate. However, this is a much weaker reporting rate assumption than those used for each method alone and is much more likely to be satisfied in real fisheries applications. Therefore, the combined method should tend to give less biased estimates in practice than either method used separately.

Brownie et al. (1985) described models that are now the standard method of analyzing wildlife tag return data. The Brownie models also provide a sound basis for many new developments in the analysis of fishery tag return data (Pollock et al. 1991; Hearn et al. 1998; Hoenig et al. 1998a, 1998b). While the basic Brownie models allow estimation of survival and tag recovery rates, the additional knowledge of the estimated tag reporting rate allows one to partition the total mortality rate into its two components, the fishing and natural mortality rates (Pollock et al. 1991, 2001; Hoenig et al. 1998a, 1998b).

In the Brownie et al. (1985) method, cohorts of animals are tagged in different years, and then, over a period of time, tags from recovered animals are collected and used to estimate the various parameters. Recovery data for each year of release have a multinomial distribution, and the overall likelihood for the model is simply the product of the individual cohort likelihoods because the cohorts are independent (Brownie et al. 1985). The model can be used to estimate survival rate S and tag recovery rate f. Note that the tag recovery rate is the product of two parts: the exploitation rate u (fraction of the cohort present at the start of a recovery year that is harvested during the year) and the probability λ that a tag on a harvested fish will be reported. Therefore, if λ can be estimated, then u can also be estimated. Hoenig et al. (1998a, 1998b) found it convenient to express the Brownie models in terms of the instantaneous rates of fishing mortality (F) and natural mortality (M), an approach that assumes fishing and natural mortality are additive. The survival rate is always of the form

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$$S_i = \exp(-F_i - M_i),$$

where the subscript i refers to the year. Generally, all the M_i are assumed equal to a constant but unknown value M. The form of the exploitation rate u depends on the timing of the fishery (Hoenig et al. 1998a, 1998b). For a Type I (pulse) fishery,

$$u_i = 1 - \exp(-F_i),$$

and for a Type II (continuous) fishery,

$$u_i = \frac{F_i}{(F_i + M)}[1 - \exp(-F_i - M)].$$

Several assumptions are inherent in these multiple-year tagging models and are crucial for their validity. The assumptions are as follows: (1) the tagged samples (both high-reward and standard) are representative of the target population; (2) tags are not lost; (3) survival rates are not affected by tagging; (4) the year of tag recovery is correctly reported; (5) the fates of all tagged fish are independent; (6) all tagged fish within a cohort have the same annual survival and recovery rates; and (7) fishing and natural mortality processes are additive.

We briefly review two methods of estimating tag reporting rates, which provides the basis for estimating F and M. One method involves high-reward tagging and the other involves a two-component fishery with observers on one component, resulting in 100% tag reporting. We then focus on combining the two methods. The results of a simulation we conducted with the SURVIV program (White 1983) are used to explore the accuracy and precision of estimates from the models when assumptions are violated. We end with our conclusions and suggestions for future research.

Methods for Estimating Reporting Rate

Several methods have been used to estimate the tag reporting rate. These include the use of tagging data alone, surreptitiously planted tags, angler or port surveys, high-reward tagging, and catch data from multiple-component fisheries with a 100% reporting rate in one component. Our previous paper (Pollock et al. 2001) reviews these methods; therefore, the present paper focuses only on the high-reward tagging and multiple-component fishery methods.

High-Reward Tagging

When both standard and high-reward tags are used, the tag reporting rate can be estimated if the reward level is high enough to produce a 100% reporting rate for high-reward tags. The standard tag return rate can then be estimated via the ratio of the recovery rate of standard tags to the recovery rate of high-reward tags (Henny and Burnham 1976; Conroy and Blandin 1984; Pollock et al. 1991). If we consider only recoveries from one cohort, then the reporting rate can be estimated as

$$\hat{\lambda} = (R_t/N_t)/(R_r/N_r) = R_tN_r/R_rN_t, \qquad (1)$$

where R_t is the number of standard tags returned, N_t is the number of standard tags released, R_r is the number of high-reward tags returned, and N_r is the number of high-reward tags released.

Two additional assumptions necessary for high-reward tagging studies are that the high-reward tags are all reported and that the high-reward tagging does not change the reporting rate of standard tags.

If the assumption that the reward is sufficient to elicit a 100% reporting rate is violated, then the estimate of the standard tag reporting rate will be positively biased. Nichols et al. (1991) used a variety of reward levels in a study on mallard ducks and found that a reward of US$100 in 1990 was necessary to attain 100% reporting of the high-reward tags. The necessary level of reward likely varies by species, location, and monetary inflation.

The assumption that angler behavior does not change in response to the high-reward tagging study might also be violated. For example, fishermen who become aware of the reward program might start returning standard tags at higher rates than normal because they are influenced by the publicity. The high-reward tagging method has been studied in detail by Pollock et al. (2001), who give many practical recommendations for its use.

If the tag reporting rate remains constant over time (the usual assumption), then recoveries need not be restricted to the first year to be incorporated into the model. Equation l does not specify units involving time and is thus dimensionless. Therefore, if 60% of the tags are reported, then the 60% rate applies to tags recovered within half a year, 1 year, 2 years, and so on. The key is that fish tagged with standard and high-reward tags experience the same mortality rate, so that their relative abundance stays constant over time.

