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Deriving Acceptable Biological Catch from the Overfishing Limit: Implications for Assessment Models

Michael H. Prager*
Southeast Fisheries Science Center
National Marine Fisheries Service, NOAA
101 Pivers Island Road
Beaufort, North Carolina 28516 USA

Kyle W. Shertzer
Southeast Fisheries Science Center
National Marine Fisheries Service, NOAA
101 Pivers Island Road
Beaufort, NC 28516 USA

* Corresponding author : mike.prager@noaa.gov

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Abstract

The recently revised Magnuson–Stevens Fishery Conservation and Management Act requires that U.S. Fishery Management Councils avoid overfishing by setting annual catch limits (ACLs) not exceeding recommendations of the Councils' scientific advisers. To meet that requirement, the scientific advisers will need to know the overfishing limit (OFL) estimated in each stock assessment, OFL being the catch available from applying the limit fishing mortality rate F_{lim} to current stock biomass. The advisers then will derive "acceptable biological catch" (ABC) from OFL by reducing OFL to allow for scientific uncertainty, with ABC becoming their recommendation to the Council. We suggest methodology, based on simple probability theory, by which scientific advisers can compute ABC from OFL and its statistical distribution, as estimated by a stock assessment. Our method includes approximations to the distribution of OFL, if not known from the assessment; however, we find that it is preferable to have the assessment model estimate the distribution of OFL directly. Probability based methods, such as this one, provide well defined approaches to setting ABC and may be helpful to scientific advisers as they translate the new legal requirement into concrete advice.

Introduction

In 2006, the U.S. Congress reauthorized the Magnuson–Stevens Fishery Conservation and Management Act. The reauthorizing statute (Magnuson–Stevens Reauthorization Act or MSRA) (MSRA 2006) established several new requirements for U.S. federal fishery management. Two widely noted requirements are that Fishery Management Councils, which manage U.S. fisheries in federal waters, must set annual catch limits (ACLs) on managed stocks, and that those limits may not exceed the recommendations of a council's scientific advisers.

To translate this law into practice, the National Marine Fisheries Service has developed National Standards Guidelines (USOFR 2009) as revisions to the U.S. Code of Federal Regulations. That document refers to two main classes of uncertainty: scientific uncertainty, which embodies uncertainties in scientific understanding, data, and estimation, and management uncertainty, which reflects the uncertain realization of management regulations in a fishery. The guidelines suggest that usually a council's Scientific and Statistical Committee (SSC) will be the scientific adviser and that the SSC's recommendations, not to be exceeded, should include the acceptable biological catch (ABC) that results from reducing the overfishing limit (OFL) to allow for scientific uncertainty. In this context, OFL is defined as the catch available from projected biomass B at the limit reference point F_{lim} in fishing mortality rate. By default, $F_{\mathrm{lim}} = F_{\mathrm{MSY}}$, the rate at which maximum sustainable yield can be obtained from a stock in equilibrium (USOFR 2009).

Here, we describe a framework that can be used to choose ABC, given three things: OFL, its statistical distribution, and the allowable probability of overfishing. Ideally, the distribution of OFL will be available from the stock assessment. If not, the distribution can be computed by propagation-of-error methods. We examine, through four examples, how well propagation-of-error methods might perform in this application.

Probability-based reference points

Several authors have demonstrated uses of probability theory to derive fishery reference points (typically denoted "targets" and "limits") that incorporate various kinds of uncertainty. Caddy and McGarvey (1996) described a procedure to set a target fishing mortality rate, given a limit fishing mortality rate F_{lim} known precisely, so that the rate realized in the next period F_{next}

would exceed F_{lim} with only some specified probability P^* (Figure 1a). The procedure assumes that F_{next} will be centered on the target, but may not equal it, because of imperfect implementation of management controls (e.g., quota overruns) or imperfect stock assessment.

Prager et al. (2003) revised and extended the work of Caddy and McGarvey (1996) in several ways. The revised procedure, which they termed REPAST, allows uncertainty both in estimating the limit reference point (a type of scientific uncertainty) and in attaining the target (a type of management uncertainty), uses ratios to reduce possible covariance between quantities, and can be applied to reference points in biomass as well as in fishing mortality rate. The authors suggested that an adjustment (bias correction) be made when the distribution of past catches has not been centered on corresponding targets. Such an adjustment would address the problem of "regulatory slippage" noted by Eagle and Thompson (2003).

