Aquat. Living Resour. 17, 175–183 (2004)

DOI: 10.1051/alr:2004016
www.edpsciences.org/alr

Aquatic
Living
Resources

Combining Bayesian and simulation approaches to compare the efficiency of two types of tags used in tropical tuna fisheries

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Received 12 December 2003; Accepted 2 April 2004

Abstract – Conventional "spaghetti" tags and tags originally designed for "sport fishing" and called Betyp tags, were used during a tuna tagging program conducted on board Dakar baitboats in 1999. With the aim of comparing the recapture rate of both types of tags, additional information obtained from previous tagging trips are used in a Bayesian context to set up an informative prior for conventional tags. We show in this study (1) how to account for the sampling uncertainty in the construction of the Beta prior with a likelihood method, and (2) how a simulation-based alternative can be useful for performing the probability density function of the difference between two posterior recapture rates. On the light of the resulting simulated difference we found that Betyp tags have a very strong negative effect on the return rate of bigeye tuna (−19.6% on average). For skipjack the strength of evidence concerning the decrease in recapture rate due to the implementation of Betyp tags (−3.2%) was supported only at a 10% level. The Bayesian approach is compared with the conventional "frequentist" approach and with a likelihood method allowing for the integration of previous information. The results obtained from different approaches indicate that the choice of the method, as well as the choice of the prior, does not modify the conclusion of the study. Potential causes for explaining the lowest efficiency of Betyp tags are discussed.

Key words: Tagging data / Tuna fisheries / Return rate / Bayesian analysis / Likelihood analysis

Résumé – **Utilisation combinée d'une approche probabiliste « Bayésienne » et de la simulation pour comparer l'efficacité de deux types de marques utilisées dans l'étude des pêches thonières tropicales.** Des marques conventionnelles de type « spaghetti » et des marques conçues à l'origine pour la pêche sportive, et appellées marques « Betyp », ont été utilisées en 1999 à bord de thoniers canneurs de Dakar. Dans le but de comparer le taux de recapture de ces deux types de marques, des informations additionnelles obtenues lors de campagnes de marquage précédentes ont été utilisées dans une approche probabiliste Bayésienne pour mettre à jour nos connaissances sur le taux de recapture a priori des marques conventionnelles. Nous montrons dans cette étude (1) comment la variabilité observée au cours des campagnes précédentes peut être intégrée lors de la construction de la distribution a priori de type Beta à l'aide d'une méthode basée sur le maximum de vraisemblance, et (2) comment construire la fonction de distribution de la différence des taux de recapture a posteriori à l'aide d'une méthode de simulation. L'analyse de la distribution simulée des différences indique que les marques « Betyp » ont un très fort effet négatif sur le taux de recapture des thons obèses (−19.6 % en moyenne, par rapport aux marques conventionnelles). Pour le listao, l'hypothèse d'une baisse de la proportion de recapture due à l'utilisation des marques « Betyp » (−3.2 %) n'est supportée par les données qu'à un seuil de crédibilité de 10 %. L'approche Bayésienne est comparée à la méthode « fréquentiste » traditionnelle et à une méthode du maximum de vraisemblance permettant l'intégration d'informations a priori. Les résultats obtenus par ces différentes approches indiquent que le choix de la méthode, aussi bien que le choix du prior dans le cas de l'approche Bayésienne, ne modifient pas les conclusions de l'étude. Enfin, les causes potentielles susceptibles d'expliquer la moindre efficacité des marques « Betyp » sont discutées.

1 Introduction

Since the middle of the eighties the bait boat fishery, operating from Dakar (Senegal), has developed a very peculiar fishing technique which consists of keeping a permanent association between the fishing boat and the fished tuna school (Fonteneau and Diouf 1994; Hallier and Delgado 2000). With the aim of analyzing the effects of this new fishing technique on the resource a specific research program, called MAC for "Mattes de thons Associées aux Canneurs", was conducted from 1996 to 2000 (Hallier et al. 2001). One of the main working tools of this program was tuna tagging. Because the objective was to tag as many fish as possible, tagging was done

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Table 1. Number of tagged and recaptured fish and recapture rates by species and by type of tag for the comparative program and for the previous trips (see text). NA = data non available for the Betyp tag type.

		Conventional tag			Betyp tag		
		BET	SKJ	YFT	BET	SKJ	YFT
Comparative program	Recaptured	687	249	50	250	47	17
	Tagged	1095	1307	61	581	297	24
	Recapture rate	0.627	0.191	0.820	0.430	0.158	0.708
Previous Trips	Recaptured	275	661	74	NA	NA	NA
	Tagged	527	2783	136	NA	NA	NA
	Recapture rate	0.522	0.238	0.544	NA	NA	NA

initially with the conventional "spaghetti" tags widely used by all large tuna tagging programs. In 1999, a new tag originally designed for opportunistic tagging of tunas and billfishes by the sport fishermen was used in addition to the conventional tags. The tag type designed for recreational fisheries was chosen for the first time for massive tuna tagging operations in the framework of the Bigeye Tuna Year Program (BETYP) of the International Commission for the Conservation of Atlantic Tunas (ICCAT). A comparative analysis of the performances of the two tag types in term of tag recapture rates and other relevant aspects was conducted by Hallier and Gaertner (2002) for the period 1999-2000.