Multiple-Component Fisheries with a 100% Reporting Rate for One Component

The multiple-component fishery method with a 100% reporting rate in one component is similar to the high-reward tagging method. For simplicity, we will examine the case of a boat-based fishery with two components, as follows: (1) boats with observers, where all tags are recovered, and (2) boats without observers, where recovery of tags depends on fishers' cooperation. The relative catch between the components must be either known or estimable. The expected ratio of tagged fish caught by the observer component to tagged fish caught by the nonobserver component is assumed to be equal to the expected ratio of total catch by component type (thorough mixing of standard and high-reward tags is assumed). If the proportion of the total catch caught by boats with observers is δ_o and the proportion caught by boats without observers is $1 - \delta_o$, then the ratio of tagged fish caught by boats with observers to tagged fished caught by boats without observers can be estimated by the overall catch ratio, $\delta_o/(1 - \delta_o)$. Let R_o be the number of tags returned by boats with observers and R_n the number of tags returned by boats without observers. Then, similar to the high-reward tag model, the tag reporting rate in the boats without observers can be estimated as follows for recoveries from one tagged cohort:

$$\hat{\lambda} = [R_n/(1 - \delta_o)]/(R_o/\delta_o) = R_n\delta_o/R_o(1 - \delta_o).$$

Several additional assumptions are needed for the multiple-component method, including: all tags are recovered from boats with observers on board; tags are assumed to be well mixed, such that tag returns by component reflect catch by component; and the catch data for each fishery component are accurate. These assumptions could be violated in practice. Some tags may still go unreported even when observers are on board. In some fisheries, if observers are placed on boats nonrandomly and if tagging effort is spatially heterogeneous, then tag return rates by component might differ greatly from catch rates by component. Clearly, observers must be placed randomly among the fishing boats for this method to work. In addition, in some fisheries, catch may be either underreported or reported differentially by component. The multiple-component fishery method was first used by Paulik (1961) and then by Kimura (1976). Hearn et al. (1999) and Pollock et al. (2002) generalized the method to multiple age-classes and applied it to southern bluefin tuna *Thunnus maccoyii* tagging data. A reasonable approach in practice might be to combine the two methods to estimate tag reporting rate in a more robust manner than is possible with either method alone. We explore this further in the next section using simulation.

TABLE 1.—Recovery probabilities for high-reward and standard tags in a high-reward tagging study. The symbols N_i and N_i* represent the numbers of standard and high-reward tags, respectively, released in year i; λ_t and λ_r are the reporting rates for standard and high-reward tags in year i; S_i is the annual survival rate; and u_i is the exploitation rate in year i.

Year of tagging	Number tagged	Year of tagging: 1	2	3
1	N_1*	$u_1\lambda_r$	$S_1u_2\lambda_r$	$S_1S_2u_3\lambda_r$
	N_1	$u_1\lambda_t$	$S_1u_2\lambda_t$	$S_1S_2u_3\lambda_t$
2	N_2*		$u_2\lambda_r$	$S_2u_3\lambda_r$
	N_2		$u_2\lambda_t$	$S_2u_3\lambda_t$
3	N_3*			$u_3\lambda_r$
	N_3			$u_3\lambda_t$

Specification of Models

Table 1 shows the cell probabilities for the high-reward tagging model in a 3-year study. Each year, two groups are released: fish with standard tags and fish with high-reward tags. The tag reporting rate for high-reward tags is λ_r and that for standard tags is λ_t. These rates are assumed not to vary by year. Typically, λ_r is assumed to be 1.0.

Table 2 shows the cell probabilities for the two-component fishery model. One tagged cohort is released each year. However, within each cohort, there are two rows of recovery cells because recoveries are tracked separately by component. The tag reporting rate for the fishery component with observers is λ_o, and the tag reporting rate for the nonobserver component is λ_n. Typically, λ_o is assumed to be 1.0. The cell probabilities parallel those of the high-reward tags, except that now they also include the probability of being caught by boats with observers (δ_o) or by boats without observers (1—δ_o). The model has the additional random variables of catch for each component. Conditional on the total catch, the catch in each component can be considered binomial for each year, with the first year distributed as $B(C_1, \delta_1)$, the second year as $B(C_2, \delta_2)$, and the third year as $B(C_3, \delta_3)$. Here, B represents the binomial distribution. In the model, C_i represents the total number of fish caught in year i. The overall likelihood is created by multiplying the three independent binomial catch likelihoods by the three independent tagged-cohort multinomial likelihoods. We emphasize that the exact value of C_i is assumed known, whereas in some fisheries C_i may have to be estimated. If

TABLE 2.—Recovery probabilities for a two-component fishery where one component has observers (ob) and one component has no observers (no-ob). The symbols λ_o and λ_n are the tag reporting rates in the components with and without observers, δ_i is the fraction of the catch harvested by the component with observers in year *i*, $1 - \delta_i$ is the fraction of the catch harvested by the component without observers, and C_i is the total catch in year *i*. Other symbols are defined in Table 1.

