HOW MANY FISH ARE THERE AND HOW MANY CAN WE KILL? IMPROVING CATCH PER EFFORT INDICES OF ABUNDANCE AND EVALUATING HARVEST CONTROL RULES FOR LAKE WHITEFISH IN THE GREAT LAKES

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ABSTRACT

HOW MANY FISH ARE THERE AND HOW MANY CAN WE KILL? IMPROVING CATCH PER EFFORT INDICES OF ABUNDANCE AND EVALUATING HARVEST CONTROL RULES FOR LAKE WHITEFISH IN THE GREAT LAKES

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My dissertation has two main objectives: 1) to explore alternative ways to use commercial lake whitefish fishery catch per effort (CPE) data as an index of abundance in 1836 Treaty-ceded waters of the Great Lakes, and 2) to evaluate alternative harvest control rules for lake whitefish. Chapter 1 was directed at exploring alternative ways to use commercial lake whitefish fishery CPE data, while Chapters 2 and 3 covered topics related to harvest control rules.

Fishery CPE data is often used to assess relative fish abundance, and assessments used in 1836 Treaty-ceded waters of the Great Lakes assume that commercial CPE (i.e., ratio of aggregate catch to aggregate effort in each year) from gill-net and trap-net fisheries is proportional to abundance. However, CPE may change due to factors other than abundance. In Chapter 1, I developed general linear mixed models (GLMMs) to account for sources of variation in CPE unrelated to abundance, and used the least-squares means (LSMs) for each year as an alternative to the current index of abundance. Effects such as license holder, boat size, and month accounted for much of the variation in CPE. LSMs and the current CPE index displayed different temporal trends among years in some areas, suggesting the importance of adjusting fishery CPE for effects like boat size, season, and license holder.

Harvest policies use control rules to dictate how fishing mortality or catch and yield levels are determined. Common control rules include constant catch, constant fishing mortality rate, and constant escapement. The "best" control rules for meeting common fishery objectives (e.g., maximizing yield) is a source of controversy in the literature, and results are seemingly contradictory. In Chapter 2, I conducted a detailed review of the relevant harvest control rule literature to compare control rules for their ability to meet widely used fishery objectives and identify potential causes for contradictory results. The relative performance of control rules at meeting common fishery objectives was affected by: fishery objectives, whether uncertainty in estimated stock sizes was included in analyses, whether the maximum recruitment level was varied in an autocorrelated fashion over time, how policy parameters were chosen, and the amount of compensation in the stock–recruit relationship. More research is needed to compare control rules while considering these and related factors.

In Chapter 3, I used an age-structured simulation model that incorporated stochasticity in life history traits and multiple uncertainties to compare the current harvest control rule for lake whitefish (constant fishing rate; CF) with a range of alternative control rules, including conditional constant catch (CCC), biomass-based (BB), and CF and BB rules with a 15% limit on the interannual change in the target catch. The CF and BB rules simultaneously attained higher average yield and spawning stock biomass than other control rules, while the CCC rule and limiting the target catch changes by 15% had the lowest yearly variability in yield. The low yearly variability in yield provided by limiting target catch changes to 15% comes at the cost of frequently reducing biomass to low levels, so that in many situations other control rules would be preferred.

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INTRODUCTION AND SUMMARY

Many fisheries are managed by using estimates of abundance and other parameters from model-based stock assessments (e.g., fitted statistical catch at age models) for setting annual fishery harvest quotas. Stock assessments are often fit to an index of abundance, and so the estimates from the stock assessments can critically rely on the accuracy of both the index and a measure of uncertainty for the index (Maunder and Starr, 2003). Harvest control rules are often used to set a quota as a function of the current estimate of the system state (e.g., an abundance estimate from an assessment). These topics, indices of abundance and harvest control rules, were the main foci of my research.

1. Indices of Abundance

Catch per effort (CPE) is usually used as the index of abundance for most fisheries, and the common assumption is that CPE changes in proportion to abundance, which is also referred to as "constant catchability" (Quinn and Deriso, 1999). Violations of this assumption can lead to inaccurate estimates of abundance from stock assessments, and consequently ineffective management, which sometimes results in fishery collapse (Rose and Kulka, 1999; Harley et al., 2001). To avoid violations of this assumption, CPE indices of abundance are ideally based on fishery independent survey data (e.g., Helser et al., 2004). Such surveys are not available for many fisheries and so many indices of abundance used in assessments are based on fishery dependent data. Fishery dependent data is more likely to violate the constant catchability assumption due to things such as systematic changes in characteristics of the fishing fleet (e.g., technological advancements, entrance and exit of individual vessels), non-random search effort, and the spatial distribution of the fish stock (Rose and Kulka, 1999; Harley et al., 2001; Maynou et al., 2003; Battaile and Quinn, 2004; Bishop et al., 2004; Campbell, 2004). Even stock assessment models that allow for some temporal changes in catchability will tend to work better when such temporal variation is lower (Wilberg and Bence, 2006; Wilberg et al., 2008).

To account for some of the variation in CPE not attributable to changes in abundance, and provide a more accurate index, CPE data can be "standardized" by fitting statistical models to the catch and effort data, and then using "year-effect" estimates as the index of abundance (Maunder and Punt, 2004; Venables and Dichmont, 2004). Year-effect estimates are commonly used because detecting trends in abundance over time is usually the objective (Maunder and Punt, 2004). Frequently, some form of general or generalized linear model is used to standardize the CPE data (Maunder and Punt 2004).

1.1. Chapter 1: Improving indices of abundance for lake whitefish

My main objective in Chapter 1 was to produce standardized indices of abundance for lake whitefish in 1836 Treaty-ceded waters of Lakes Huron, Michigan, and Superior, but this work also allowed me to develop expertise in statistical techniques (e.g., mixed models) that I used to parameterize the simulation model of chapter 3. Currently, statistical catch at age assessments are fit in each of 18 management units, and a quota is also set for each unit. The assessments are fit using two separate CPE indices of abundance from gill-nets and trap-nets, with CPE estimated as the ratio of sum of aggregate catch to sum of aggregate effort in each year. I developed general linear mixed models (GLMM) for each gear type to standardize the fishery CPE data. Factors included in the GLMMs were fixed effects of year, month, and boatsize (gill-net fishery only), and random effects of license holder (i.e., analogous to boat captain), grid (i.e., location), and all two and three way interactions. The effect of the standardization by using the GLMM method was evaluated by examining the temporal trends in the proportional difference (PD) between the least squares means for each year (LSM) and CPE (i.e., aggregate catch divided by aggregate effort for each year). Since both the LSMs and CPE are relative indices, changes in PD over time were of interest and not whether average PD differed from 1.0. Factors that were particularly influential in the GLMM models were month, boat size, and license holder, which was similar to factors important for marine commercial fisheries where standardization is more widely applied than in freshwater systems. The proportional difference between the LSMs and CPE trended through time in some management units, suggesting that adjusting fishery CPE for effects such as boat size, season, and license holder was important. So, I concluded that model-based indices of abundance should replace non-standardized CPE in some lake whitefish stock assessment models, especially those management units where the proportional difference trended through time. In management units where the proportional difference did not trend through time, using a model-based index of abundance may still be beneficial. Accounting for variability due to random effects led to year specific estimates of uncertainty (e.g., the standard errors for the LSMs) that were not available when using non-standardized CPE. Using improved years-specific estimates of uncertainty to weight the influence of indices of abundance can increase the accuracy of stock assessment estimates (Helser et al., 2004; Maunder and Starr, 2003).

2. Harvest Control Rules

Harvest control rules are guidelines that specify an amount of catch, fishing effort, or fishing mortality as a specific, and usually simple, function of a current estimate of the system state (e.g, spawning biomass; Deroba and Bence, 2008). Common control rules include constant catch, constant fishing mortality rate, constant escapement, or a few variations of these. Each control rule is also defined by a number of policy parameters. For example, the constant fishing mortality rate control rule is defined by one policy parameter, the target level of fishing mortality. Ideally, a harvest control rule is chosen because it meets fishery objectives (e.g., maximize yield, minimize interannual variability in yield). 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 on specific characteristics of the fishery and underlying population dynamics that are incorporated into an evaluation. Consequently, selecting a harvest control rule and policy parameters can be a difficult task.

2.1. Chapter 2: A review of harvest control rules

In Chapter 2 I reviewed the harvest control rule literature with two objectives: 1) to compare and contrast the relative performance of various control rules at meeting common fishery objectives, and 2) to identify reasons for what seem to be contradictory results. The findings were also relevant for designing the harvest control rule evaluation of Chapter 3 (see below). I found that the relative performance of control rules at meeting common fishery objectives was affected by: the given fishery objective, whether uncertainty in estimated stock sizes was included in analyses (i.e., assessment error), whether the maximum recruitment level (e.g., the asymptote of a Beverton–Holt stock–

recruit function) varied in an autocorrelated fashion over time, and the amount of compensation in the stock–recruit relationship. Also, 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. Lastly, 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.