Updating a prior state of knowledge about a parameter in light of a new data set is defined as a Bayesian approach. This approach is being increasingly involved in related fishery studies in recent years. For example, Bayesian methods have been applied in many stock assessment analysis (Hoenig et al. 1994; Walters and Ludwig 1994; Meyer and Millar 1999; Chen et al. 2000; among others), for estimating the proportion of active fishermen and related fishing effort (Holbert and Johnson 1989), in tagging data studies (Rivot and Prévost 2002), as well as for estimating run size indicators in salmon stocks (Fried and Hilborn 1988). The development of Bayesian methods in fishery studies is widely due to the possibility of incorporating all available information to the current data set and to account for uncertainty about different hypothesis on model structure (Punt and Hilborn 1997; McAllister and Kirkwood 1998). The purpose of this paper is to show how previous knowledge can be combined with tagging data into a Bayesian framework in order to quantify the influence of a specific type of tags on the recovery rate. Since the probability density function of the difference of two recapture rates cannot be obtained directly by an analytical solution, we use simulation-based alternative methods.

2 Material and methods

2.1 Data

Because the technical aspects related to the implementation of the two types of tags were discussed by Hallier and Gaertner (2002), we restrict the description of the tagging operation to its main features. Conventional and new designed tags (i.e., Betyp tags) were provided by ICCAT with the objective of tagging skipjack (*Katsuwonus pelamis*), juvenile yellowfin (*Thunnus albacares*) and juvenile bigeye (*Thunnus obesus*). Conventional "spaghetti" tags have a smaller head with only one barb on one side and are generally chosen for tagging large numbers of small to medium size tunas that are pulled out of the sea onto a tagging cradle and then returned to the sea with their tag on (Kearney 1982). In contrast, Betyp tags have a bigger head with one hook on each side which gives a firmer hold of the tag into the fish. This design is well suited for tagging small numbers of large size billfishes and tunas directly at sea during sportfishery activities (Bayliff and Holland 1986; Prince et al. 2002). Both types of tags were placed at the base of the second dorsal fin of the fish in order to firmly attach the barbs of the tag's head into the bones supporting the fin.

The tagging database used to compare the efficiency of both tag types in terms of recapture rate was obtained from three tagging trips done in 1999. Tagging took place off the Mauritanian coast in a square from 16° N to 21° N and 16°30 W to 19°30 W and from August to December 1999. During this comparative analysis a total of 2463 tunas were tagged with conventional tags and 902 with Betyp tags. As the fishes were tagged alternatively with both tag types during the same tagging operations it can reasonably be assumed that every tag has approximately the same chance of being recaptured. Tag recapture rate is calculated as the percentage of recaptured fish over the total number of tagged fish (Table 1).

As mentioned in the introduction section, in the first years of the MAC Program other tagging trips were conducted from 1996 to 1999, but using conventional tags only. Among the 24 trips involved, five of them (four in 1997 and one in 1999) have similar features with the tagging operations done during the comparative analysis (e.g., mean size of the tagged fish, place and season of the tagging, characteristic of the tagging vessel, etc.). Consequently we used information provided by these five cruises (hereafter, "previous trips") to specify our prior belief about the return rates for each tuna species (Table 2).

2.2 Method

Tagging data involve Bernoulli variables with two possible outcomes, a recapture and a non-recapture (with probabilities θ and $1-\theta$ respectively), and the binomial applies to the aggregation of such outcomes over several cases. We can say that the distribution of r recaptures out of m tagged fishes is given by the binomial distribution:

$$\Pr(data/\theta) = \left[\frac{m\,!}{r!\,(m-r)!}\right] \theta^{r}\,(1-\theta)^{m-r}\,.$$

Table 2. Observed recapture rates for conventional tags during the previous tagging trips (with a minimum of 10 tagged fish per trip).

BET	SKJ	YFT
0.667	0.245	0.533
0.564	0.245	0.647
0.468	0.157	0.412
0.685	0.103	0.700
	0.323	

Thus, in the "frequentist" context comparing the proportion of recapture between a "case control group" (i.e., conventional tags "c") with an "exposed group" (i.e., Betyp tags "b") can be done with the aid of the two binomial distributions: $r_c \sim \text{Bin}(\theta_c, m_c)$ and $r_b \sim \text{Bin}(\theta_b, m_b)$. Since the independence assumption between return rates is based on the fact that each fish was randomly assigned a tag type, the confidence interval for their difference has expectation:

$$(\theta_b - \theta_c) \pm z_{\alpha/2} \left[\frac{\theta_b\ (1-\theta_b)}{m_b} + \frac{\theta_c\ (1-\theta_c)}{m_c} \right]^{1/2}.$$

Because a difference in proportion may have greater importance when both proportions are close to 0 or 1 than when they are near the middle of the range, it could be argued than the log relative risk is more appropriate measure (Agresti 1990). However, with the aim of comparing different methods we used the simple difference in proportion.

One of the main objectives of this study is to show how to incorporate previous information on some parameters of interest in the analysis of tagging data. In the Bayesian approach, a population parameter θ is considered as a random variable (i.e., not fixed as in the frequentist viewpoint) and the current state of knowledge about its distribution can be reflected by a prior distribution (Berger and Berry 1988). The prior distribution depicts the relative credibility that we have about a parameter and consequently includes the information from all knowledge before any new data are available. This prior information is then combined with the information contained in the data, resulting in the posterior distribution. The computation of the posterior distribution uses the Bayes' theorem as follows:

$$\Pr(\theta/data) = \frac{\Pr(data/\theta)\Pr(\theta)}{\int \Pr(data/\theta)\Pr(\theta)}$$

where, $\Pr(\theta/data)$ is the posterior distribution of θ given the data, $\Pr(data/\theta)$ is the likelihood of the data given parameter θ, $\Pr(\theta)$ is the prior probability of the parameter θ.