Year of tagging	Number	Year of tagging: 1	2	3	Component
		Tagged			
1	N_1	$u_1\delta_1\lambda_o$	$S_1u_2\lambda_o$	$S_1S_2u_3\delta_3\lambda_o$	ob
		$u_1(1 - \delta_1)\lambda_n$	$S_1u_2(1 - \delta_2)\lambda_n$	$S_1S_2u_3(1 - \delta_3)\lambda_n$	no-ob
2	N_2		$u_2\delta_2\lambda_o$	$S_2u_3\delta_3\lambda_o$	ob
			$u_2(1 - \delta_2)\lambda_n$	$S_2u_3(1 - \delta_3)\lambda_n$	no-ob
3	N_3			$u_3\delta_3\lambda_o$	ob
				$u_3(1 - \delta_3)\lambda_n$	no-ob
		Catch			
1	C_1	δ_1			ob
		$(1 - \delta_1)$			no-ob
2	C_2		δ_2		ob
			$(1 - \delta_2)$		no-ob
3	C_3			δ_3	ob
				$(1 - \delta_3)$	no-ob

total catch is estimated, then additional variation in the model will be unaccounted for.

Table 3 shows the cell probabilities for the combined high-reward and two-component fishery model. The upper part of the table shows the recovery probabilities for standard tags in each component, the middle part of the table shows the recovery probabilities for high-reward tags in each component, and the bottom part of the table shows the catch probabilities by component. The tag re-

TABLE 3.—Recovery probabilities for the combined high-reward and two-component fishery. Symbols introduced in this table are as follows: λ_{ot} = tag reporting rate for standard tags in the component with observers; λ_{nt} = reporting rate for standard tags in the component without observers; λ_{or} = reporting rate for high-reward tags in the component with observers; and λ_{nr} = reporting rate of high-reward tags in the component without observers. Other symbols are defined in Tables 1 and 2.

Year of tagging	Number	Year of tagging: 1	2	3	Component
		Standard tags			
1	N_1	$u_1\delta_1\lambda_{ot}$	$S_1u_2\delta_2\lambda_{ot}$	$S_1S_2u_3\delta_3\lambda_{ot}$	ob
		$u_1(1 - \delta_1)\lambda_{nt}$	$S_1u_2(1 - \delta_2)\lambda_{nt}$	$S_1S_2u_3(1 - \delta_3)\lambda_{nt}$	no-ob
2	N_2		$u_2\delta_2\lambda_{ot}$	$S_2u_3\delta_3\lambda_{ot}$	ob
			$u_2(1 - \delta_2)\lambda_{nt}$	$S_2u_3(1 - \delta_3)\lambda_{nt}$	no-ob
3	N_3			$u_3\delta_3\lambda_{ot}$	ob
				$u_3(1 - \delta_3)\lambda_{nt}$	no-ob
		High-reward tags			
1	N_1*	$u_1\delta_1\lambda_{or}$	$S_1u_2\delta_2\lambda_{or}$	$S_1S_2u_3\delta_3\lambda_{or}$	ob
		$u_1(1 - \delta_1)\lambda_{nr}$	$S_1u_2(1 - \delta_2)\lambda_{nr}$	$S_1S_2u_3(1 - \delta_3)\lambda_{nr}$	no-ob
2	N_2*		$u_2\delta_2\lambda_{or}$	$S_2u_3\delta_3\lambda_{0r}$	ob
			$u_2(1 - \delta_2)\lambda_{nr}$	$S_2u_3(1 - \delta_3)\lambda_{nr}$	no-ob
3	N_3*			$u_3\delta_3\lambda_{or}$	ob
				$u_3(1 - \delta_3)\lambda_{nr}$	no-ob
		Catch			
1	C_1	δ_1			ob
		$(1 - \delta_1)$			no-ob
2	C_2		δ_2		ob
			$(1 - \delta_2)$		no-ob
3	C_3			δ_3	ob
				$(1 - \delta_3)$	no-ob

TABLE 4.—Simulation results for the combined model with the reporting rate for high-reward tags with observers (λ_{or}) = 1.0 and various values for the reporting rate for high-reward tags without observers (λ_{nr}) assumed to be equal to the reporting rate for standard tags with observers (λ_{ot}). Data generated are based on the following assumptions: exploitation rate (u) = 0.4, survival = 0.5, and λ_{nt} = 0.6. All reporting rates except λ_{or} were estimated in the model. For each scenario, the first row presents the median with the 5th and 95th percentiles in parentheses; the second row presents the mean with the standard error in parentheses. The proportional biases based on the median and the mean are also presented.