2.2. Chapter 3: Evaluating harvest control rules for lake whitefish

Chapter 3 addressed some of the harvest control rule research needs identified in Chapter 2, and was based on a simulation analysis with the objective of evaluating the ability of alternative control rules to meet fishery objectives for lake whitefish in 1836 Treaty-ceded waters. Currently, a quota is set for each management unit so that total annual mortality rate equals 65% for ages experiencing the highest levels of fishing mortality. Because assessments in these waters assume a constant natural mortality rate across ages and time (Ebener et al., 2005), this is equivalent to a constant fishing mortality rate (constant-*F*) control rule. The constant-*F* control rule and the parameter for the control rule (i.e., 65% total annual mortality rate) are based on analyses conducted over 30 years ago (Healey, 1975), and so may not be optimal for meeting fishery objectives.

Lake whitefish stocks in 1836 Treaty-ceded waters are characterized by temporal and spatial variation in various population parameters. For example, lake whitefish growth in some areas of the Great Lakes declined during the 1990s and 2000s, coincident with declines in an important prey source, *Diporeia* (Hoyle et al., 1999; Pothoven et al., 2001; Mohr and Nalepa, 2005), but similar declines have not occurred everywhere despite similar ecosystem changes (e.g., Cook et al., 2005; Lumb et al., 2007). Growth rates, maturity ogives, natural mortality, and stock-recruit relationships also likely differ spatially among some of the management units (e.g., Wang et al., 2008).

Drawing from my experiences with GLMMs from Chapter 1 and partially based on the results of Chapter 2, I developed a stochastic age-structured simulation model that incorporated stochasticity in life history traits, uncertainty in future lake whitefish growth, and other sources of uncertainty to compare the current harvest control rule with a range of alternative control rules, including conditional constant catch (CCC), constant-*F*, biomass-based (BB), and constant-*F* and BB rules with a 15% limit on the interannual change in the target catch. Separate sets of growth parameters were estimated for fast and slow growth stocks, and separate sets of simulations were done for these two categories of individual stocks. Furthermore, I developed two variants of a growth model to represent alternative hypotheses about future lake whitefish growth; one with temporally autocorrelated changes in growth and another where growth remained similar to more recent patterns. Uncertainty in the stock-recruitment relationship was incorporated by drawing stock-recruit parameters for each simulation from a set of possible values, which were based on data from each management unit and estimated using a GLMM (i.e., similar statistical model used in Chapter 1). The simulations also included assessment and implementation error. Some of the model features mentioned above were included because the results of Chapter 2 indicated that these can affect relative control rule performance, in particular, accounting for uncertainty in the stock-recruit relationship and assessment error. Each control rule was evaluated over a range of the policy parameters that define the control rules. The performance of the control rules was evaluated by examining trade-off plots of spawning stock biomass (*SSB*) versus yield (*Y*), interannual variability in yield (*Yvar*) versus the proportion of years that *SSB* fell below 20% of the unfished level ($SSB_{F=0}$), *Y* versus *Yvar,* and *Y* versus the proportion of years that *SSB* fell below 20% of $SSB_{F=0}$.

While treating future growth as known, the rank order performance of the control rules for each of the performance metrics was generally robust to sources of uncertainty. For example, the constant-*F* and BB rules simultaneously attained higher average yield and spawning stock biomass than all other control rules. The CCC rule and limiting the constant-*F* or BB rules to a 15% change in target catch had the lowest yearly variability in yield. The low yearly variability in yield provided by limiting target catch changes to 15%, however, came at the cost of frequently reducing biomass to low levels, so that in many situations other control rules would be preferred.

The sensitivity of results to uncertainty about future lake whitefish growth was control rule specific and depended on whether stock growth was fast or slow. For fast growth stocks, selecting control rules and policy parameters by incorrectly assuming that future growth will be autocorrelated resulted in little cost from the optimum levels relative to the alternative of incorrectly assuming future growth will be similar to recent levels. For slow growth stocks, however, the robustness to choosing policy parameters based on an erroneous assumption about future lake whitefish growth depended on the control rule and trade-off plot. The decision about how best to select control rules and policy parameters will ultimately depend on how competing fishery objectives are weighted relative to each other. Generally, however, control rules and policy parameters for fast growth stocks should likely be selected assuming future growth will be autocorrelated, but a universal recommendation for slow growth stocks is less clear (i.e., depends on the control rule and fishery objectives).

Depending on how important different fishery objectives are, a control rule and policy parameters other than the one currently in use (i.e., constant-*F* based on a total annual mortality rate of 65%) may be worth considering. For example, a BB control rule with appropriately selected policy parameters could likely produce nearly the same or more yield, spawning stock biomass, and less risk with little cost in variability in yield relative to the currently used policy. Similarly, the CCC control rule can likely provide less variability in yield, but at the cost of yield. So, if maintaining low variability in yield is more desirable than maximizing yield, a CCC control rule may want to be considered.

3. Overall Conclusions and Future Directions

The results of this dissertation have implications for the improved management of lake whitefish in the Great Lakes, but the results are also more generally applicable. In Chapter 1, I found that model-based indices of abundance should likely replace non-standardized indices in fitting stock assessment models. The factors important to the standardization process also seem to be consistent among systems, and so should be considered when standardizing CPE data for most fisheries. Likewise, updating stock assessments for most fisheries to include standardized indices of abundance and associated measures of uncertainty would likely produce more accurate estimates of abundance and other population parameters, and so reduce assessment error, which in

Chapter 2 was shown to affect relative control performance. In addition to assessment error, Chapter 2 highlighted several other characteristics and uncertainties of harvest policy evaluations that have affected control rule performance, and so should be considered when developing harvest policy analyses for any fishery. The results of Chapter 2, however, also revealed that little research has historically considered these characteristics. Chapter 3 added to the body of research that has considered factors important to control rule performance. The CCC control rule, which was first published in an analysis of Pacific halibut *Hippoglossus stenolepis*, had never been evaluated while considering assessment error (Clark and Hare, 2004). Similarly, few published analyses have considered control rules with limits on the interannual change in target catch. Lake trout *Salvelinus namaycush* in 1836 Treaty-ceded waters are managed with such a restraint, but given the generally poor performance of these control rules another option may be warranted. Chapter 3 also evaluated the sensitivity of relative control rule performance to one form of time-varying growth that had never been considered before, and time-varying population parameters have been shown to affect control rule performance (Chapter 2). The results in regards to the rank order and sensitivity of the control rules to this source of uncertainty are likely generally applicable to any fishery experiencing similar conditions.

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CHAPTER 1

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The content of this chapter is intended to be identical to the cited publication and is based on the accepted manuscript with changes that reflect corrections made during copy editing. Any differences should be minor and are unintended.

Abstract

Fishery catch per effort (CPE) is often used to assess relative fish abundance, and in many Great Lakes and other freshwater applications this is based on either an average or the ratio of sum of aggregate catch to sum of aggregate effort. In particular, assessments used to estimate the abundance of lake whitefish and recommend harvest quotas in the 1836 Treaty-Ceded waters of Lakes Huron, Michigan, and Superior assume that commercial CPE from gill-net and trap-net fisheries is proportional to abundance, but CPE may change due to factors other than abundance, leading to violations of this assumption. To account for sources of variation in CPE not attributable to abundance, general linear mixed models (GLMMs) were developed for each management unit, and least squares means (LSMs) for each year were used as the index of abundance. The effect of the standardization by using the GLMM method was evaluated by examining the temporal trends in the proportional difference between the LSMs and CPE (i.e., aggregate catch divided by aggregate effort for each year). Of the random effects included in the final GLMM for the gill-net fishery, license holder accounted for the most variation. The fixed effect of boat size category on CPE depended on lake, where on average in Lake Superior there was little difference, but in Lakes Michigan and Huron large boats had lower CPE than medium and small boats. CPE was on average higher from October to December than in other months. The proportional difference between the LSMs and CPE trended through time in some management units, suggesting that adjusting fishery CPE for effects such as boat size, season, and license holder is important. Factors influential to lake whitefish commercial fishery CPE are similar to factors that have been shown to be important in marine commercial fisheries.

Introduction

Lake whitefish, *Coregonus clupeaformis*, has supported a historically important fishery for Native American bands and a highly valued commercial fishery in the upper Great Lakes (Lakes Huron, Michigan, and Superior). In the late 1800s and early 1900s, lake whitefish were often the most highly valued commercial species and usually comprised the greatest proportion of total yield from each of the upper Great Lakes (Koelz 1926; Brown et al. 1999). Lake whitefish stocks collapsed in each of these lakes in the 1930s and 40s due to overexploitation, sea lamprey, *Petromyzon marinus*, predation, and pollution (Smiley 1882; Koelz 1926; Jensen 1976; Brown et al. 1999; Ebener and Reid 2005). From the 1960s through the 1980s, lake whitefish stocks rebounded in each of the lakes largely due to improved management of commercial harvest, sea lamprey control, pollution remediation, and the introduction of salmonines that reduced the abundance of the invasive alewife, *Alosa pseudoharengus*, and rainbow smelt, *Osmerus mordax* (Ebener 1997; Mohr and Ebener 2005a). In the 1990s, lake whitefish once again became the main commercial species, particularly in Lake Huron where the species comprised over 80% of the total commercial yield (Mohr and Ebener 2005b).