Shertzer et al. (2008) described a procedure (PASCL), extended considerably from that of Prager et al. (2003), and intended for setting ABCs, ACLs, and annual catch targets (ACTs) in a series of several years, generally the period from one stock assessment until the next. (The relationship among reference points is ACT ≤ ACL ≤ ABC ≤ OFL, with at least one of the inequalities strict; use of an ACT is optional [USOFR 2009].) The Shertzer et al. (2008) procedure uses a stochastic projection model, starting from estimates of F_{lim} and terminal-year abundance; it can incorporate major forms of scientific uncertainty and management uncertainty.

Single-year computations

In this management brief, we describe a simple probabilistic approach related to those previous methods. Rather than computing multi-year ABCs and ACTs as in PASCL, this simpler approach computes only a single year's ABC, given a projected biomass and an estimate of the distribution of OFL under scientific uncertainty. Because that distribution may be unavailable, we examine a group of methods for approximating it from the variances of the projected biomass and F_{lim}, and possibly their covariance.

We present this work because we expect that some Fishery Management Councils will take a stepwise approach, annually, in complying with the new federal requirements. In one step, they will ask their scientific advisers for annual ABCs for a managed stock or stocks, derived from the OFL and taking scientific uncertainty into account, as required by USOFR (2009). In a later step, the Council will set ACLs (and possibly ACTs) from those ABCs, taking management uncertainty into account. This paper addresses only the first step, the work of the scientific advisers. In the language of Eagle and Thompson (2003), methods like REPAST control the probability of both the scientific and regulatory forms of overfishing, while the present method controls only scientific overfishing.

We propose setting ABC from the statistical distribution of OFL, which in many cases can be estimated by stock-assessment software that is suitably programmed. If so, one can apply a procedure like that of Caddy and McGarvey (1996) to set $\mathrm{ABC} < \mathrm{OFL}$ such that $\mathrm{P}(\mathrm{ABC} > \mathrm{OFL})$ equals some chosen value P^* (Figure 1b). In other words, we propose that the ABC be chosen as the percentile of the distribution of OFL that results in $\mathrm{P}(\mathrm{ABC} > \mathrm{OFL}) = P^*$ (Figure 1b). This is a mirror image of the approach of Caddy and McGarvey (1996) in that they considered the limit reference point F_{lim} to be fixed and the corresponding target uncertain, but here, the situation is reversed: the limiting value OFL is uncertain, while the ABC will be expressed as a point value (Figure 1). This probabilistic approach requires two inputs: the value of P^* and the distribution of OFL; i.e., its central tendency and some description, empirical or parametric, of the uncertainty around that central value (Figure 1b).

Approximating the distribution of OFL

Ideally, the distribution of OFL will be estimated by the stock assessment software. However, the distribution is not available from all commonly used software. If not, and if the software estimates the distributions (or simply the variances) of current stock biomass B and limit fishing mortality F_{lim}, propagation-of-error methods can be used to approximate the distribution of OFL.

To accomplish that, error is propagated through the catch equation (the equation giving catch as a function of stock size, fishing mortality rate, and other factors) used to model the stock. Letting fishing mortality rate $F = F_{\mathrm{lim}}$, and disregarding age structure, the Baranov catch equation, widely used in age-structured fishery models, expresses the overfishing limit as a function (G) of F_{lim} and current biomass B:

$$\mathrm{OFL} = G(F_{\mathrm{lim}}, B) = \frac{F_{\mathrm{lim}} B (1 - e^{-M - F_{\mathrm{lim}}})}{F_{\mathrm{lim}} + M}, \qquad (1)$$

where M is the natural mortality rate. If the assessment is based on a different catch equation, such as the logistic stock–production catch equation (Prager 1994), the overfishing limit will still be a function of F_{lim} and B, and possibly other factors.

We considered two methods for examining propagation of error. The delta method, an approximation based on Taylor series (Seber 1973), has been applied in many contexts, including fishery stock assessment models (e.g., Prager and MacCall 1988). Its main advantage here would be computational economy, due to the existence of analytical derivatives of the Baranov and logistic catch equations. Its disadvantage would be its requirement to assume a parametric form (usually normal) for the probability distributions of biomass, F_{lim}, and OFL. The main competing method, Monte Carlo simulation, does not require that assumption. Its drawback, computational intensity, is not significant in this application and given today's computers. Thus, we chose it for this study.