Scenario ($\lambda_{nr} = \lambda_{ot}$)	$\hat{u}$	Bias	$\hat{\lambda}_{nr}$	Bias	$\hat{\lambda}_{nt}$	Bias	$\hat{\lambda}_{ot}$	Bias
1.0	0.42 (0.38–0.56)	0.05	0.94 (0.68–1.00)	−0.06	0.57 (0.42–0.63)	−0.05	0.94 (0.70–1.00)	−0.06
	0.44 (0.059)	0.10	0.91 (0.109)	−0.18	0.55 (0.065)	−0.08	0.91 (0.103)	−0.18
0.95	0.41 (0.36–0.56)	0.03	0.92 (0.66–1.00)	−0.03	0.58 (0.43–0.66)	−0.04	0.92 (0.68–1.00)	−0.04
	0.43 (0.065)	0.07	0.89 (0.118)	−0.06	0.57 (0.073)	−0.05	0.89 (0.112)	−0.06
0.9	0.40 (0.35–0.57)	0.00	0.90 (0.60–1.00)	0.00	0.60 (0.42–0.69)	0.00	0.89 (0.63–1.00)	−0.01
	0.42 (0.069)	0.05	0.87 (0.130)	−0.03	0.58 (0.082)	−0.03	0.87 (0.123)	−0.03
0.8	0.39 (0.35–0.57)	−0.02	0.81 (0.59–1.00)	0.01	0.61 (0.42–0.70)	0.02	0.81 (0.59–1.00)	0.01
	0.42 (0.068)	0.05	0.80 (0.147)	0.00	0.60 (0.109)	0.00	0.80 (0.143)	0.00

porting rates by boats with observers are λ_{ot} and λ_{or} for standard and high-reward tags, respectively. The tag reporting rates for the nonobserver component are λ_{nt} and λ_{nr} for standard and high-reward tags, respectively.

Simulation

Methods

We used maximum likelihood (ML) estimators to evaluate the effect of errors in the assumption of 100% reporting rate for boats with observers and for high-reward tags. The SURVIV program (White 1983) was designed to perform simulations and give ML estimates of parameters in any multinomial model. In all our simulations, the exploitation rate was set at 0.4 for all 3 years. Similarly, the survival rate was set at 0.5 for all 3 years. All simulation results were based on 1,000 repetitions, and all standard-tagged cohort sizes were set at 1,000.

For the high-reward tagging simulations, the high-reward-tagged cohort sizes were either 100 or 200 per year. The true high-reward tag reporting rate was varied (1.0, 0.95, 0.9, or 0.8) within the simulation. In each scenario, the standard tag reporting rate was set at 0.6. A constraint that the high-reward tag reporting rate had to equal 1.0 was placed on the model estimation solution in all scenarios.

For the two-component simulations, the observer component was either 10% or 20% of the catch. The observer tag reporting rate was varied (1.0, 0.95, 0.90, or 0.8). In each scenario, the nonobserver tag reporting rate was set at 0.6. For all scenarios, we placed the constraint on the model solution that the observer tag reporting rate had to equal 1.0. Our simulations did not include variation due to catch estimation.

In the combined method simulations, the high-reward-tagged cohort size was 100, and the observer component of the fishery had a 10% share of the catch. In all simulations, the reporting rate of standard tags in the nonobserver component (λ_{nt}) was set at 0.6, the reporting rate of high-reward tags in the observer component (λ_{or}) was set at 1.0, and the solutions were constrained so that the high-reward tag reporting rate in the observer component always equaled 1.0. The high-reward tag reporting rate assumption of 100% (without observers) and the observer tag reporting rate assumption of 100% (with standard tags) were violated in various combinations. As with the two-component method, our combined method simulations did not include variation due to catch estimation.

Results of the simulations were calculated as the mean estimate and standard error for each scenario in Tables 4–8. However, in Table 4, we also present the median estimate and the 5th and 95th percentiles because some distributions were skewed to the left when the true values of the parameters were close to 1.0.

Results

High-Reward Tagging Model

Results based on 200 reward tags were similar to those based on 100 reward tags in terms of bias, so only the latter results are reported. Parameter estimates were close to the actual values when the high-reward tag reporting rate was equal to 1.0. However, when the high-reward tag reporting rate was not 1.0 but the model solution forced it to that

TABLE 5.—Simulation results for the combined model when λ_{or} = 1.0, and λ_{nr} (= λ_{ot}) assumes various values. The reporting rates λ_{nr} and λ_{nt} were estimated in the model, and λ_{or} and λ_{ot} were fixed at 1.0. See the caption to Table 4 for additional details.

Scenario ($\lambda_{nr} = \lambda_{ot}$)	$\hat{u}$	Bias	$\hat{\lambda}_{nr}$	Bias	$\hat{\lambda}_{nt}$	Bias
1.0	0.41 (0.028)	0.02	0.96 (0.055)	−0.04	0.59 (0.042)	−0.02
0.95	0.39 (0.026)	−0.02	0.96 (0.058)	0.01	0.61 (0.043)	0.02
0.9	0.38 (0.025)	−0.06	0.96 (0.061)	0.06	0.64 (0.046)	0.07
0.8	0.34 (0.025)	−0.16	0.95 (0.068)	0.19	0.72 (0.057)	0.20

value, there were increasingly negative biases in the exploitation rates (about −5% for λ_r = 0.95, −10% for λ_r = 0.9, and −20% for λ_r = 0.8) and increasingly positive biases in the standard tag reporting rates (about 5% for λ_r = 0.95, 11% for λ_r = 0.9, and 25% for λ_r = 0.8).