In 1979, the rights of Native American bands to fish in the Michigan waters of the upper Great Lakes, as reserved in a treaty signed in 1836, were reaffirmed by U.S. federal courts. Since the reaffirmation of treaty fishing rights, periodic stock assessments have been conducted for stocks within spatially defined management units, with the fishery data and harvest from within each management unit treated as applying to a reproductively isolated stock (Figure 1; Ebener et al. 2005). Stock assessments are conducted and harvest recommendations based on the assessments are made annually for each individual management unit. Within each management unit commercial fishery catch and effort data are reported on a 10-minute by 10-minute statistical grid basis, which allows for some spatial resolution within management units.

Since 2000, guidelines for the management of lake whitefish have been set according to a Consent Decree. The 2000 Consent Decree created a Technical Fisheries Committee (TFC) and its Modeling Subcommittee (MSC) to conduct stock assessments and specify total allowable catches (TACs) and harvest regulating guidelines (HRGs, see below). TACs are limits to catch, and are used in management units where some yield is allocated to the state licensed fishery and some to the tribal fishery. HRGs are targets for yield used to guide regulations for lake whitefish in units where all yield is allocated to the tribal fishery.

The MSC fits statistical catch-at-age (CAA) models to commercial fishery data to estimate population numbers, mortality rates, fishery harvest, and other population parameters of interest. The estimates of the population parameters are then used to project each stock's abundance into the future, and then a TAC or HRG is calculated by applying a reference mortality rate to the estimate of the next year's abundance.

The CAA models use fishery effort data and an assumed relationship between fishing mortality and fishery effort. Age (a) and year (y) specific fishing mortality rates (F) are estimated as the product of age specific selectivity (S) and year specific "fishing intensity" (f) for each of two fishery gears, gill-nets and trap-nets:

$$F_{i,a,y} = S_{i,a} f_{i,y}\text{;} \quad (1)$$

where i denotes gear type and,

$$f_{i,y} = E_{i,y} q_{i,y} \varepsilon_{i,y}\,; \quad (2)$$

where E is fishery effort specific to each gear type, q is catchability, and ε is multiplicative observation error. The details of the CAA models have been described in Ebener et al. (2005). Equation 2 is equivalent to assuming that the commercial fishery catch per effort (CPE), estimated as the ratio of sum of aggregate catch to sum of aggregate effort in each year, is on average proportional to average abundance over the fishing year, and that deviations from this average relationship are independent variations from year to year.

Violations of the assumption that CPE is proportional to average abundance can occur due to changes in fishing power of gear, or if the spatial and temporal distribution of fishery effort is non-random (Quinn and Deriso 1999). Violations of this assumption are called hyperdepletion when CPE declines faster than abundance at high stock sizes, and hyperstability when CPE does not decline as drastically as abundance at high stock sizes (Quinn and Deriso 1999). For example, an increase in the number of fishing operations could cause some fishermen to operate in lower quality habitat. Thus, CPE could decline even if fish abundance did not, resulting in hyperdepletion. Hyperstability is the more common occurrence and leads to overestimation of biomass and underestimation of fishing mortality, which has too often gone unrecognized and led to fishery collapses (Rose and Kulka 1999; Harley et al. 2001).

To account for some of the variation in CPE not attributable to changes in abundance, and improve assessments and associated fishery management, CPE can be "standardized" by fitting statistical models to the catch and effort data, and then using "year-effect" estimates as the index of abundance (Maunder and Punt 2004; Venables and

Dichmont 2004). Commonly, some form of general or generalized linear model is used to standardize the CPE data (Maunder and Punt 2004). Year is usually included as one of the explanatory variables because detecting trends in abundance over time is usually the objective (Maunder and Punt 2004). Other explanatory variables often include a spatial element or some measure of individual vessel fishing power (e.g., boat size) (Battaile and Quinn 2004; Bishop et al. 2004).

Our objectives were (1) to standardize lake whitefish CPE data in the upper Great Lakes to attain an index of abundance that more accurately reflected changes in lake whitefish biomass than CPE; (2) gain an improved understanding of factors that influence commercial fishery CPE for lake whitefish; and (3) compare the factors that are important for this fishery with those found to influence CPE in other fisheries of the world. Currently for lake trout, *Salvelinus namaycush*, in these waters, indices of abundance are based on the least squares means (LSMs) for each year from a general linear mixed model (GLMM; Deroba and Bence in press). Consequently, we explored the use of a similar GLMM for lake whitefish, and compared the temporal trends in the LSMs for each year to that of the CPE. Our concern here is that the LSMs account for sources of variation in CPE not considered when CPE is estimated as a ratio of sum of aggregate catch to sum aggregate effort in each year, and might reveal substantially different interannual trends in apparent relative abundance.

Methods

Study Area

Our study area was the waters relevant to the 1836 Treaty, which encompassed the majority of Michigan waters of Lakes Superior, Huron, and Michigan (Figure 1).

These waters were stratified into 18 management units with individual surface areas ranging from 69,000 to 733,000 ha, and a total surface area of 5.8 million ha (Figure 1; Ebener et al. 2005). Analyses were done separately for each management unit because these are treated as reproductively isolated stocks and define the resolution of spatial stratification used to manage lake whitefish (see introduction; Ebener et al. 2005).

Data and Analyses

Data were collected from commercial fishing operations as part of a requirement for all licensed vessels to submit monthly reports that describe for each day of the month the weight of fish landed, the amount of gear lifted, the 10-minute by 10-minute statistical grid where the catch and effort occurred, and other auxiliary information (Ebener et al. 2005). Monofilament large-mesh gill-nets with $\geq$ 114-mm stretched mesh and 6-14 m tall trap-nets accounted for nearly 100% of the lake whitefish commercial harvest, and analyses were only conducted on these two gear types. The range of years included in this study differed by management unit and gear type, and some years are missing because no catch or effort was reported (Table 1). Analyses were only conducted on 12 of the 18 management units for the gill-net fishery, and 10 of the 18 management units for the trap-net fishery because few or no observations were recorded within most years for some management units and gears.

CPE was estimated separately for gill-nets and trap-nets as the ratio of sum of aggregate catch to sum of aggregate effort in each year, as is currently used in the CAA models. Catch was measured as the round mass of whitefish for both gears, while effort was measured in 1000s of feet of net for gill-nets, and number of lifts for trap-nets.

GLMMs were fit separately for gill-nets and trap-nets, with $\log_e$ (CPE+1) as the dependent variable. We applied a $\log_e$ transformation because examination of the distribution of the data showed that this was necessary to meet the assumption of normality for general linear models (McCulloch and Searle 2001; Gelman and Hill 2007). We added 1.0 to all CPE observations prior to transformation to address the (infrequent, ~0.001% for both gear types) occurrence of zero CPE observations. This added constant represents a low CPE for gill nets and the lowest possible CPE for trap nets, and more than 99% of CPE values exceeded 1.0 (the constant) for both gear types.

Our initial full model for gill-nets included fixed effects of year, month, and boat size, and random effects of license holder, grid, and all possible two and three way interactions. In preliminary analyses, interactions of a higher order than three ways were not estimable for any management units, and so were excluded from further consideration. Because not enough individual license holders fished with multiple boat sizes, license holder and boat size were confounded when two and three way interactions with license holder and two and three way interactions with boat size were included in the same model. Furthermore, in preliminary analyses interactions with license holder were only estimable for two management units, while interactions with boat size were estimable in all management units. Consequently, all interactions with license holder were also excluded from further consideration. Thus, the new "full" model included fixed effects of year (α_y), month (β_m), boat size (γ_b), and random effects of license holder (c_l), grid (k_g), and all two and three way interactions except those with license holder:

$$\log_e(CPE+1) = \mu + \alpha_y + \beta_m + \gamma_b + c_l + k_g + o_{ym} + p_{yb} + q_{yg} + r_{mb} + s_{mg} + t_{bg} + u_{mbg} + d_{gmy} + h_{gyb} + j_{ymb} + \varepsilon_{iymbgl};$$

where μ is the overall mean, o_{ym} is the interaction of year and month, p_{yb} is the interaction of year and boat size, q_{yg} is the interaction of year and grid, r_{mb} is the interaction of month and boat size, s_{mg} is the interaction of month and grid, t_{bg} is the interaction of boatsize and grid, u_{mbg} is the interaction of month and boat size and grid, d_{gmy} is the interaction of grid and month and year, h_{gyb} is the interaction of grid and year and boat size, j_{ymb} is the interaction of year and month and boat size, and ε_{iymbgl} is residual error for each observation, *i*. This model assumes that the random effects and residual error are all independent and identically distributed as normal with a mean of zero. Boat size was a categorical effect and sizes were defined as: small (≤ 20 ft), medium (20-30 ft), and large (≥ 30 ft).