Because the denominator is a normalising factor which ensures that the posterior probabilities sum to 1, we have: *posterior distribution* $\propto$ *likelihood* x *prior distribution*, where $\propto$ means equal to except for a constant of proportionality:

$$\Pr(\theta/data) \propto \Pr(data/\theta)\Pr(\theta).$$

As a result, the posterior distribution can be viewed as a revised version of the prior distribution updated in light of information contained in the data.

Assuming binomial distribution for the recovery rate θ, it is reasonable to consider the beta distribution to model our prior knowledge because (1) distributions in the beta family take values in the interval (0,1), and (2) both mathematical forms are similar, making it easy to find the posterior (i.e., the beta distribution is a conjugate prior to the binomial):

$$\Pr(\theta) \propto \theta^{\alpha-1}(1-\theta)^{\beta-1}.$$

The posterior distribution is also a beta distribution, involving the terms θ and $(1-\theta)$ with the updated exponents $\alpha^* = r + \alpha$ and $\beta^* = m - r + \beta$ (Leonard and Hsu 1999; Bernier et al. 2000).

$$\Pr(\theta/data) \propto \theta^{r+\alpha-1}(1-\theta)^{m-r+\beta-1}.$$

Since in a beta distribution the prior mean is the ratio $\xi = \alpha/(\alpha+\beta)$, the posterior mean $E(\theta/data)$ is $\xi^* = \alpha^*/(\alpha^*+\beta^*) = (r+\alpha)/(m+\alpha+\beta)$. With respect to the variability, as the prior variance of θ is $\xi(1-\xi)/(\alpha+\beta+1)$, the posterior variance $\text{var}(\theta/data)$ is the ratio $\xi^*(1-\xi^*)/(\alpha+\beta+n)$.

From expert opinions or from our past experience, there are several methods for determining the prior distribution (Punt and Hilborn 1997; Hilborn and Liermann 1998; Vose 2001). For Betyp tags, there was no previous tagging survey and consequently we have no prior knowledge about what the proportion of recaptures could be. To account for this complete ignorance we used a neutral prior (sometimes called an uninformative prior or a flat prior), letting $\alpha = \beta = 1$. In such a situation, the shape of the distribution can be represented by a horizontal line (i.e., the rectangular distribution) that implies that every value of θ between 0 and 1 is equally likely. This type of prior, which is equivalent to an uniform distribution (0,1), provides no extra information, except it specifies a possible range of the parameters of interest.

For conventional tags, on the other hand, we know from previous tagging trips that the recovery rate is relatively low for skipjack whereas it can be larger for the two other species (Table 1). From this state of knowledge, we can build a conjugate prior which has the same functional form in θ as the likelihood function. In order to characterize the state of uncertainty about the recovery rate in the form of a probability distribution we can use directly the total of conventional tags released and recovered during the previous trips. However, because the return rate can change dramatically between tagging trips (Table 2), one can argue that this variability should be introduced into the creation of the prior. To account for this uncertainty we used the observed previous return rates (p_i) in the following way (Fig. 1):

(1) initial values of the parameters α and β are calculated by the method of moments, with the aid of the following relationships:

$$\alpha = \mu\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right] \quad \text{and} \quad \beta = [1-\mu]\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right],$$

where μ and σ^2 represent the mean and the variance of the observed return rates (p_i) for conventional tags during the previous tagging trips,

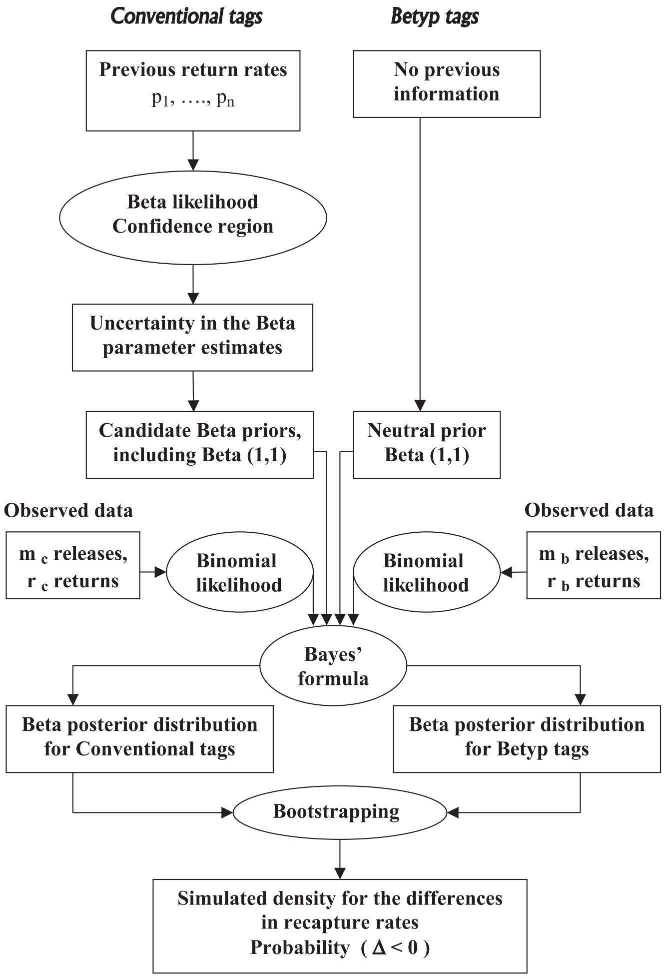

Fig. 1. Representation of the methodology combining Bayesian and simulation-based approaches used to compare the recapture rates of two types of tags.