Two-Component Fishery Model

The results for 10% and 20% shares of the catch in the observer component were similar in terms of bias, so only those for the 10% share are reported. Parameter estimates were close to the actual values when the observer tag reporting rate was equal to 1.0. However, when the actual observer tag reporting rates were not equal to 1.0 but the model solution forced it to that value, exploitation rates had increasingly negative biases and the nonobserver tag reporting rates had increasingly positive biases. The two-component fishery simulation results were identical in magnitude to simulation results for the high-reward tagging model.

High-Reward Tagging Model Combined with the Two-Component Fishery Model

In our models, we considered the bias in estimates of exploitation rates and various reporting rates; however, survival estimates were not biased for any of the scenarios because survival estimation does not require knowledge of the tag reporting rate. The results from several combined simulation scenarios are presented in Table 4, and the only constraint on the solution was that the reward tag reporting rate in the observer component equal 1.0 (λ_{or} = 1.0). Thus, all other parameters were estimated. The first scenario presented in Table 4 is where $\lambda_{nr} = \lambda_{ot}$ = 1.0 (i.e., the assumptions were not violated). In this case, the exploitation rate estimate was positively biased by about 10%, and all the tag reporting rate estimates were negatively biased by about 8–18%. Though the negative bias in tag reporting rates may at first appear odd because no constraints were placed on the solutions, there is a simple explanation. When the parameters were estimated from the simulation data, parameter values near the extreme (i.e., 1.0) had variability in the estimates, but clearly the estimates could never be greater than 1.0. Thus, many replications will produce estimates of the parameters that are slightly below 1.0, but none will produce estimates that are above 1.0. The distribution of the 1,000 replications was therefore negatively skewed, which is why we report medians and 5th and 95th percentiles as well as means and standard errors. The median bias was +5% for the exploitation rate and −6% for the reporting rate estimates. Maximum likelihood estimators are asymptotically unbiased and consistent, which means that, as all sample sizes become large, the variance and the bias shrink if the fitted model is correct.

The other scenarios in Table 4 show what happens when the 100% reporting rate assumptions are violated. As the reporting rates move away

TABLE 6.—Simulation results for the combined model when λ_{or} = 1.0 and λ_{nr} (= λ_{ot}) assumes various values; λ_{nt} was estimated and the other reporting rates were fixed at 1.0 when the model was fitted.

Scenario ($\lambda_{nr} = \lambda_{ot}$)	$\hat{u}$	Bias	$\hat{\lambda}_{nt}$	Bias
1.0	0.42 (0.092)	0.06	0.58 (0.097)	−0.04
0.95	0.39 (0.053)	−0.03	0.62 (0.063)	0.04
0.9	0.36 (0.020)	−0.09	0.66 (0.038)	0.10
0.8	0.33 (0.017)	−0.19	0.74 (0.044)	0.23

TABLE 7.—Simulation results for the combined model when λ_{or} = 1.0 and λ_{nr} = (λ_{ot}) assumes various values. Only λ_{nt} was estimated in the model; λ_{or}) was fixed at 1.0 and λ_{nr} and λ_{ot} at 0.9.

Scenario ($\lambda_{nr} = \lambda_{ot}$)	$\hat{u}$	Bias	$\hat{\lambda}_{nt}$	Bias
1.0	0.44 (0.038)	0.10	0.55 (0.04)	−0.09
0.95	0.42 (0.019)	0.05	0.57 (0.03)	−0.05
0.9	0.40 (0.019)	0.00	0.60 (0.034)	0.00
0.8	0.36 (0.018)	−0.10	0.67 (0.04)	0.12

TABLE 8.—Comparison of the three models in terms of mean estimated exploitation rate, with standard errors in parentheses; proportional biases are also presented. For high-reward model scenarios, λ_r was set to 1.0 in fitting the model. For two-component model scenarios, λ_o was set to 1.0, and for all combined-model scenarios, λ_{or} was set to 1.0. Additional constraints in fitting the models were as follows: λ_{ot} = 1.0*; λ_{nr} = λ_{ot} = 1.0**; and λ_{nr} = λ_{ot} = 0.9***. The cases in boldface type have the minimum bias.