The full model for trap-nets included fixed effects of year and month, and random effects of license holder, grid, and all two and three way interactions:

$$\log_e(CPE+1) = \mu + \alpha_y + \beta_m + c_l + k_g + o_{ym} + v_{yl} + w_{ml} + s_{mg} + x_{gl} + q_{yg} \\ + z_{yml} + d_{gmy} + a_{ygl} + e_{mgl} + \varepsilon_{iymgl};$$

where v_{yl} is the interaction of year and license holder, w_{ml} is the interaction of month and license holder, x_{gl} is the interaction of grid and license holder, z_{yml} is the interaction of year and month and license holder, a_{ygl} is the interaction of year and grid and license holder, e_{mgl} is the interaction of month and grid and license holder, and all other terms are defined as for gill-nets. In four of the 10 management units analyzed for the trap-net fishery, all of the observations came from one boat size category, and so this effect was not evaluated.

Final models for both gear types were determined by evaluating which effects could be removed using corrected Akaike's information criterion (AICc) (Burnham and Anderson 2002). Our model selection approach was to first consider which random effects would be removed from the final model while keeping all fixed effects in the model (Ngo and Brand 1997). Random effects were selected prior to fixed effects so that the final models had the simplest error structure possible (i.e., a random effect would be eliminated rather than a fixed effect that explained similar sources of variation). Our approach to selecting random effects was to drop each random effect one at a time, while keeping all other effects in the model. Once a random effect was removed, ΔAICc was then calculated by subtracting AICc for the reduced model from AICc for the full model. If ΔAICc was greater than 2.0 (Burnam and Anderson 2002), the factor not present in the reduced model was eliminated from the final model, otherwise the factor was retained. We followed this approach because with 22 management unit and gear combinations and 12 potential random effects to consider for each, fitting and comparing all possible models was not practical. A random effect was also dropped from the final model if the variance estimate for that factor was zero. Restricted maximum likelihood (REML) was used for model fitting when comparing models with different random effects, given its superior performance in estimating random effects (McCulloch and Searle 2001).

Once the best set of random effects was selected, the best set of fixed effects was selected by comparing AICc values for all possible combinations of fixed effects. Models were fit using maximum likelihood (ML) instead of REML because comparisons with AICc based on REML are not valid when comparing models with different fixed effects (SAS 2003). During this process the previously determined best random effects portion of the model was used. Year (α_y) was not evaluated during model selection because the objective is to estimate a yearly index of abundance, and so year must be retained in the final model. The ΔAICc values are not reported in the results because this would require reporting a value for each factor that was included in the full models for each management unit and gear type (i.e., 298 values). Rather, we report the ΔAICc values between a means model (i.e., a model with only a year effect) and the final model (ΔAICc = AICc means model – AICc final model) to quantify the likely improvement that the final models offer over the current indices of abundance that do not account for factors other than year.

Generally, the same effects were included in the final model for each management unit, but the models for some management units could be improved by the elimination of an effect that improved model fit for the majority of the management units, or inclusion of an effect that did not improve model fit for the majority of the management units. For the simplicity of reporting results in these analyses, we eliminated an effect in all management units if it only improved model fit in a minority of management units. LSMs for each year were calculated by summing the overall mean (μ), the coefficient estimate for each year (α_y), and the average of the coefficient estimates over all levels of fixed effects other than year in the final models (SAS 2003). The LSMs for each year from the final model, as determined by the majority, were nearly identical to the LSMs from other models that improved model fit for a minority of management units. Consequently, we believe that the conclusions of these analyses are robust to this approach. However, if the estimated uncertainty (e.g., standard errors) associated with

LSMs (or alternatively year effects or other functions of model parameters) is important, as in fitting stock assessment models to indices of abundance where the standard errors are used to weight the indices of abundance relative to other data (e.g., Maunder 2001; Maunder and Starr 2003), a different model than that reported as the final model here may be warranted for some management units.

Differences in the back-transformed LSMs for each year and CPE+1 were qualitatively examined by plotting the proportional difference (PD) between the two measures across years for each management unit included in this analysis. PD was calculated as:

$$PD = \frac{(CPE + 1)}{\exp(LSM)}.$$

The PD is a measure of how much larger or smaller CPE is than the LSMs. For example, if PD=2 then the CPE is two times larger than the index of abundance based on the mixed model. Since both the LSMs and CPE are relative indices, changes in PD over time are of interest and not whether average PD differs from 1.0. Consequently, if PD varied without trend we concluded that the two approaches generally suggested similar trends in abundance through time, although differences may have existed for a given year. Conversely, if PD trended through time we concluded that the index of abundance provided by the two approaches suggested different temporal trends.

The relative effect of factors included in the final model on CPE was determined by averaging coefficient estimates across management units and comparing the average values. For random effects, the variance component estimates for each effect were used in estimating the average; while for fixed effects, the coefficient estimates for each level of a factor were used. For boat size, the averages were estimated separately for each lake because different boat sizes may perform differently in each lake.

Results

Gill-net Fishery

The final model for the gill-net fishery included fixed effects of year, month, and boat size, and random effects of license holder and the interaction of year and month:

$$\log_e(CPE+1) = \mu + \alpha_y + \beta_m + \gamma_b + c_l + o_{ym} + \varepsilon_{iymbgl} \cdot$$

The final model improved model fit over a means model in all but one management unit, with an average ΔAICc value of 362.5 and values ranging from -10 to 2514 (Table 2). The final model may not have improved fit over a means model in WFM-06 because this management unit had the smallest sample size (N=308; mean N=1452), which may not provide enough data to adequately capture the variability in CPE caused by the various factors. Of the random effects, the license holder effect accounted for the most variation in CPE (Table 3). The effect of boat size depended on lake (Table 4). In Lake Superior, CPE did not vary much among boat size classes. On Lake Huron, small and medium boats had similar CPE, which was less than that for large boats. On Lake Michigan, CPE ordered as medium > small > large boats. CPE was generally low during January through September, highest in October and November, and intermediate between these levels in December (Figure 2).

The index of abundance provided by the GLMMs suggested different temporal patterns than CPE (i.e., PD trended through time) over some or all of the time series in some management units for the gill-net fishery (Figure 3). In Lake Huron, the PD for management units WFH-01 and WFH-04 generally varied without trend, while in WFH-

02 PD declined during 1982-1983, but varied without trend for the remainder of the time series. In Lake Michigan, PD in WFM-02 increased during 1987-1988 and then decreased. In WFM-03, PD increased in variability over the time series and increased during 1999-2001. PD in WFM-04 generally declined through time. In WFM-05, PD generally varied without trend, but declined during 1997-1999 and then increased. In WFM-06, PD declined during 1993-1997. In Lake Superior, the PD in WFS-05, WFS-06, WFS-07, and WFS-08 generally varied without trend, except during 1999-2001 in WFS-05 when PD declined.

Trap-net Fishery

The final model for the trap-net fishery included fixed effects of year and month, and random effects of the interactions of month and year, year and license, and month and year and license:

$$\log_e(CPE+1) = \mu + \alpha_y + \beta_m + k_{my} + v_{yl} + p_{myl} + \varepsilon_{iyml}\,.$$

The final model improved model fit over a means model in all management units by an average ΔAICc value of 170.1, with values ranging from 2.2 to 478.2 (Table 2). Of the random effects, the interaction of year and license holder accounted for the most variation in $\log_e$(CPE+1), even more than residual error (Table 3). CPE was generally low during January through September, with the exception of May, highest in October and November, and intermediate between these levels in December (Figure 2).

The index of abundance provided by the GLMMs showed different temporal trends than CPE (i.e., PD trended through time) over all or some of the time series in some management units for the trap-net fishery (Figure 4). In Lake Huron, the PD in WFH-01 and WFH-02 generally varied without trend, while the PD in WFH-04 varied without trend until 1998 when PD increased to 2000 and then decreased. In Lake Michigan, the PD in WFM-01, WFM-02, and WFM-03 generally varied without trend, except during 2000-2001 in WFM-01 when PD increased. In WFM-04 and WFM-05, PD varied cyclically with a period of approximately two years in WFM-04 and six years in WFM-05. In Lake Superior, the PD in WFS-07 generally varied without trend, while the PD in WFS-08 increased during 1984-1986, but varied without trend during the few other years of data.

Discussion

CPE is often assumed to be proportional to abundance, but CPE can change due to factors other than abundance that cause violations of this assumption (Quinn and Deriso 1999; Battaile and Quinn 2004). Violations of the assumption of proportionality can lead to inaccurate estimates of abundance from stock assessments, and in particular hyperstability can increase the risk for fishery collapse (Rose and Kulka 1999; Harley et al. 2001). Indices of abundance based on commercial fishery catch and effort data are at an especially high risk of violating the assumption of proportionality due to things such as systematic changes in characteristics of the fishing fleet (e.g., technological advancements, entrance and exit of individual vessels), non-random search effort, and the spatial distribution of the fish stock (Rose and Kulka 1999; Harley et al. 2001; Maynou et al. 2003; Battaile and Quinn 2004; Bishop et al. 2004; Campbell 2004). For these reasons, fishery CPE data from many major marine fisheries are now often standardized using various statistical models (e.g., general linear mixed models, generalized linear models) that account for some of the variation in CPE not attributable to abundance, so that the “year-effect” becomes a more accurate index of abundance (Maunder and Punt

2004; Venables and Dichmont 2004). Factors commonly included in models used to standardize CPE data include factors for time (usually year), location (e.g., grid in this study), individual vessels, characteristics of vessels that affect catchability (e.g., vessel size, horsepower, GPS), among other factors (Maunder and Punt 2004).