Monte Carlo simulation is straightforward to implement, e.g., through such computer packages as WinBUGS (Lunn et al. 2000) or R (R Development Core Team 2008); it can accommodate any distributions of F_{lim} and B, including empirical distributions; and it estimates a complete distribution of OFL, not just parameters of a given distributional form. How well does Monte Carlo simulation work in this context? It seems unlikely that any simulation study could answer that question exhaustively, given the very many stocks and assessment models of interest. To obtain some preliminary impressions, we examined results of four stock assessments using two assessment models, comparing results of four Monte Carlo configurations to direct estimates of OFL distributions.

Methods

Of our four cases, three were taken from recent stock assessments in the southeastern U.S. of black sea bass *Centropristis striata*, red porgy *Pagrus pagrus*, and tilefish *Lopholatilus chamaeleonticeps*, and one from analysis of an historical data set on swordfish *Xiphias gladius*. Black sea bass, red porgy, and swordfish were analyzed with a nonequilibrium logistic production model (Schaefer 1957, Pella 1967) in the formulation of Prager (1994), modeled with ASPIC software (Prager 1995). The tilefish data were analyzed with a statistical catch–age model, whose form and implementing software were generally similar to the Stock Synthesis model of Methot (1989). The catch–age model and software are described in detail in the assessment report (SEDAR 2004).

Each assessment estimated the distribution of OFL or the distributions of its components (B and F_{lim}), from which we computed the distribution of OFL by application of the corresponding catch equation to paired realizations of B and F_{lim}. The ASPIC software uses bootstrapping to estimate the OFL distribution, which we bias-corrected (Efron 1987) before use. The catch–age model uses a mixed Monte Carlo and bootstrap approach (Legault et al. 2001) to estimate the OFL distribution, which did not require bias correction. In each case, the OFL distribution from the assessment was used as a reference value.

Some assessment software may estimate means and variances of F_{lim} and B, and possibly the covariance between them, but not the empirical OFL distribution itself. For example, models that use the Hessian matrix to derive variances assume that distributions are asymptotically normal. We evaluated four configurations of a Monte Carlo approximation that could be used in such cases. *Configuration one* assumed normality of F_{lim} and B in arithmetic space with zero covariance between them; *configuration two* assumed normality in log space with zero covariance; *configuration three* assumed normality in arithmetic space with covariance known; and *configuration four* assumed normality in log space with covariance known.

We programmed Monte Carlo simulations in the statistical language R (R Core Development Team 2008), using the function rnorm to generate univariate normal random numbers and the function mvrnorm from package MASS (Venables and Ripley 2002) to generate bivariate normal random numbers with nonzero covariance. In each simulation, 1000 draws were made from the univariate distributions of F_{lim} and B or from the bivariate distribution of F_{lim} and B. Each draw was transformed by the corresponding catch equation (equation [1] in the age-structured example and equation [6] of Prager 1994 in the production-model examples) into a corresponding value of OFL. The resulting 1,000 values of OFL were taken together to approximate the distribution of OFL. As when the distribution was known directly from the stock assessment, ABC was taken as the percentile of the OFL distribution corresponding to $P*$.

For each stock, allowable biological catch ABC was computed from the reference OFL distribution and from each Monte Carlo configuration, evaluated using values of $P*$ from 0.2 to 0.5 in steps of 0.05. We examined graphically the consequences to ABC that would ensue from using each of the four approximations in place of corresponding percentiles of the reference distribution of OFL. We also tabulated relative differences from the reference ABCs at P^* = 0.35, a mid-range, representative value.

Results

Correlations between estimates of F_{lim} (here $F_{\text{lim}} = F_{\text{MSY}}$) and B varied by type of assessment model from which they were obtained. Estimates from the three production models were negatively correlated; results for black sea bass (Figure 2a) are typical. In contrast, estimates from the statistical catch–age model used for tilefish were positively correlated (Figure 2b). In all four cases, the correlation was significantly different from zero ($P < 0.0001$).