Simulated conditions	$\hat{u}$	Proportional bias
High-reward model, λ_r = 1.0	**0.40** (0.023)	**0.00**
Two-component model, λ_o = 1.0	**0.40** (0.041)	**0.00**
Combined model, λ_{nr} = λ_{ot} = 1.0	0.44 (0.059)	0.10
Combined model, λ_{nr} = λ_{ot} = 1.0*	0.41 (0.028)	0.02
Combined model, λ_{nr} = λ_{ot} = 1.0**	0.42 (0.092)	0.06
High-reward model, λ_r = 0.95	0.38 (0.021)	−0.05
Two-component model, λ_o = 0.95	0.38 (0.040)	−0.05
Combined model, λ_{nr} = λ_{ot} = 0.95	0.43 (0.065)	0.08
Combined model, λ_{nr} = λ_{ot} = 0.95*	**0.39** (0.026)	**−0.02**
Combined model, λ_{nr} = λ_{ot} = 0.95**	**0.39** (0.053)	**−0.02**
High-reward model, λ_r = 0.9	0.36 (0.020)	−0.10
Two-component model, λ_o = 0.9	0.36 (0.039)	−0.10
Combined model, λ_{nr} = λ_{ot} = 0.9	0.42 (0.069)	0.05
Combined model, λ_{nr} = λ_{ot} = 0.9*	0.38 (0.025)	−0.06
Combined model, λ_{nr} = λ_{ot} = 0.9**	0.36 (0.020)	−0.09
Combined model, λ_{nr} = λ_{ot} = 0.9****	**0.40** (0.019)	**0.00**
High-reward model, λ_r = 0.8	0.32 (0.020)	−0.20
Two-component model, λ_o = 0.8	0.32 (0.032)	−0.20
Combined model, λ_{nr} = λ_{ot} = 0.8	**0.41** (0.081)	**0.02**
Combined model, λ_{nr} = λ_{ot} = 0.8*	0.34 (0.025)	−0.15
Combined model, λ_{nr} = λ_{ot} = 0.8**	0.33 (0.017)	−0.18

from 1.0, thus solving the boundary problems, the parameter estimates improve and biases decrease. When $\lambda_{nr} = \lambda_{ot} = 0.9$ or 0.8, both the exploitation rate and the tag reporting rate biases are very small, in terms of median or mean bias. For the combined method, the estimation relies exclusively on the high-reward tags recovered by the observers to determine the tag reporting rates.

The same scenarios from Table 4 are repeated in Table 5, but in this case, the assumption of a 100% reporting rate in the observer component is maintained for both standard and high-reward tags. The estimation procedure forces $\lambda_{or} = \lambda_{ot} = 1.0$, but it does not require λ_{nr} to equal 1.0. These scenarios again vary λ_{nr} and λ_{ot}. The first scenario in the table sets $\lambda_{nr} = \lambda_{ot} = 1.0$. Other scenarios gradually reduce these reporting rates. The best results are achieved when $\lambda_{nr} = \lambda_{ot} = 1.0$; in this case, λ_{nt} is only slightly biased (−2%), and the exploitation rate is positively biased (2%). As the two reporting rates λ_{nr} and λ_{ot} are reduced to 0.8, the exploitation rate bias becomes large (−16%), and the positive bias in λ_{nt} is 20%. There are also increasing positive biases in λ_{nr}.

Table 6 repeats the same scenarios as Tables 4 and 5, but with the restriction that all high-reward tags are returned. Therefore, the solutions force $\lambda_{or} = \lambda_{ot} = \lambda_{nr} = 1.0$. The first scenario in the table shows what happens when the assumptions are not violated, such that $\lambda_{nr} = \lambda_{ot} = 1.0$. Thus, the solution is forced to estimate these parameters correctly. The exploitation rate has a slight positive bias (6%), and the λ_{nt} estimate has a slight negative bias (−4%). As the assumption that $\lambda_{nr} = \lambda_{ot} = 1.0$ is violated more and more, the exploitation rate becomes increasingly negatively biased, with a bias of −19% at $\lambda_{nr} = \lambda_{ot} = 0.8$. The estimate of λ_{nt} has an increasingly positive bias of about the same magnitude as that of the exploitation rate.

Although unrealistic in practice, Table 7 shows what happens when the constraint $\lambda_{nr} = \lambda_{ot} = 0.9$ is forced on the solution. The four scenarios show the results when the true λ_{nr} and λ_{ot} actually equal 0.9, as well as the results when the values were varied slightly in either direction. When the true $\lambda_{nr} = \lambda_{ot} = 0.9$, there are virtually no biases in the estimates. When the true $\lambda_{nr} = \lambda_{ot} = 1.0$, there is a positive bias in the exploitation rate of about 10% and a negative bias in the λ_{nt} estimate of about 9%. When the true $\lambda_{nr} = \lambda_{ot} = 0.95$, there is a positive bias in the exploitation rate of about 5%, and when the true $\lambda_{nr} = \lambda_{ot} = 0.8$, there is a negative bias of about 10%. Estimates of λ_{nt} have biases similar to those of the exploitation rate but in the opposite direction.

Comparison of the Three Models

Comparisons of the exploitation rate estimates of all three models are shown in Table 8. The upper quarter of the table shows the results when all but the tag reporting parameter for standard tags in the nonobserver component is in fact 1.0, a perfect reporting rate. The high-reward tag model and the two-component model are effectively unbiased. The combined model estimates have small positive biases.

The second quarter of Table 8 shows the results when the true high-reward tag reporting rate is 0.95 in the high-reward model and the true observer component reporting rate is 0.95 in the two-component model. Similarly, both λ_{nr} and λ_{ot} are simulated as 0.95 in the combined model. In this case, the exploitation rate estimates from the high-reward and two-component models have negative biases of about 5%. The combined model biases range from −2% to +8%. When λ_{ot} and λ_{or} are constrained to equal 1.0, the bias is only −2%. When λ_{ot}, λ_{nr}, and λ_{or} are all constrained to equal 1.0, the bias is again only −2%, which is slightly better than the high-reward or two-component models.