The temporal trends exhibited by standardized CPE data (e.g., LSMs) have differed from that of non-standardized CPE data (e.g., ratio of aggregate catch to aggregate effort in each year) in other studies (Maynou et al. 2003; Battaile and Quinn 2004), as was true for some management units in our evaluation of Great Lakes whitefish fisheries. Thus, we believe that model-based indices of abundance should replace non-standardized CPE in some lake whitefish stock assessment models, especially those management units where PD was shown to trend through time. Converting to the use of model-based indices of abundance in the stock assessment models for these management units would likely produce more accurate estimates (e.g., abundance estimates) than the current approach of treating raw effort as an index of fishing mortality (equivalent to using CPE as an abundance index). This outcome would also likely hold true for other freshwater systems, where model based methods for standardizing CPE data have not been used as frequently as in marine systems.

The reason for the changes in PD in this study can be partially explained by when most fishing occurred and who fished in each year. For example, in 1988 in the WFM-02 gill-net fishery, fewer observations were made in the spring (i.e., when CPE is lower relative to other times of year) and more observations were taken from license holders with relatively high CPE than in other years, which may explain the spike in PD. Similarly, in the WFM-04 trap-net fishery, peaks in PD occurred in years when more observations came from license holders who did well in that year relative to other license holders. Consequently, indices of abundance based on CPE in these and other areas would most likely be driven by differences in the number of observations taken among seasons or from difference license holders, and not due to changes in abundance as is being assumed in stock assessments.

In addition to providing a more accurate index of abundance, the use of mixed effects models also allows the uncertainty around the indices of abundance to be more accurately quantified for each year, and this can be especially important if these estimates of uncertainty are used to weight the importance of the yearly CPE indices in stock assessment models (Helser et al. 2004, Maunder and Starr 2003). Maunder and Starr (2003) describe methods for how yearly indices of abundance can be weighted by their coefficient of variation in fitting stock assessment models, and also found that stock assessment estimates (e.g., abundance estimates) can be less accurate when each yearly index of abundance is weighted equally, instead of using a year specific weight. Furthermore, Helser et al. (2004) found that ignoring the variability due to random effects, including vessel and the interaction of vessel and year, similar to the effects of license and the interaction of license and year in this study, may lead to an underestimation of uncertainty in indices of abundance. Thus, if the CPE data used in fitting lake whitefish stock assessment models were replaced with model-based standardized CPE indices and an associated estimate of uncertainty for each year (e.g., the standard errors around the LSMs), uncertainty in the indices of abundance would be more accurately quantified and CAA stock assessment estimates would also likely be more accurate. This benefit would accrue even in areas where CPE and model-based indices showed similar temporal patterns (i.e., PD did not show any trends or systematic temporal patterns).

We do not believe that calculating a fishery CPE index, by combining CPE each year over strata defined based on statistical modeling, provides a viable alternative to the use of indices directly derived from model-based methods. This conclusion applies especially in the presence of the types of random effects we saw for Great Lakes lake whitefish data and that appear to be common to fishery CPE data from marine systems. A large advantage of a model-based approach is that the complex correlated error structure resulting from such random effects can be parsimoniously accounted for. The studies cited above suggest that a stratification approach would either underestimate uncertainty in the indices of abundance and lead to inaccurate stock assessment results by ignoring variability attributable to random effects, or would require so many strata with so few observations per stratum that the resulting indices would be poorly estimated. For example, our model for the gill-net fishery would suggest strata need to account for seasonality, boat size, and individual license, but available data only consist of monthly summaries by license. Even if data were combined over similar months, few observations would be available per stratum. Perhaps in some situations (e.g., if random effects were less important), data from each year could be post-stratified into relatively few strata. In such a situation, calculating indices based on combining raw results over strata might be a viable approach, with the advantage of not requiring refitting of statistical models each time a new year of data is collected.

An alternative approach to using model-based output as an index of abundance in stock assessments is to integrate the standardization process into the estimation procedure of the stock assessment models (Maunder 2001; Maunder and Langley 2004). Such an approach still models CPE data in the same way as in our analysis here, but integrates the CPE model as a sub-model of the overall assessment. Maunder (2001) found that integrating the CPE standardization into the estimation procedure of the stock assessment model provided a more accurate representation of the uncertainty in stock assessment parameter estimates. The reason for this result, however, was unclear, and so more research is needed in this area, especially given the programming and data management challenges associated with integrating complex GLMM and related models for fishery CPE into assessment models.

Standardization techniques used for fishery CPE data cannot ensure that all sources of variation in CPE not attributable to changes in abundance have been considered. For example, changes that are confounded with year and universally affect the fishing fleet, or density dependent changes in catchability, cannot be accounted for using model based standardization methods. Factors left untreated by standardization methods should be addressed in the stock assessments where the CPE indices of abundance are used, for example by allowing for time-varying catchability (Wilberg and Bence 2006).

The factors in the final models for both the gill-net and trap-net fishery were similar to models developed for other fisheries (Maynou et al. 2003; Battaile and Quinn 2004; Bishop et al. 2004; Helser et al. 2004). This commonality suggests that similar factors are likely to be important and necessary for consideration when standardizing CPE data for most fisheries. Year is usually included as one of the explanatory variables because detecting trends through time is often the objective for developing indices of abundance, as in this study (Maunder and Punt 2004). Temporal factors on a finer scale than year have also been included in statistical models used for CPE standardization in order to account for systematic temporal patterns in fish abundance or catchability (Battaile and Quinn 2004). Battaile and Quinn (2004) used a fixed effects analysis of variance to standardize CPE data for the eastern Bering Sea walleye pollock, *Theragra chalcogramma*, trawl fishery, and found a significant effect of time of day (i.e., categorical variable for daylight versus nighttime hours), with higher catch rates during the daylight hours. They suggested that catch rates were higher during daylight hours because walleye pollock school during those times, but spread out to feed during nighttime, which reduces catchability. In this study, month was included in the final model for the gill-net and trap-net fisheries, with higher catch rates from October to December. The higher catch rates in those months were likely caused by an increase in the catchability of lake whitefish facilitated by spawning aggregations, which usually occurs during those times in most areas of the Great Lakes (Becker 1983). The results of these studies suggest that temporal factors that account for systematic changes in fish aggregating behaviors should be considered in models used to standardize CPE data whenever possible

Various measures of vessel “power” have also been included in models used for standardizing CPE data. Vessel “power” is any measure of the boat or crew that likely affects catchability, and so affects the indices of abundance that result from CPE data taken from those vessels. In the eastern Bering Sea walleye pollock trawl fishery, longer vessels tended to have higher catch rates than shorter vessels as indicated by the coefficient estimates for each vessel participating in the fishery (Battaile and Quinn

2004). For the trawl fishery directed at Norway lobster, *Nephrops vorvegicus*, and deep-water red shrimp, *Aristeus antennatus*, in the northwestern Mediterranean Sea, generalized linear models used for CPE standardization included measures of the gross tonnage of vessels, engine horsepower, and total length (Maynou et al. 2003). Generally, longer more powerful vessels had higher catch rates. In the absence of direct measures of vessel power, some surrogate could also be used. For example, Punt et al. (1996) included the number of crew on the vessel as a surrogate for vessel length in generalized linear models used to standardize albacore, *Thunnus alalunga*, longline CPE data. For the lake whitefish fishery in this study, a categorical effect of vessel length was used for the gill-net fishery as a measure of vessel power, but the affects on CPE were inconsistent across lakes. This inconsistency makes broad conclusions about the relative success of various vessel sizes difficult, but the explanation may be in the characteristics of the lakes themselves. The depth gradient of Lake Superior is relatively steep and permits access to fishing grounds by all boat sizes, and so all boat sizes performed similarly. Conversely, Lake Michigan offers more shallow fishing grounds that are more accessible to small and medium sized boats, and this may have resulted in higher catch rates than longer boats in that lake. The reason for the relative performance of each boat size in Lake Huron, however, is not clear.

A factor for individual vessel, such as license holder in this study, is also commonly included in models for CPE standardization (Maynou et al. 2003; Battaile and Quinn 2004; Bishop et al. 2004; Cooper et al. 2004; Helser et al. 2004). Similar to results here, an individual vessel factor explained the most variability in CPE in the eastern Bering Sea walleye pollock trawl fishery (Battaile and Quinn). Generalized linear models that included vessel also explained the most variation in CPE for the deep-water red shrimp trawl fishery in the Mediterranean (Maynou et al. 2003). Cooper et al. (2004) and Helser et al. (2004) also found that individual vessel and interactions with vessel should be included in the final models used to standardize U.S. west coast groundfish bottom trawl surveys. The results of Cooper et al. (2004) and Helser et al. (2004) suggest that even with survey data, standardizing CPE may be necessary, and the availability of model-based indices should not replace the use of consistent survey sampling.

The consistent inclusion of an individual vessel effect indicates that individual vessel may serve as a "catch all" for characteristics of boats not included in models (Battaile and Quinn 2004). For example, Maynou et al. (2003) suggested that the inclusion of individual vessel likely accounts for the expertise of individual fishers or unmeasured technical characteristics, such as investment in technology. The large amount of variation explained by the random effect of license holder and interactions with license holder in this study for both fishery gears also suggests that this factor is accounting for the effects of some unmeasured characteristics, such as those suggested by Maynou et al. (2003).