(2) values that maximise the likelihood function of the Beta distribution (hereafter, MLE estimates) are calculated (Vose 2001):

$$L(\alpha,\beta/p) = \prod_i \frac{p_i^{\alpha-1}\,(1-p_i)^{\beta-1}}{\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}}.$$

To obtain alternative value for α and β to use in the tests of sensitivity we performed their 95% confidence bounds with the help of the bivariate likelihood profile which occurs at minimum negative log-likelihood + $(\chi^2_{2\,(95\%)})/2$. Because too informative priors may have a large influence on the posterior, we included also an uninformed prior ($\alpha = \beta = 1$) in the sensitivity.

Although posterior of recapture rate by tag type follows a Beta distribution, the difference of two beta distributions does not have a beta distribution. The usual approach for dealing with this problem is to use a simulation-based alternative: (1) a sample of values ($n = 1000$) was randomly drawn from the Beta posterior distribution of each tag type (i.e., a parametric bootstrap), (2) the difference in recapture rate was computed for each pair of drawn values, and (3) from the resulting probability density function we performed an approximate credible interval with the aid of the percentiles method.

Table 3. Maximum likelihood estimates (MLE) and joint confidence intervals for the Beta parameters values used to construct the prior distributions of the return rates; π and σ represent the corresponding average proportion and standard deviation, respectively.

Species	Estimates	α	β	π	σ
	MLE	19.04	12.92	0.596	0.085
BET	Lower C. I.	1.79	1.60	0.528	0.238
	Upper C. I.	73.00	48.04	0.603	0.044
	MLE	5.57	20.42	0.214	0.079
SKJ	Lower C. I.	0.82	3.26	0.201	0.178
	Upper C. I.	18.73	67.13	0.218	0.044
	MLE	11.34	8.47	0.572	0.109
YFT	Lower C. I.	1.12	1.08	0.509	0.280
	Upper C. I.	43.34	30.89	0.584	0.057

An alternative methodology for combining diverse statistical information is based on the likelihood principle, which consists of adding independent components into the likelihood function. The concept of indirect likelihood can be used to operationalize in likelihood terms the sampling variation and the scientific uncertainty obtained from previous studies (Schweder 1998). If the indirect likelihood of a parameter is based on previous data, the inclusion of the indirect likelihood in the new study consists in combining the old and the new data. For the conventional tags, the new distribution of R_c recaptures out of M_c tagged fishes is given by the binomial distribution $R_c \sim \text{Bin}\,(\theta_c', M_c)$, with $R_c = r_c + r_c^*$ and $M_c = m_c + m_c^*$; r_c^* and m_c^* being the recaptures and the tagged fishes from previous studies. The confidence interval for the difference is then calculated in the same way as for the frequentist method.

3 Results

For Bigeye tuna, the MLE's Beta parameters correspond to $\alpha = 19.04$ and $\beta = 12.92$ (Table 3). The shape of the joint likelihood profile provides an insight on the uncertainty about the two Beta hyperparameters (Fig. 2). It can be seen that the parameter distributions of α and β are correlated. This means that ignoring this dependence and drawing separately each Beta parameter from its marginal distribution would not reflect accurately our prior knowledge about the recovery rate. It can be assumed that every pair of parameters for which the negative log-likelihood is lower than 3 log-likelihood units up from the minimum (i.e., $(\chi^2_{2\,(95\%)})/2$ equals 3) can be used as a reasonable input for performing the prior distribution. As the Beta parameters are decreased from the upper to the lower credible interval, the prior standard deviation will increase (Table 3). In light of information contained in the data collected during the comparative analysis the return rate for conventional tags is now estimated at 0.63 (Fig. 3).

The range of characterizing our prior belief about the proportion of recoveries for skipjack tagged with conventional tags is displayed in Figure 4 (the axis are scaled as for bigeye

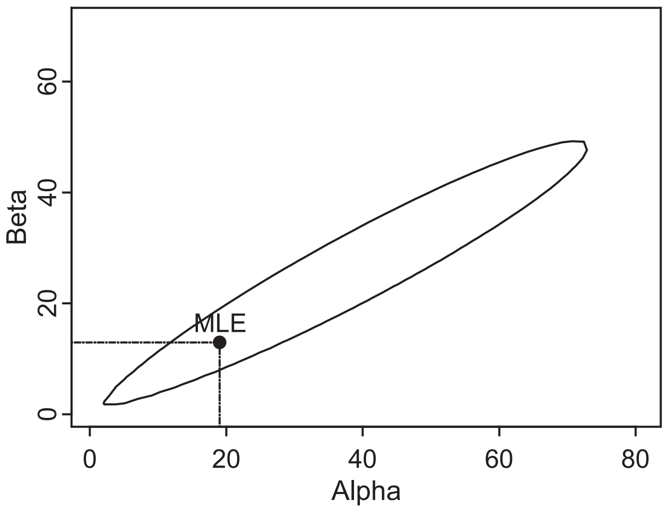

Fig. 2. Joint maximum likelihood estimate and approximate 95% confidence region for the Beta parameters for the prior return rate of bigeye tagged with conventional tags.