When ABC was approximated with the Monte Carlo configurations, the differences from the reference ABC were considerably larger in analyses of black sea bass and swordfish (Figures 3a, 3b) than in analyses of red porgy and tilefish (Figures 3c, 3d). Most large differences were negative; i.e., use of the approximations gave lower estimates of ABC (Table 1). The Monte Carlo configuration most closely approaching the reference ABC varied by stock, but when we considered only the two stocks (black sea bass and swordfish) exhibiting large differences in performance among configurations, the lognormal configuration with known covariance performed appreciably better than other Monte Carlo configurations (Table 1).

Discussion

Our results imply that, when using probability-based methods, it is highly desirable for the assessment model to generate an estimated distribution of OFL, as estimates of ABC derived from our approximations could differ from the reference values considerably (Figure 3). In the two more extreme cases we considered (black sea bass and swordfish), approximations of ABC were too low, although we have no reason to believe that this is a general result. If an estimate of the OFL distribution is not available, Monte Carlo simulation can be used to approximate it, as long as the assessment provides estimates of the components (F_{lim} and B) of OFL and their variances. In this application, Monte Carlo simulation tended to perform better when the covariance between F_{lim} and B was also available. Our results (Figure 3, Table 1) suggest that, of the Monte Carlo configurations examined, the one in logarithmic space with covariance performed best, and therefore should be used when possible. Unfortunately, we can make no ad hoc recommendation about a value that might be assumed for covariance when an estimate is not available, because in our examples, sign of the covariance depended on the assessment model used (Figure 2).

The production model used here (Prager 1994, 1995) incorporates observation error (e.g., error in the abundance index), but not process error (e.g., variability in production at a given biomass), and, like most production models, has few estimated parameters. The relative inflexibility of that modeling scheme almost certainly contributes to the consistent pattern of negative correlation seen between estimates of terminal biomass and F_{lim} (Figure 2a). The age-structured model, in constrast, incorporates process error in recruitment as well as observation error in the data and has dozens of estimated parameters. We have found its correlation patterns to vary among applications. The positive relationship of Figure 2b appears to be driven by variation in natural mortality, which correlates positively with both terminal biomass and F_{lim}.

Several caveats should be kept in mind if applying the methods described here. Because in fisheries analyses, statistical assumptions are rarely (if ever) met, it is unlikely that picking a percentile from the distribution of OFL will result in a perfectly realized probability of overfishing. To consider one issue, small values of P* (say, P* < 0.2) may produce inconsistent results, because distributions that vary from their estimates tend to do so most strongly in the tails. To consider another, if precision estimates from an assessment are unreliable or the assessment has not exhibited stability over time, it may be desirable to explore other methods, such as ad hoc proportional reductions of catch from OFL or of F from F_{lim}. An approach being explored by the South Atlantic and Mid-Atlantic Fishery Management Councils is to use a framework similar to this one but to reduce P^* from a baseline value in response to various factors. These might include excessive age of the last assessment, known data limitations, incomplete variance estimation, status of the stock, or life-history characteristics that increase vulnerability or susceptibilty.

What sort of values are appropriate for P^*, either for direct application or to be adjusted as just described? Because that is a policy issue and also may vary by application, no definitive or universal answer can be given. As noted earlier, setting ABC < OFL is an early step in a longer process. A council is then charged with setting an annual catch limit (and possibly an annual catch target) for each stock such that ACL ≤ ABC and ACT (if used) ≤ ACL. Because the P^* described here is only one buffer of a multi-buffer system, it seems reasonable to set P^*

higher than if it were the only buffer. A plausible range might be around $0.25 \leq P^* < 0.5$. Assigning a value to P^* is necessarily somewhat subjective, as it will generally reflect risk tolerance as well as scientific considerations. Nonetheless, we think that making that decision explicit, rather than burying it as an implicit value in an ad hoc procedure, contributes to clarity and transparency in fishery management.

Once the value of P^* has been chosen, methods based on probabilities are desirable because they are clearly defined, repeatable, and computable from standard assessment outputs (or clear assumptions about variance). They emphasize the need for explicit specification of the allowable probability (P^*) of exceeding the limit reference point, and perhaps most importantly, are easily communicated.

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Table 1. Percentage differences in ABC (acceptable biological catch), relative to values directly estimated by an assessment model, obtained by using four configurations of Monte Carlo simulation on abbreviated assessment estimates. Tilefish was analyzed with a statistical catch–age model; the other species, with a nonequilibrium production model. All values were computed using $P* = 0.35$, where $P*$ is the allowable probability that ABC > OFL, and OFL is the overfishing level.