Making inference about the causal or biological mechanisms for some of the two- and three-way interactions included in the final models in this study is not straightforward. However, as Battaile and Quinn (2004) note, identifying causal mechanisms is not required when standardizing CPE data, because the purpose is to account for effects coincident with the variables included in the model. So, the specific higher order interactions may not be indicative of anything biologically meaningful, only that CPE varies coincident with combinations of those factors, either due to those factors themselves or other variables that co-vary with them.

The random effect of grid was not included in the final models for either the gill-net or trap-net fisheries, which is surprising considering that typically there is spatial variation in fish density or fishing success. Campbell (2004) found that non-randomly sampled locations led to biased indices of abundance, unless the total habitat area of the stock was spatially stratified and each CPE observation was weighted by the relative amount of sampling effort in the strata from where the observation was taken. This result suggests that not accounting for spatial variation in sampling effort can lead to biased indices of abundance. The effect of grid in this study may have not been included in final models because the analyses were already run on spatially stratified stocks delineated by management unit. However, the results of Campbell (2004) and the spatial variability that likely exists in fish density and fishing success for most fisheries suggests that spatial effects should always be considered when standardizing CPE data.

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Figure 1.— 1836 Treaty-ceded waters and lake whitefish management units in Lakes Superior, Huron, and Michigan (Ebener et al. 2005).

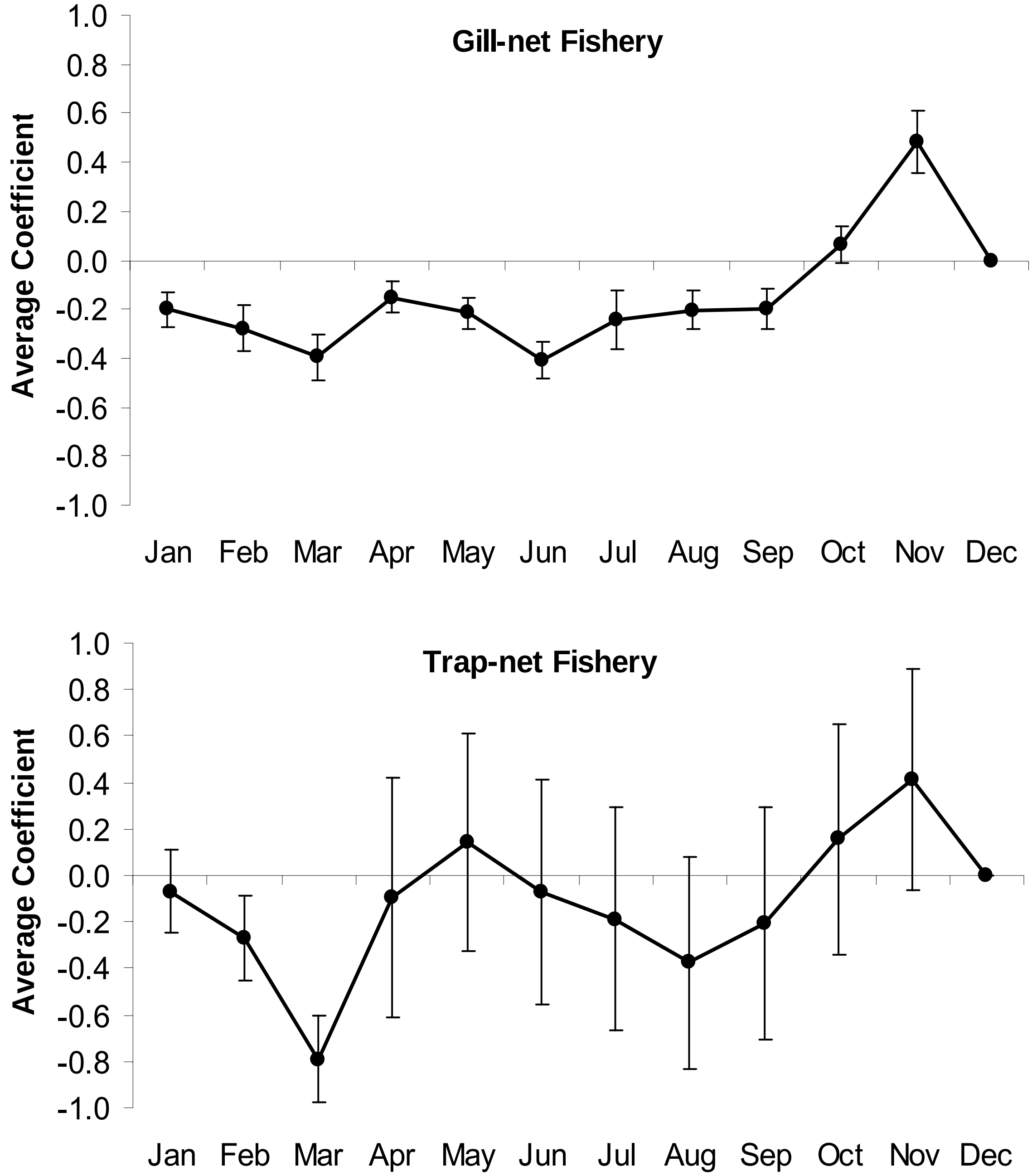

Figure 2.—Average coefficient estimates (± SE representing uncertainty resulting from variability among management units) for the effect of month from a general linear mixed effects model standardizing catch per effort (catch = aggregate round mass of lake whitefish) for the lake whitefish gill-net fishery (top panel; effort = aggregate length of net in 1000s of feet) and trap-net fisheries (bottom panel; effort = number of lifts) in the 1836 treaty-ceded waters of Lakes Superior, Huron, and Michigan. Coefficient estimates were averaged across various years (generally 1981-2001) and lake whitefish management units included in this analysis.

Figure 3.—Proportional difference between the index of abundance from a general linear mixed model (i.e., least squares means for each year) and catch per effort (ratio of round mass of lake whitefish to aggregate feet of length of net for each year) from a gill-net lake whitefish fishery for various years (generally 1981-2001) and lake whitefish management units in the 1836 treaty-ceded waters of Lakes Superior, Huron, and Michigan included in this analysis.