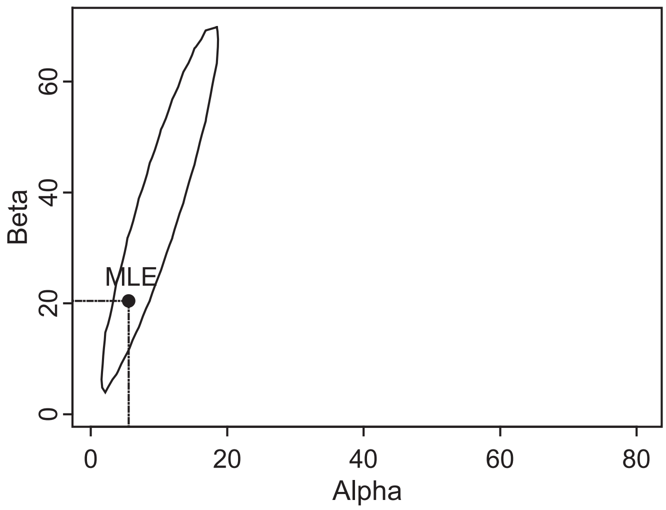

Fig. 4. Joint maximum likelihood estimate and approximate 95% confidence region for the Beta parameters of the prior return rate for skipjack tagged with conventional tags.

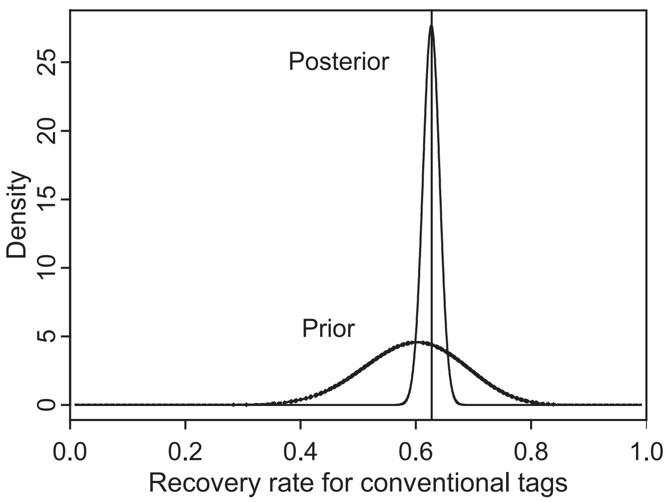

Fig. 3. Prior (thick line), based on the MLEs beta parameters, and posterior (solid line) distributions for the recapture rate of bigeye tagged with conventional tags. The vertical line indicates the location of the proportion of recoveries observed during the comparative analysis (i.e., the binomial MLE).

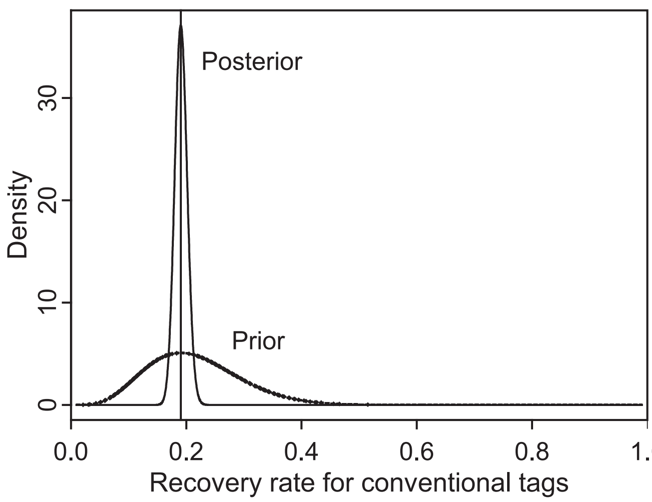

Fig. 5. Prior (thick line), based on the MLEs beta parameters, and posterior (solid line) distributions for the recapture rate of skipjack tagged with conventional tags. The vertical line indicates the location of the proportion of recoveries observed during the comparative analysis (i.e., the binomial MLE).

in order to facilitate the comparison). The most likely values were estimated at about 5.57 and 20.42 for α and β respectively (Table 3). While our prior knowledge about the recapture rate was quite diffuse, the updated distribution is sharper (Fig. 5). Consequently, as seen for bigeye, we obtain a significant gain in precision due to the Bayesian analysis. This is partly due to the fact that likelihood functions based on large samples reflect more precise information in the data than those based on small sample sizes or based on conflicting results. As expected, the posterior recovery rate for skipjack is lower (0.19) than for the two other species.

With respect to yellowfin, the joint likelihood between the prior parameters depicts a large variability (Fig. 6). This pattern is due to the small size of some samples and reflects our uncertainty about these parameters. Comparatively to the two other species, the posterior distribution is more spread (Fig. 7). The updated return rate for conventional tags is a weighted average of our prior guess and the sample proportion observed during the comparative analysis. After our initial guess is combined with the objective function for the data the proportion of returns for spaghetti tags moved from 0.57 to 0.76.

Concerning the effect of the Betyp tags on the change in recovery rate (Δ), we took into account different priors. For practical convenience we incorporated in the tests of sensitivity the priors for which the pairs of parameters corresponded approximately to the edges of the approximate 95% confidence ellipse (i.e., defined thereafter as Minimum and Maximum estimates). For bigeye tuna the posterior using the MLE's Beta parameters suggests a substantial decrease in return rate when using Betyp tag ($\Delta = -19.6\%$; Table 4).