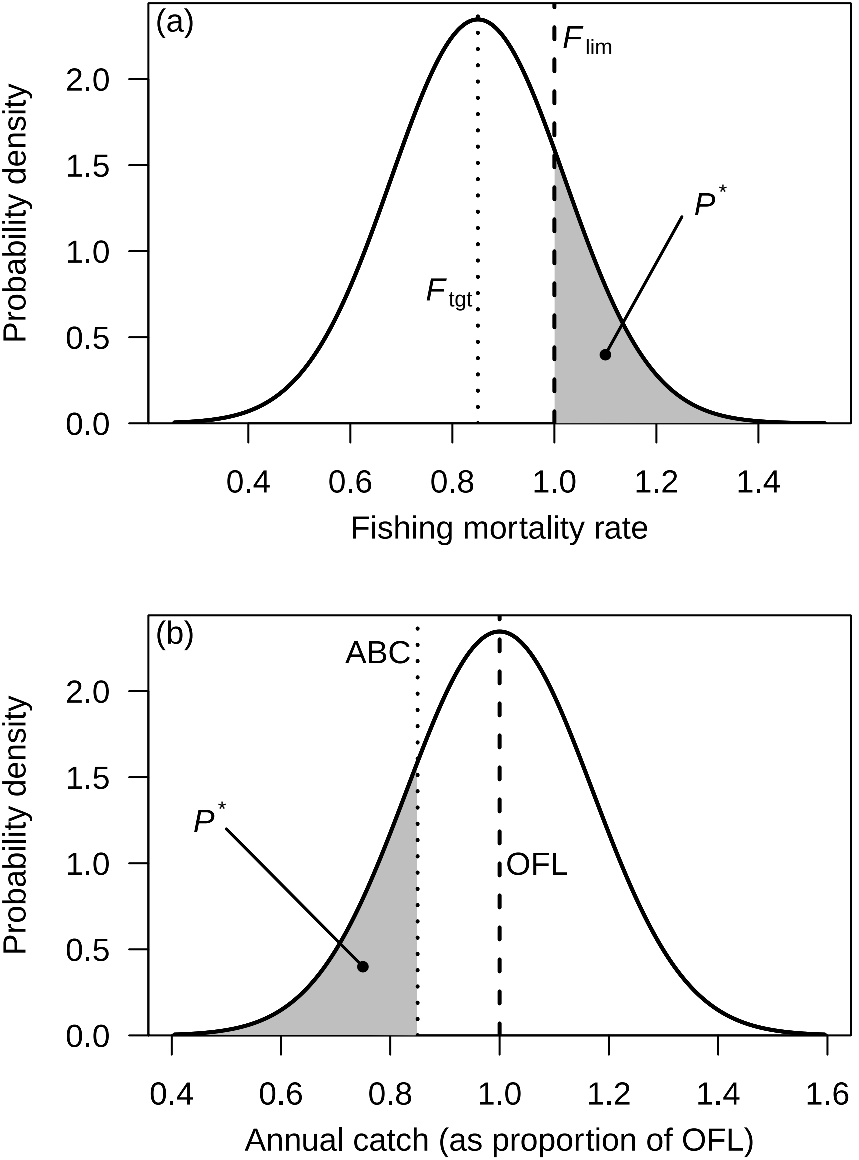
Monte Carlo approximation configuration	Species			
	Black sea bass	Swordfish	Red porgy	Tilefish
Normal	–48.3	–21.6	–0.6	–11.0
Lognormal	–24.9	–12.3	9.6	0.6
Normal with covariance	–39.8	–16.4	0.6	–8.2
Lognormal with covariance	–10.3	–2.6	5.5	–1.6