The third quarter of Table 8 shows the results when the true high-reward tag reporting rate is 0.90 in the high-reward model and the true observer component reporting rate is 0.90 in the two-component model. Similarly, both λ_{nr} and λ_{ot} are simulated as 0.90 in the combined model. In this case, the high-reward and two-component models have negative biases of about 10%. The combined model biases range from −9% to 0%, so that the combined model always outperformed the high-reward and the two-component models.

The bottom quarter of Table 8 shows the results when the true high-reward tag reporting rate is 0.80 in the high-reward model and the true observer component reporting rate is 0.80 in the two-component model. Similarly, both λ_{nr} and λ_{ot} are simulated as 0.80 in the combined model. In this instance, the high-reward and two-component models have negative biases of about 20%. Again, the combined model always does at least as well as the other two models, with biases ranging from −18% to +2%. The combined model does best when the number of constraints (in this case, incorrect) is minimized and only λ_{or} is forced to be 1.0.

Precision of the Various Estimators

When catch has to be estimated, the precision will be worse than that given in Tables 4–8. The relative precision (standard error divided by estimate expressed as a percentage) of the exploitation rate estimators in our simulations was less than 10% except for the most general model, where three tag reporting rates had to be fit (Tables 4 and 8). Even then, the relative precision of the exploitation rate estimators was about 15%.

A common reporting rate estimated in all the models was λ_{nt}, the reporting rate of standard tags in the nonobserver component of the fishery. The relative precision of this reporting rate estimator improved from about 15% when all three tag reporting rates had to be estimated (Table 4) to 5–10% when λ_{nt} was the only tag reporting rate estimated (Tables 6 and 7).

Both of the other tag reporting rates (λ_{nr} and λ_{ot}) had true values close to 1.0, and the relative precision of the reporting rates in Table 4 reached almost 20%. In Table 5, where λ_{ot} was specified and λ_{nr} estimated, the relative precision of λ_{nr} estimates was 6–7%.

Discussion

For all of the models and scenarios, survival estimates are essentially unbiased because they are not dependent on knowing the tag reporting rate (Brownie et al. 1985). Estimates of the exploitation rate, fishing and natural mortality rates, and various reporting rates are essentially unbiased only when the model assumptions are met. For the high-reward tag and two-component models, doubling the number of high-reward tags or the share of catch in the observer component does not affect the bias in any of the parameter estimates, but it does reduce the variability of those estimates. Bias results from specification errors in the model rather than from sampling variability.

The combined model does not invariably produce improved estimates over the separate models. When model assumptions are not violated (i.e., the reporting rates of all high-reward tags and observer component standard tags are 1.0) the combined model performs slightly worse than the others in terms of bias in estimating exploitation rates, unless all three tag reporting parameters involving a high-reward or observer are constrained to equal 1.0. However, the biases are not large. When the reporting-rate assumptions are violated for high-reward tags and observer component tags, the combined model does much better than the others. Constraining only the observer component reporting rate of high-reward tags to equal 1.0 in the combined model produces the most consistently accurate estimates of exploitation rate over all scenarios. The combined model with this constraint does worst in the scenario where nonobserver high-reward tag reporting and observer standard tag reporting rates both equal 1.0, producing a positive bias of 5%. However, the combined model does much better in scenarios where nonobserver high-reward tag reporting and observer standard tag reporting rates are not equal to 1.0, and the model has no bias when both reporting rates equal 0.9 (based on the medians in Table 4).

The combination of a high-reward tagging method with a two-component fishery method appears to provide an improvement over existing methods, especially when assumptions of perfect tag reporting rates are violated. For the combined approach, high-reward tags in the observer component are assumed to have perfect reporting rates. A key advantage of the combined approach is that reporting rates can be estimated for high-reward tags in the absence of observers and for standard tags in the presence of observers, which allows assessment of the validity of the assumptions required for the two separate methods of estimating tag reporting rates. The design of tagging studies should always focus on testing model assumptions and using robust methods with weaker assumptions (Pollock et al. 2001).

In selecting an approach for tagging studies, the cost of implementing the combined method rather than the high-reward tagging or multiple-component fishery method would need to be considered. The extra money spent on the combined method could instead be used to increase the reward level for high-reward tags or to increase observer coverage. One cannot escape the fact, however, that each method used separately has assumptions that are hard to verify, whereas the combined method allows weaker assumptions about reporting rates and allows testing of the standard assumptions of the separate methods. Furthermore, the cost of estimating catch by component in multiple-component fisheries may not be trivial.

In this paper, we emphasize use of high-reward tagging with a two-component fishery that contains observers in one component. We also briefly considered a related situation (for which results were not reported) of two components (e.g., different fleets) combined with high-reward tagging, and we assumed different reporting rates of standard tags in the two components. With valid assumptions of 100% reporting of high-reward tags for both fleets, there was no loss in precision of the natural and fishing mortality estimates when we combined the data and estimated one overall reporting rate for the whole fleet rather than separate reporting rates for each fleet. However, the advantage of estimating parameters separately for each fleet is that satisfaction of various model assumptions can be checked. A high-reward tag reporting rate of 100% is only needed in one component to estimate all parameters. By estimating fleet-specific reporting rates, we obtain two estimates of each parameter. Inconsistency between the two estimates indicates violation of one or more of the following assumptions: the tagged fish are mixed in the general population; the reporting rate of high-reward tags in each component is 100%; and the catch of one or more of the components is correctly reported.