Figure 3

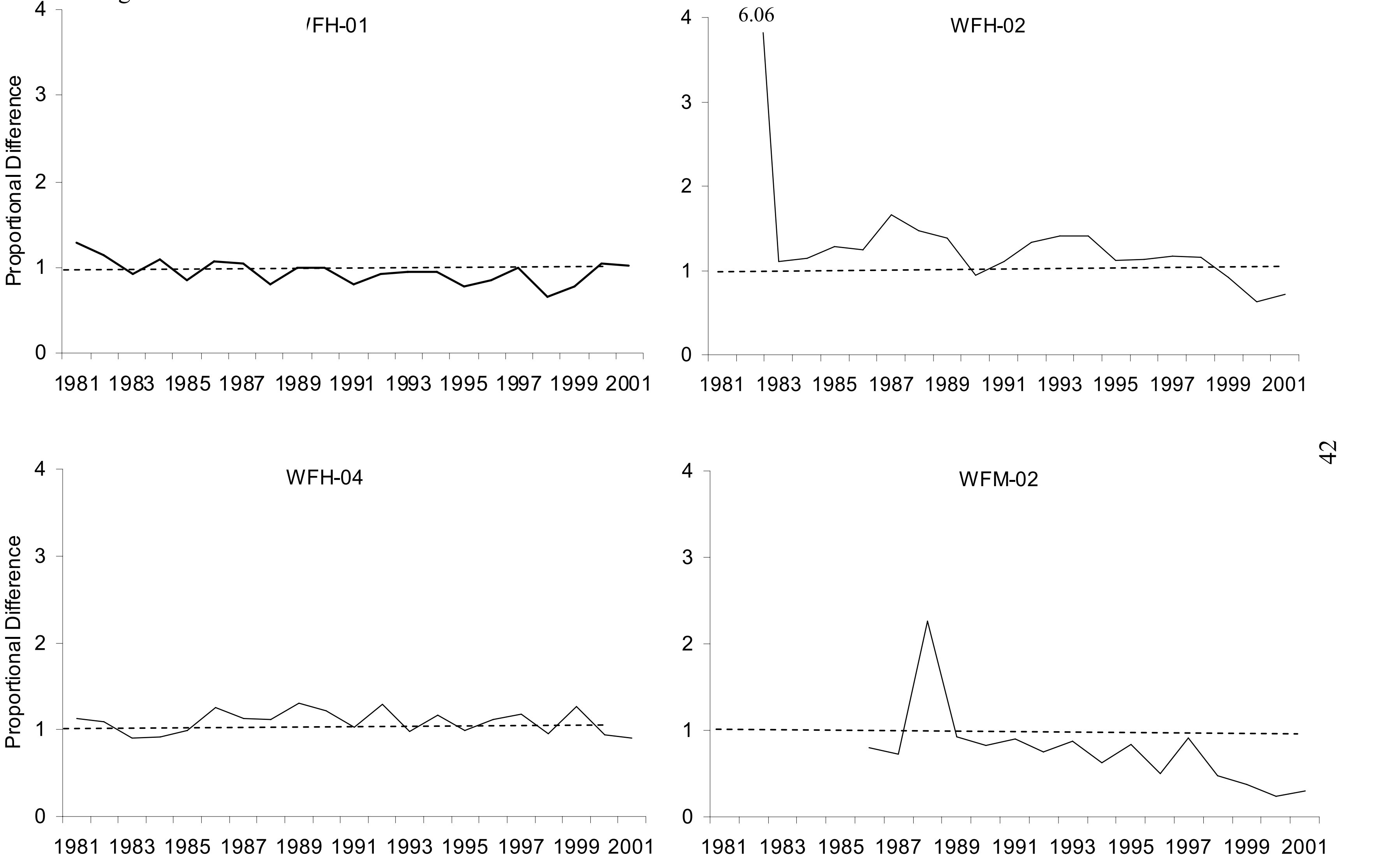
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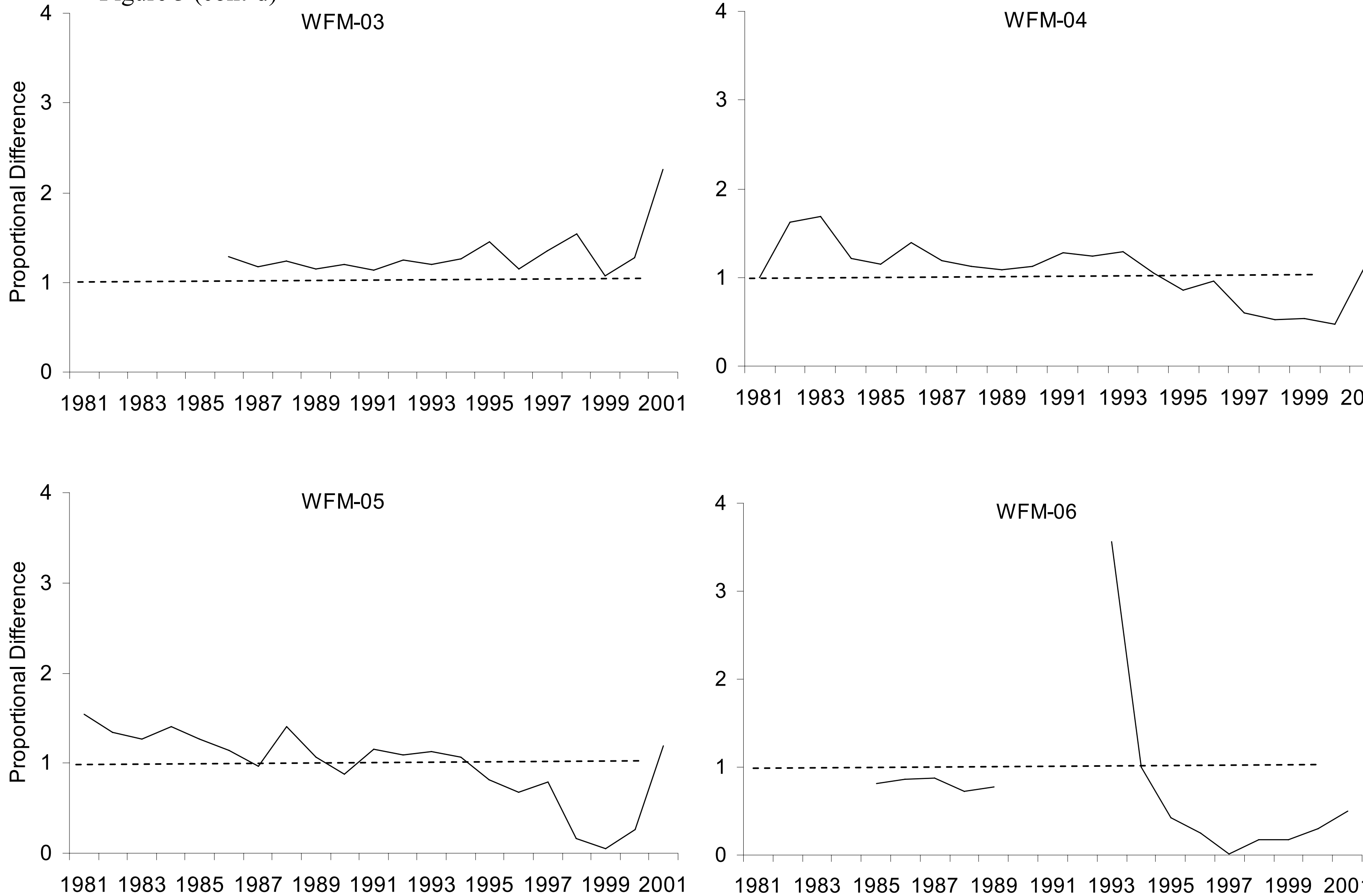
Figure 3 (cont'd)



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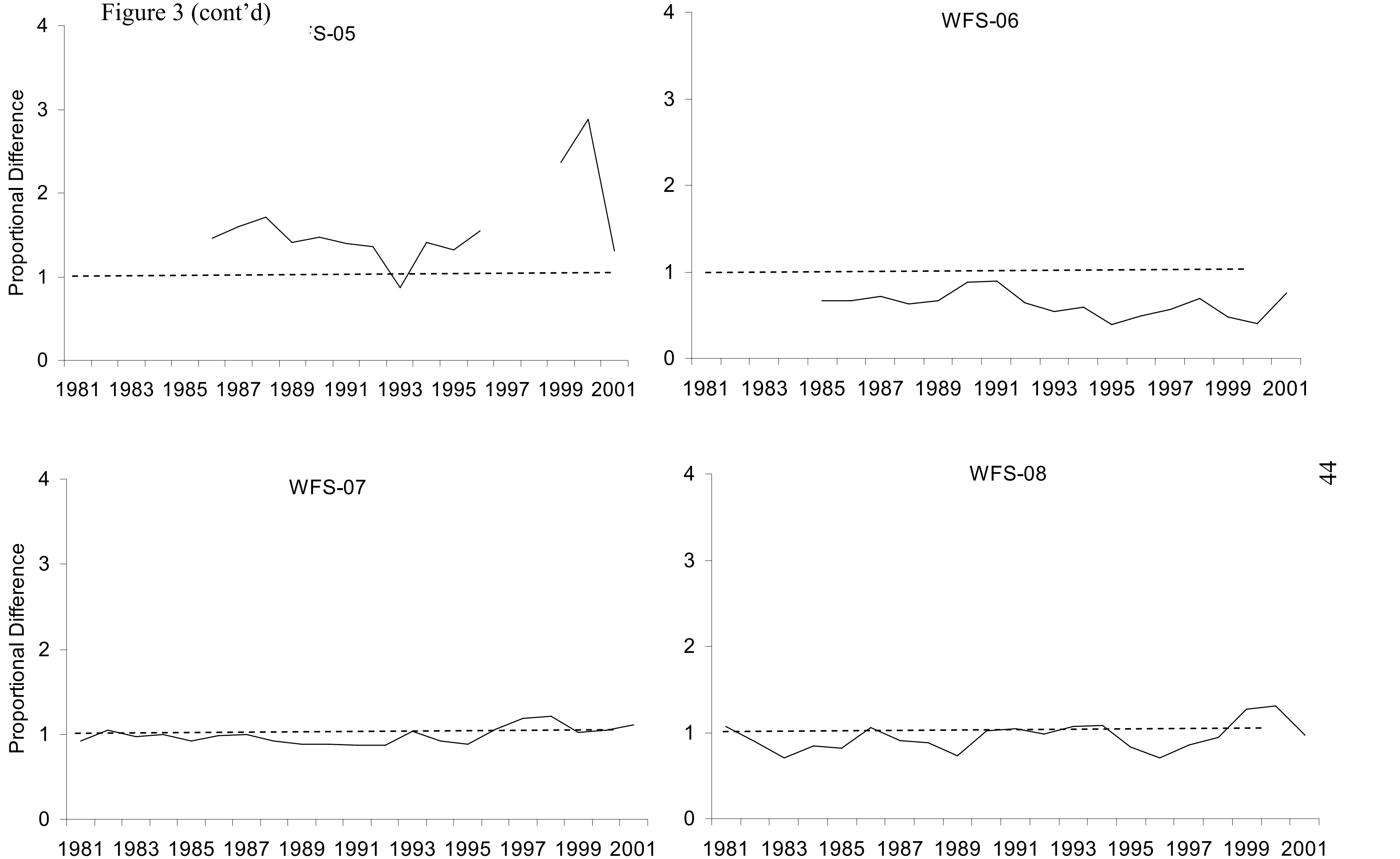
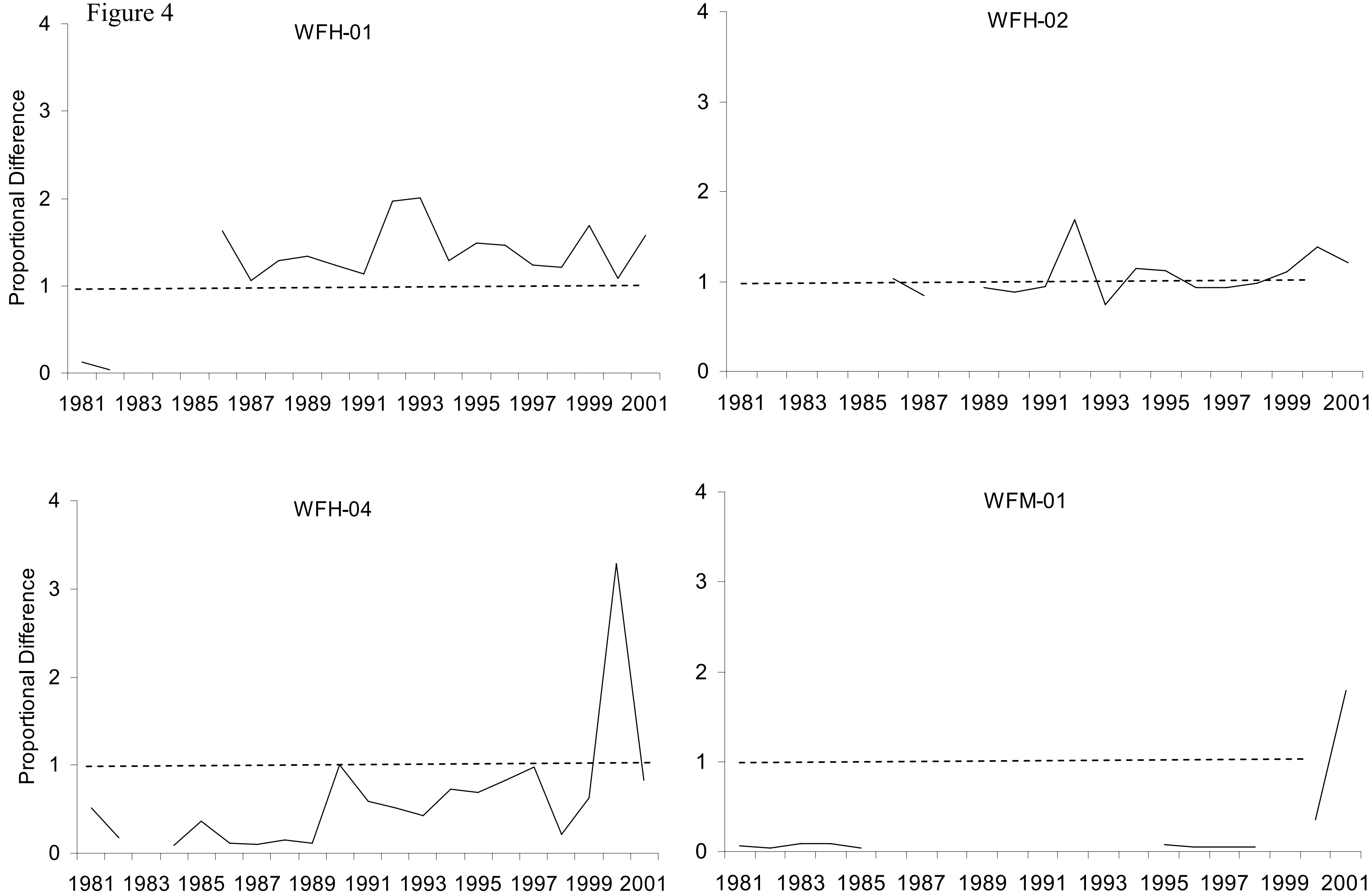


