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Review

A review of harvest policies: Understanding relative performance of control rules

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ABSTRACT

Harvest policies use control rules and associated policy parameters to dictate how fishing mortality or catch and yield levels are determined, and are necessary for rational management. Common control rules include constant catch, constant fishing mortality rate, constant escapement, or a few variations of these. The "best" among these control rules for meeting common fishery objectives (e.g., maximizing yield) is a source of controversy in the literature, and results are seemingly contradictory. To compare the ability of control rules to meet widely used fishery objectives and identify potential causes for these apparently contradictory results, we did a detailed review of relevant literature. The relative performance of control rules at meeting common fishery objectives is affected by: whether uncertainty in estimated stock sizes is included in analyses, whether the maximum recruitment level (e.g., the asymptote of a Beverton–Holt stock–recruit function) is varied in an autocorrelated fashion over time, fishery objectives, and the amount of compensation in the stock–recruit relationship. Few studies have compared control rules using optimal parameters (e.g., those that maximize some objective function) that were found while including assessment error. More commonly, parameters that are optimal without assessment error are used in a comparison of control rules that includes assessment error. This approach can produce misleading results. Ideally, selection of a control rule and policy parameters is done within the framework of a stochastic simulation that considers key uncertainties. If this is not feasible, an alternative option is to "borrow" control rules from a similar fishery and set policy parameters based on biological reference points developed for a species with similar taxonomy and life-history traits. More research is needed to compare control rules when accounting for uncertainty in key population parameters, when stock–recruitment or other population dynamic parameters vary over time, and for fisheries with non-yield-based or competing objectives.

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1. Introduction

Rational management of fish stocks requires determination of harvest or yield levels that are consistent with management objectives. Historically, the "rules" for setting harvest levels have been vague or non-existent (NRC, 1994). In many cases, this resulted in forsaking long-term objectives for short-term gains. Consequently, examples of fish stock declines and collapses are widespread (Myers and Worm, 2005). To prevent future stock collapses, and allow rebuilding of stocks that are already depleted, more explicit guidelines are required on how harvest levels should be set. Such guidelines are referred to as harvest policies. When these guidelines specify the amount of catch, effort, or fishing mortality by a specific, and usually simple, function of the current estimate of the system state (e.g., the amount of spawning biomass) they are called control rules.

Fishery objectives partially determine the relative performance of different control rules and are represented quantitatively in simulations and analyses through the use of objective functions. Selection of objectives or objective functions can affect which control rule is preferred, and thus it is critical to ensure resource user preferences and broader societal goals for sustainability of the resource are incorporated into the chosen objectives. The use of an objective that conflicts with the interests of the fishery could cause mistrust from the fishing industry, or even fishery collapse. For example, in a recreational fishery, where high catch rates and the size of harvested fish are likely to be important, using a maximum yield objective function would be inappropriate. Although this is true, most harvest policy work emphasizes yield-based objectives, and hence by necessity, much of this review evaluates these.

Several methods are used to evaluate control rules for meeting given fishery objectives. A variety of analytical methods can be used to show that a given control rule performs better than all other candidates (i.e., is optimal) at achieving a given objective (e.g., Gatto and Rinaldi, 1976). While these methods can provide quite general results, they are feasible only for simple models of fishery systems that often are deterministic or ignore key uncertainties. Stochastic dynamic programming is an efficient method for selecting an optimal strategy at each time step, so that the result over the entire time-horizon best meets a specified objective (e.g., Walters and Parma, 1996). While the method can be analytical or numerical, most fishery applications are numerical. This method is useful when one is interested in considering more flexible policies than a simple control rule that remains constant over time. The computational cost of searching over a wide range of strategies has also generally limited this approach to relatively simple models. Much of the recent harvest policy literature considers models too complex for the above methods, and often the focus is on trade-offs among different measures of performance, rather than finding the policy that is optimal for a single objective. Consequently, much harvest policy work uses Monte Carlo simulations to evaluate the performance of a specified control rule (function) and policy parameters for the control rule (e.g., Eggers, 1993). Typically, multiplicative annual process error is included in the stock–recruit relationship, which may or may not include autocorrelation. Alternatively, or additionally, annual process error can be added to specific model parameters. Other random error terms are often included to model assessment or implementation error. When these simulations attempt to model uncertainty associated with the stock assessment process and implementation of the control rule, this is called a management strategy evaluation (MSE; Polacheck et al., 1999). Typically, a range of different policy parameters are considered. In some cases a wide enough range of policy parameters is considered that this essentially constitutes a grid search, and optimal results for a given control rule and objective can be identified. In rare cases, usually for very simple stochastic models, an automated numerical search is done for parameters that maximize an objective function. The results obtained by these "brute force" simulation approaches are limited to the specific policy parameters (and other assumptions) chosen for inclusion in simulations, and thus cannot prove that a particular control rule is optimal for a given objective over a broad range of conditions. However, we believe induction based on these studies, combined with consideration of results known from analytical studies, can be very useful.

In many fisheries, managers must decide on a level of yield each fishing season, ideally by using a harvest policy that is chosen because it meets fishery objectives (i.e., produces a large value for the objective function). Theoretically, a harvest policy could be to set yield each year so that the objective function is maximized given the information available at that time (Ricker, 1958; Larkin and Ricker, 1964; Tautz et al., 1969). Such a policy would generally mean that yield is determined in a complex way by current stock assessment results and other information (e.g., using stochastic dynamic programming; Frederick and Peterman, 1995). In practice, determination of such optimal policies can be a daunting or an infeasible computational task. Furthermore, such an approach can lack appeal to managers and stakeholders because the intuitive basis of the policy and why the current year's allowable catch has changed from the previous year may not be apparent. Perhaps as a consequence, nearly all harvest policies are based on relatively simple control rules that can be viewed as relating fishing mortality to stock abundance (usually biomass; Fig. 1). However, which rules are best at meeting certain fishery objectives is a source of controversy in the literature. Furthermore, the relative performance of control rules depends upon the specific characteristics of the fishery and underlying fish population dynamics that are incorporated into an evaluation. Consequently, selecting an appropriate control rule can be an arduous task.

The objectives of this review are to (1) compare and contrast the performance of various control rules for meeting common fishery objectives and (2) identify potential reasons for what seem to be contradictory results. First, we discuss a range of control rules and objectives that are used in harvest policy studies. Second, we consider the performance of different control rules when perfect knowledge is assumed about the fishery, after which we examine the effect of imperfect information on stock size, which is a feature of harvest policy analyses that has a particularly strong effect on control rule performance. Other features of harvest policy analyses also affect policy performance, such as the level of compensation in the stock–recruit relationship and whether certain stock–recruit parameters are autocorrelated through time, and these are addressed within the framework of the perfect and imperfect information sections. Third, we consider approaches