Figure captions

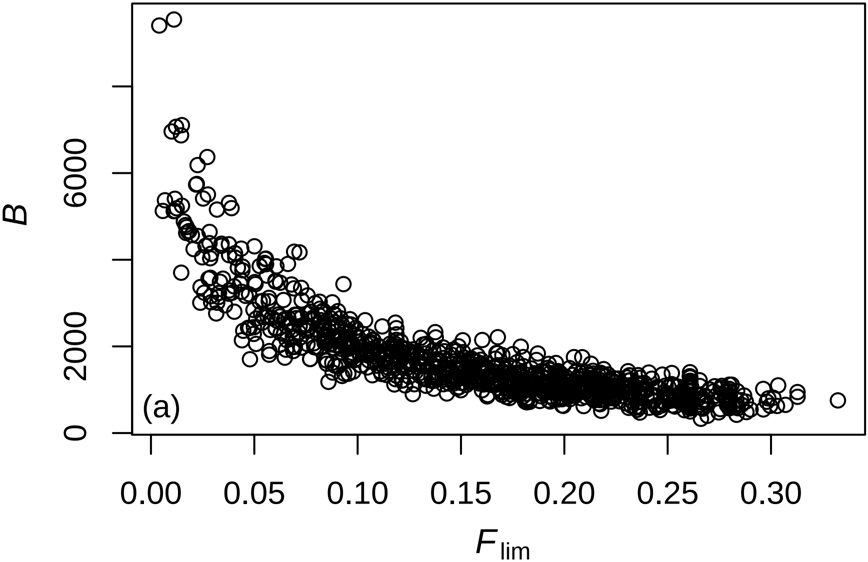
Figure 1: (a) Method of Caddy and McGarvey (1996) for deriving a target reference point from a limit reference point. Given the distribution of realized fishing mortality F around its target F_{tgt}, the limit reference point F_{lim} is adjusted so that the probability (shaded area) that realized F exceeds F_{lim} equals the pre-set value P^*. (b) Proposed procedure for setting acceptable biological catch (ABC) from distribution of overfishing limit (OFL). Given the distribution of OFL, ABC is adjusted so that the probability that ABC > OFL equals the pre-set value P^*.

Figure 2: Bivariate distribution of estimates of limit fishing mortality rate F_{lim} and biomass in final year B from (a) nonequilibrium production model of black sea bass and (b) statistical catch–age model of tilefish.

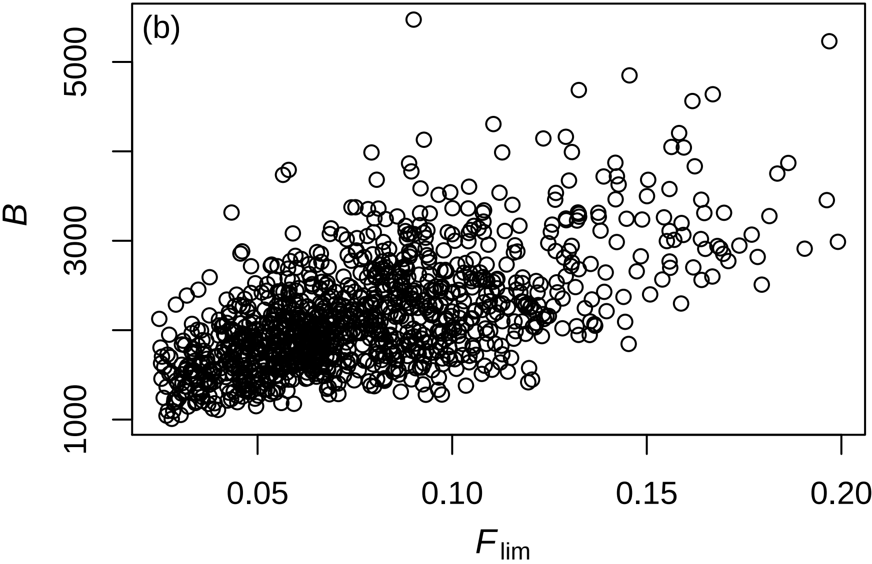
Figure 3: Comparison of acceptable biological catch (ABC) determinations over a range of P^*, where P^* is the allowable probability that ABC will exceed the overfishing limit (OFL). Reference ABCs were determined from OFL distributions from stock assessments; other ABCs were computed from four Monte Carlo methods that approximate the OFL distribution (see text for details). Examples are (a) black sea bass, (b) swordfish, (c) red porgy, and (d) tilefish.