Table 4. Sensitivity analysis on the simulated posterior difference in recapture rate (Delta) by species, assuming different priors; Delta = Posterior recapture rate Betyp tags (Posterior recapture rate conventional tags), L.C.I. and U.C.I. = Lower and Upper credible intervals, respectively.

	Method	Prior	Delta	L. C. I. (0.025)	U. C. I. (0.975)	Probability (Delta < 0)
	Frequentist		–0.197	–0.248	–0.146	1
	Bayesian	Neutral	–0.197	–0.244	–0.145	1
BET	Bayesian	Beta_min.	–0.197	–0.244	–0.145	1
	Bayesian	Beta_MLE	–0.196	–0.243	–0.146	1
	Bayesian	Beta_max.	–0.195	–0.243	–0.148	1
	Integrated		–0.163	–0.211	–0.115	1
	Frequentist		–0.032	–0.081	0.016	0.887
	Bayesian	Neutral	–0.032	–0.076	0.018	0.907
SKJ	Bayesian	Beta_min.	–0.031	–0.076	0.018	0.905
	Bayesian	Beta_MLE	–0.032	–0.076	0.018	0.908
	Bayesian	Beta_max.	–0.033	–0.077	0.016	0.914
	Integrated		–0.064	–0.109	–0.019	0.994
	Frequentist		–0.111	–0.346	0.124	0.798
	Bayesian	Neutral	–0.117	–0.313	0.071	0.877
YFT	Bayesian	Beta min.	–0.117	–0.325	0.067	0.890
	Bayesian	Beta_MLE	–0.066	–0.284	0.125	0.738
	Bayesian	Beta_max.	–0.001	–0.203	0.189	0.499
	Integrated		0.079	–0.138	0.296	0.297

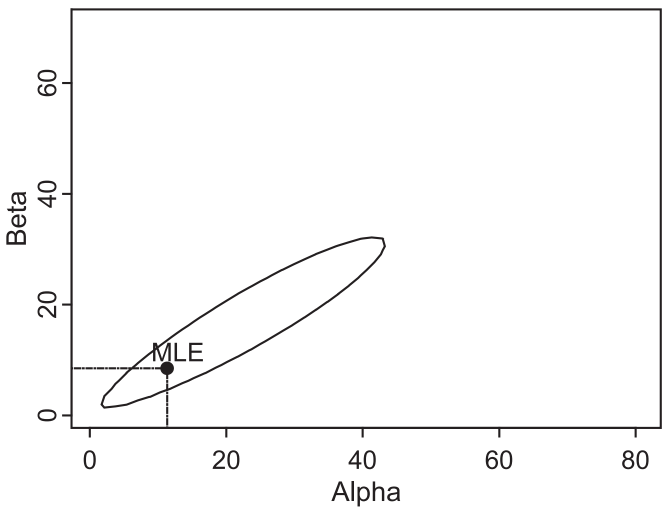

Fig. 6. Joint maximum likelihood estimate and approximate 95% confidence region for the Beta parameters of the prior return rate for yellowfin tagged with conventional tags.

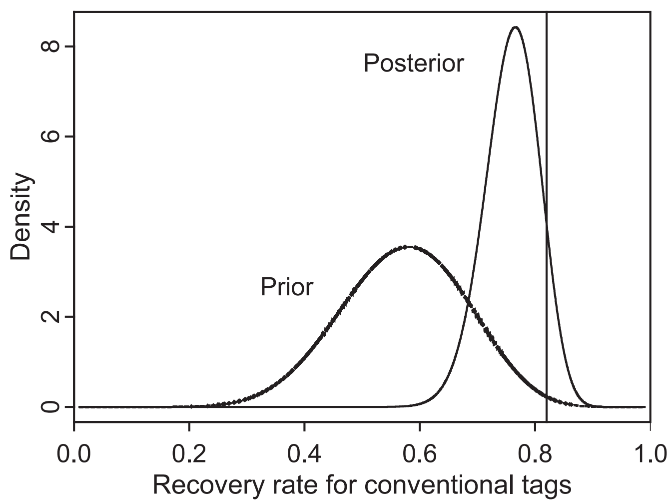

Fig. 7. Prior (thick line), based on the MLEs beta parameters, and posterior (solid line) distributions for the recapture rate of yellowfin tagged with conventional tags. The vertical line indicates the location of the proportion of recoveries observed during the comparative analysis (i.e., the binomial MLE).

Figure 8 confirms that zero is outside the range of the x-values of the posterior distribution. Because the posterior distributions using the "minimum" prior ($\alpha = 1.79, \beta = 1.60$), the "maximum" prior ($\alpha = 73.00, \beta = 48.04$), or in absence of previous information ($\alpha = \beta = 1$) are very close we can conclude that whenever the choice of the prior, there is a strong evidence in favour of a negative impact of Betyp tags (Table 4). The results obtained from the standard frequentist method and from the integrated method are in agreement with the Bayesian approach.