Another combined method of estimating reporting rates is to use planted tags in one component of a multiple-component fishery in which catch is known for each component (W. S. Hearn and others, unpublished). We believe that other combined methods of estimating the tag reporting rate, such as adding planted tags to a high-reward tagging program, would be very beneficial. The possible combinations of methods are numerous, and the choice of methods would often be determined by the practical experimental conditions.

In the present paper, we have only considered fisheries where all tagged fish are assumed to have been harvested before being reported. There can be additional problems in fisheries with a catch-and-release element. A fisher may decide to keep and report a high-reward tagged fish, whereas he might release a standard-tagged fish. Selective retention of high-reward tagged fish would violate the assumption that all fish have equal survival irrespective of tag type. This situation might also violate the assumption that the reporting rate of standard tags is unchanged in the presence of high-reward tagging. We plan to discuss tagging studies in catch-and-release fisheries in a future paper. Smith et al. (2000) also discuss this issue.

The relative precision of our estimates was very reasonable, even in the most general models fitted (Table 4). We assumed, for simplicity, that tag reporting rates were constant during the study. However, in practice, tag reporting rates are likely to be time dependent, and this possibility should be tested as part of any estimation procedure. Simulations with time-dependent reporting rates would have similar biases but lower precision than those presented here. Also, estimation of catch would lower the precision of the estimates.

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References

Brownie, C., D. R. Anderson, K. P. Burnham, and D. S. Robson. 1985. Statistical inference from band recovery data: a handbook. U.S. Fish and Wildlife Service Resource Publication 156.

Conroy, M. J., and W. W. Blandin. 1984. Geographical and temporal differences in band reporting rates for American black ducks. Journal of Wildlife Management 45:23–36.

Hearn, W. S., T. Polacheck, K. H. Pollock, and W. Whitelaw. 1999. Tag reporting rates: taking age structure into account with applications to southern bluefin tuna (*Thunnus maccoyii*). Canadian Journal of Fisheries and Aquatic Sciences 56:1255–1265.

Hearn, W. S., K. H. Pollock, and E. N. Brooks. 1998. Pre- and post-season tagging models: estimation of reporting rate and fishing and natural mortality rates. Canadian Journal of Fisheries and Aquatic Sciences 55:199–205.

Henny, C. J., and K. P. Burnham. 1976. A reward band study of mallards to estimate band reporting rates. Journal of Wildlife Management 40:1–14.

Hoenig, J. M., N. J. Barrowman, W. S. Hearn, and K. H. Pollock. 1998a. Multiyear tagging studies incorporating fishing effort data. Canadian Journal of Fisheries and Aquatic Sciences 55:1466–1476.

Hoenig, J. M., N. J. Barrowman, K. H. Pollock, E. N. Brooks, W. S. Hearn, and T. Polacheck. 1998b. Models for tagging data that allow for incomplete mixing of newly tagged animals. Canadian Journal of Fisheries and Aquatic Sciences 55:1477–1483.

Kimura, D. K. 1976. Estimating the total number of marked fish present in a catch. Transactions of the American Fisheries Society 105:664–668.

Nichols, J. D., R. J. Blohm, R. E. Reynolds, R. E. Trost, J. E. Hines, and J. P. Bladen. 1991. Band reporting rates for mallards with reward bands of different dollar values. Journal of Wildlife Management 55: 119–126.

Paulik, G. J. 1961. Detection of incomplete reporting of tags. Journal of the Fisheries Research Board of Canada 18:817–832.

Pollock, K. H., W. S. Hearn, and T. Polacheck. 2002. A general model for tagging on multiple component fisheries: an integration of age-dependent reporting rates and mortality estimation. Environmental and Ecological Statistics 9:57–69.

Pollock, K. H., J. M. Hoenig, W. S. Hearn, and B. Calingaert. 2001. Tag reporting rate estimation: 1. An evaluation of the high-reward tagging method. North American Journal of Fisheries Management 21:521–532.

Pollock, K. H., J. M. Hoenig, and C. M. Jones. 1991. Estimation of fishing and natural mortality when a tagging study is combined with creel or port sampling. Pages 423–434 *in* D. Guthrie, J. M. Hoenig, M. Holliday, C. M. Jones, M. J. Mills, S. A. Moberly, K. H. Pollock, and D. R. Talhelm, editors. Creel and angler surveys in fisheries management. American Fisheries Society, Symposium 12, Bethesda, Maryland.

Smith, D. R., K. P. Burnham, D. M. Kahn, X. He, C. J. Goshorn, K. A. Hattala, and A. Kahnle. 2000. Bias in survival estimates from tag-recovery models where catch-and-release is common, with an example from Atlantic striped bass. Canadian Journal of Fisheries and Aquatic Sciences 57:886–897.

White, G. C. 1983. Numerical estimation of survival rates from band-recovery and biotelemetry data. Journal of Wildlife Management 47:716–728.