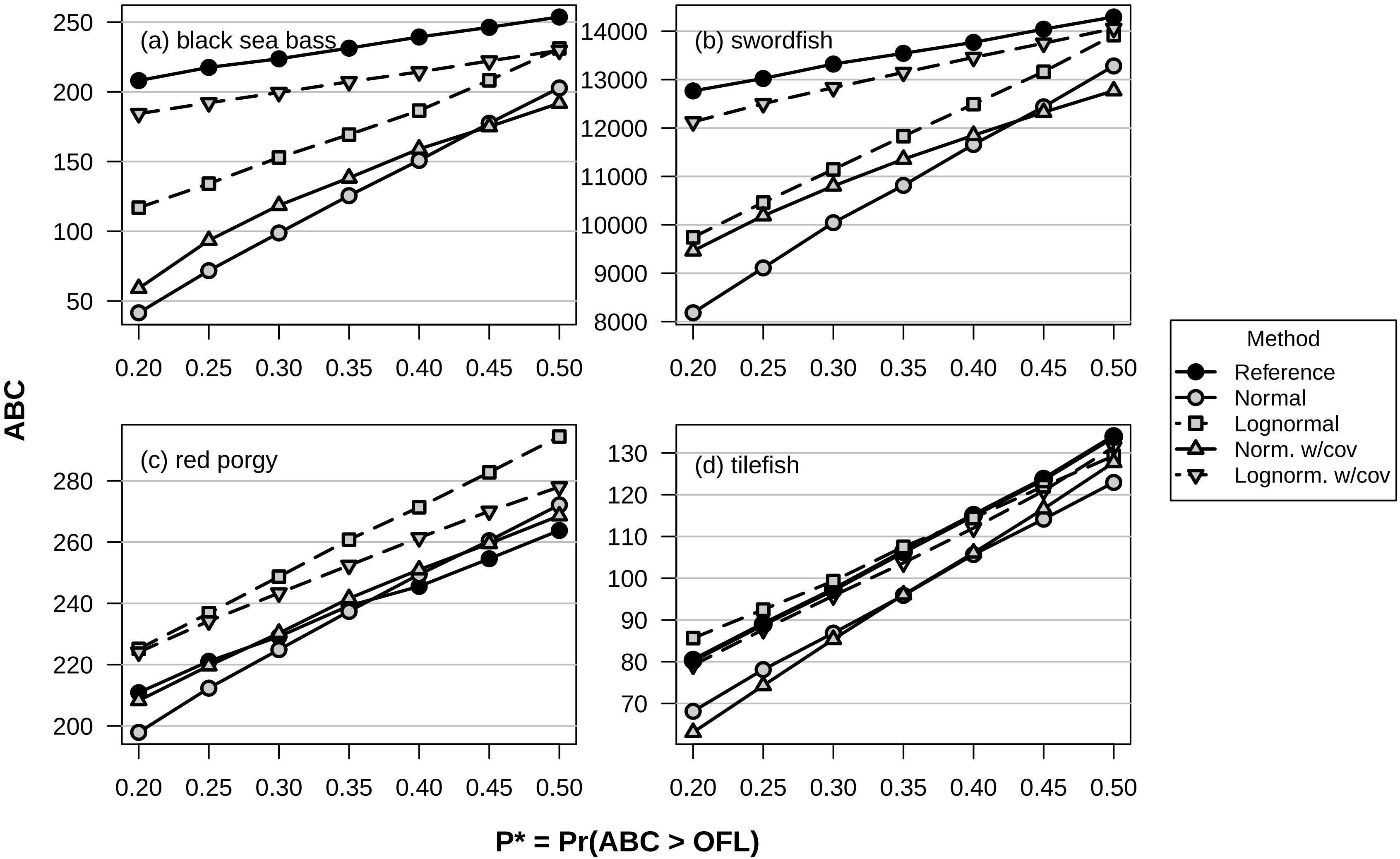
(a)
Flim
Ftgt
P*
Probability density
0.0
0.5
1.0
1.5
2.0
0.4
0.6
0.8
1.0
1.2
1.4
Fishing mortality rate
(b)
ABC
OFL
P*
Probability density
0.0
0.5
1.0
1.5
2.0
0.4
0.6
0.8
1.0
1.2
1.4
1.6
Annual catch (as proportion of OFL)



(a)
B
0
2000
6000
0.00
0.05
0.10
0.15
0.20
0.25
0.30
F_{lim}



(b)
B
1000
3000
5000
0.05
0.10
0.15
0.20
F_{lim}


(a) black sea bass
(b) swordfish
(c) red porgy
(d) tilefish
ABC
P* = Pr(ABC > OFL)
Method
Reference
Normal
Lognormal
Norm. w/cov
Lognorm. w/cov