In the case of skipjack the decrease in recovery rate due to the implementation of Betyp tags is close to 3.2% (Fig. 9). Table 4 indicates that assuming a negative efficiency of Betyp tags is not supported by the data at the level of 5% (lower and upper credible intervals equal –0.076 and 0.018, respectively). However because 90.8% of the posterior density is lower than zero, this assumption is plausible at a 10% level. Notice that using the frequentist approach we conclude to the absence of effect at the same α level. In contrast, summarizing previous

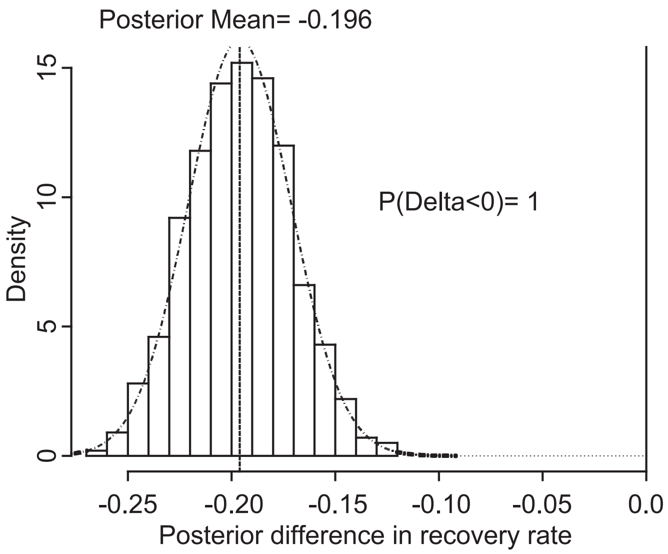

Fig. 8. Posterior density of the change in return rate (Δ) due to Betyp tags for bigeye.

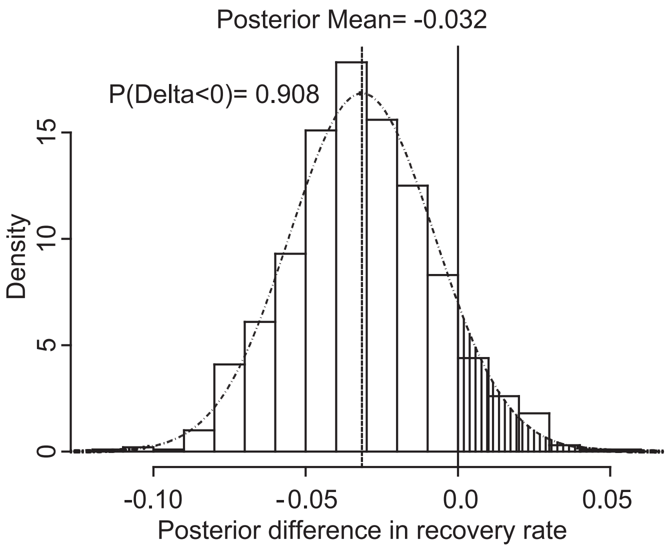

Fig. 9. Posterior density of the change in return rate (Δ) due to Betyp tags for skipjack.

information and new data into the integrated likelihood function leads to the conclusion that Betyp tags have a very strong negative impact on the proportion of recoveries ($\Delta = -6.4\%$; $p(\Delta < 0) = 99.4\%$).

With respect to yellowfin, the recapture rate is 6.6% lower for Betyp tags than for conventional tags (Fig. 10). In spite, this value is greater than it was seen for skipjack, we cannot reject here the hypothesis which assumes that there is no effect of the tag type on the proportion of recoveries (the value 0 is included in the 95% credible intervals of the posterior differences: −0.284 and 0.125; Table 4). The approximate probability for obtaining a difference lower than 0 is estimated at 73.8%, and consequently the potential tag type effect is not considered as plausible. The result provided by the integrated approach reinforces this conclusion.

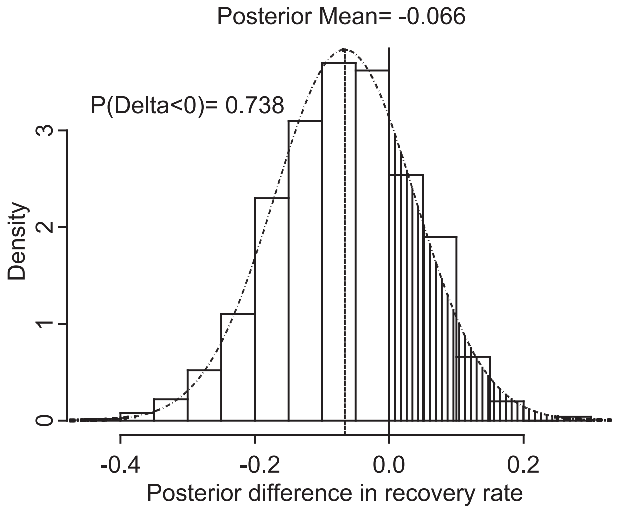

Fig. 10. Posterior density of the change in return rate (Δ) due to Betyp tags for yellowfin.

4 Discussion

One issue of concern in this study is to summarize our prior belief into a probability distribution. Often both expert knowledge and mathematical convenience play a role in selecting a particular form of prior. In this paper we show how information obtained from previous tagging trips, can be fruitful to construct the prior distribution of the return rate. However, even considering similar conditions in term of season, fishing area, type of tagging vessel used, size of the tagged fish, etc., there may be limits to the incorporation of ad hoc guesses to the current comparative analysis. For instance, one can argue that the variability of the proportion of recoveries from one tagging trip to another limits the incorporation of information additional to that contained in the sample data. In such situation, the previous information, while still usable, may be down-weighted by choosing a vaguer prior (i.e., increasing the variance). In this paper we adopted an objective method which consists in integrating directly the variability observed in previous trips when determining the uncertainty about the Beta prior distribution (notice that choosing the minimum values for the Beta parameters is equivalent to down-weighting the prior). Transferring directly uncertainty within different step procedures is not an advantage found only in Bayesian analysis, but is also pointed out in integrated methods (Schweder 1998; Maunder 2001; 2003). The basic distinction between Bayesian and integrated likelihood is that previous information and uncertainty are expressed in probabilistics terms and in likelihood terms, respectively.

Concerning the potential influence of the priors on the updated beliefs, the sensitivity analysis shows that informative and neutral priors provide similar results (at least for bigeye and skipjack). This suggests that even in absence of previous information, the uniform distribution (i.e., Beta distribution with $\alpha = \beta = 1$) might be a reasonable choice for the binomial distribution. However, it may be stressed that there are other candidate forms for a neutral prior, but because they must have a minimal impact on the posterior of the parameter of interest, the selection procedure is not so trivial. It must be keep in mind that (1) the property of being un-informative is not transformation invariant (e.g., if p has a flat distribution from 0 to 1, the transformed parameter $-\log p$ has an exponential distribution; Schweder 1998), (2) a uniform prior for a specific parameter might not be un-informative with respect to another one (Punt and Hilborn 1997; McAllister and Kirkwood 1998) and (3) because of the nature of Bayes theorem, care needs to be taken against inadvertently assigning zero prior probabilities to some subset of possible parameter values (the posterior probabilities will always equal zero for these subsets; Punt and Hilborn 1997). Among the candidate priors, the Jeffreys prior provides a prior invariant under any transformation and therefore determines one version of what could be described as an uninformed prior. Based on the second partial derivative of the loglikelihood function, the Jeffreys prior for a binomial probability is the Beta $(1/2, 1/2)$. Unfortunately, because such prior peaks at $p = 0$ and $p = 1$ and reaches its lowest value at $p = 0.5$ its shape does not depict a flat distribution (Vose 2001). Applications and limits of Jeffreys priors in fishery models were also discussed by Millar (2002). Because Bayesian paradigm cannot formally handle complete ignorance, in such situation it appears suitable to use likelihood methods if there is a sampling model available. However, Bayesians can handle situations where the prior information is fairly vague (Leonard and Hsu 1999).

The present study reinforces the results found by Hallier and Gaertner (2002), who indicated a significant negative effect of Betyp tags on the recapture rate for bigeye tuna. For skipjack the strength of evidence for a decrease in return rate due to Betyp tag is lower than for bigeye but appears plausible at a 10% level. A difference in returns rate between both types of tags may be due to different causes: (1) tag shedding (immediate and/or continuous), (2) non report of recovered tags, and (3) mortality directly attributable to the tag (immediate and/or continuous). Analysing tag reporting, Hallier and Gaertner (2002) concluded that there was no difference between both types of tags, according to the discovery locations. With respect to tag shedding, they suggested that if it would not be the same for both type of tags, it should be to the detriment of conventional tags (due to of its technical characteristics Betyp tag should hold better into the fish than conventional tag; Prince et al. 2002). The assumption concerning a better anchorage of the Betyp tags into the body of the fish is reinforced by the fact that more Betyp tags are returned without heads (Hallier and Gaertner 2002); that is to say that the tag finder being forced to cut off the tag as it is too hard to pull it out of the fish.

For all these reasons, if we assume a similar behaviour of tagged tunas whatever the type of tag used, only a difference in mortality rate can account for these results. For explaining why Betyp tags induce a higher mortality rate for bigeye than for skipjack we can envision several assumptions (we do not address this question for yellowfin as there is at first a problem of small sample size). First of all, tagged bigeye are all juvenile fish ($FL < 103$ cm, average $FL = 56.6$ cm, $\sigma = 137.6$) while most skipjack are adult fish ($FL > 45$ cm, average $FL = 49.7$ cm, $\sigma = 23.7$). It is generally considered that juveniles are weaker than adults therefore bigeye might suffer more than skipjack from the bigger injury inflicted by the Betyp tag. Secondly, as recapture rate of skipjack is much lower than for bigeye, 21.8% and 55.0% respectively for all tag combined, statistical tests to demonstrate a possible mortality rate induced by tagging will be less sensitive for skipjack than for bigeye.

5 Conclusion

Bayesian methods are now being used so widely that one could believe that a study not conducted using this approach is somehow inferior. Obviously this is not the case and depending on the objectives and the nature of the study, conventional statistical methods can also be applied successfully. Neither method is perfect and the balance between advantages and disadvantages of both approaches must be considered. In this way of idea, Schweder (1998) introduced the concept of indirect likelihood, as a manner of combining additional data (gathered from the literature or from expert opinion) with direct data (data at hand or published data, for which the likelihood function is available). In many situations before a new study starts it makes sense to collect the evidence from many sources in order to develop priors which reflect the state of knowledge about the parameters of interest instead of assuming that nothing is known. Bayesian analysis and integrated analysis are compatible paradigms that can coexist and can be entwined with each other (Maunder 2003). In the present study we showed that even when prior information is fairly vague, it is still possible to incorporate the uncertainty in the construction of the prior distribution. Furthermore when the distribution of a quantity of interest is not analytical defined, simulation-based alternative can provide accurate outputs to set up the corresponding posterior density. As mentioned above, Bayesian and frequentist approaches appear complementary for dealing with complex related-fishery studies.

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