Figure 4.—Proportional difference between the index of abundance from a general linear mixed model (i.e., least squares means for each year) and catch per effort (ratio of round mass of lake whitefish to aggregate number of lifts for each year) from a trap-net lake whitefish fishery for various years (generally 1981-2001) and lake whitefish management units in the 1836 treaty-ceded waters of Lakes Superior, Huron, and Michigan included in this analysis.

Figure 4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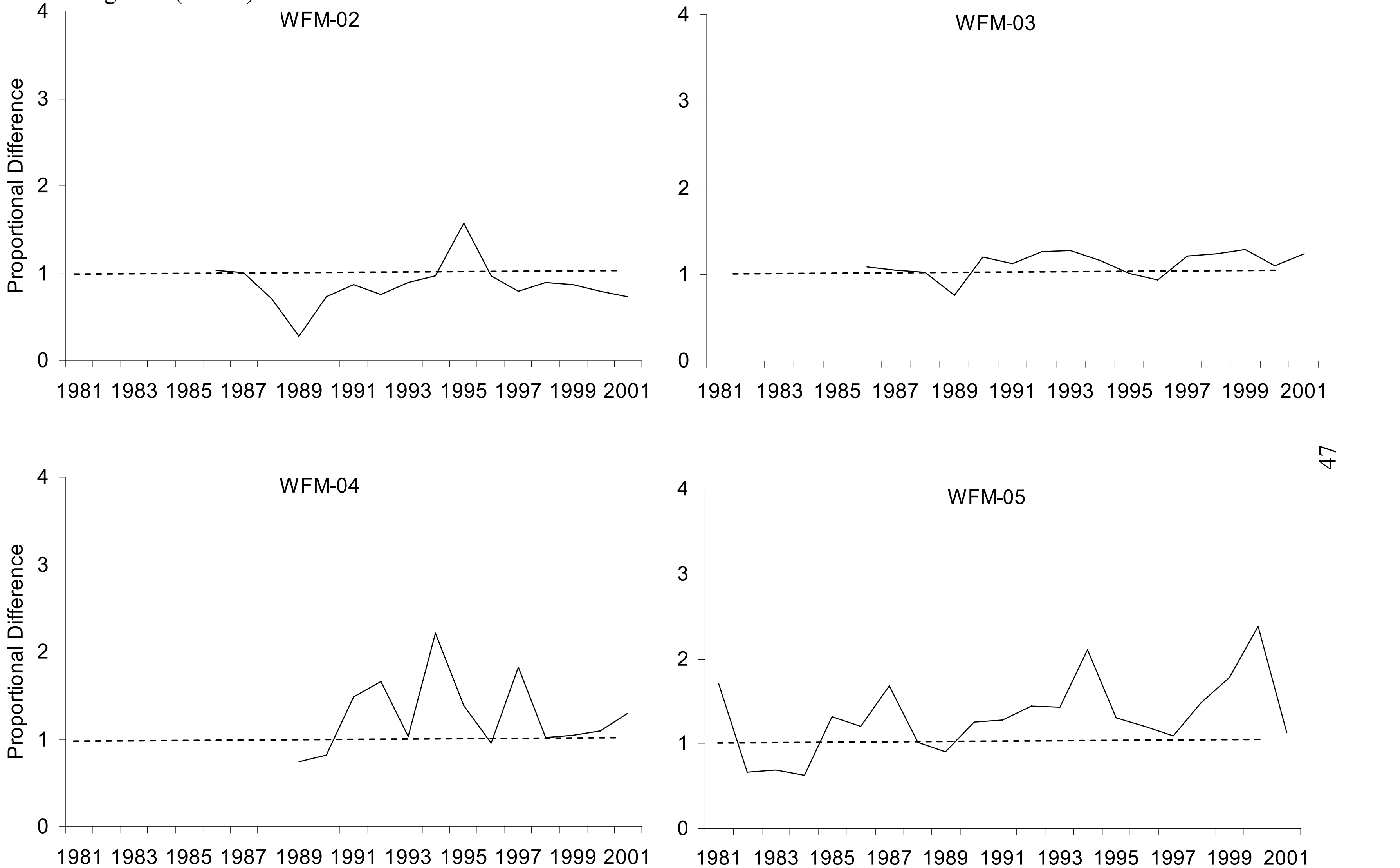

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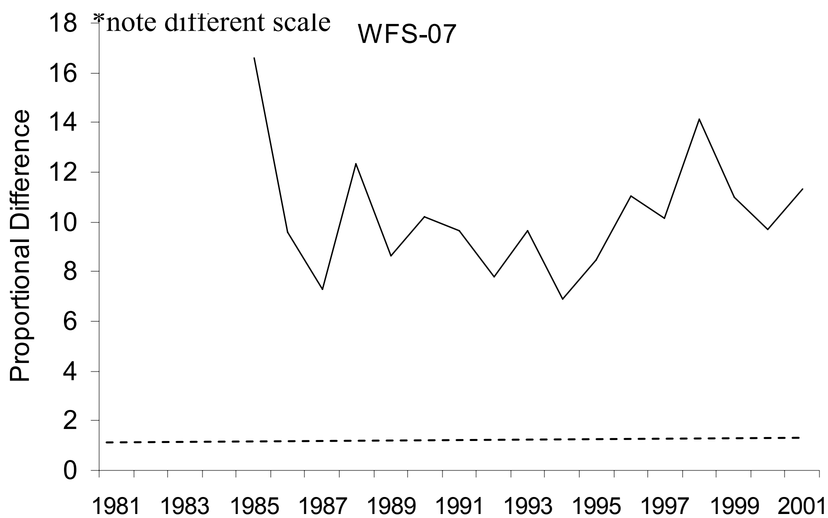

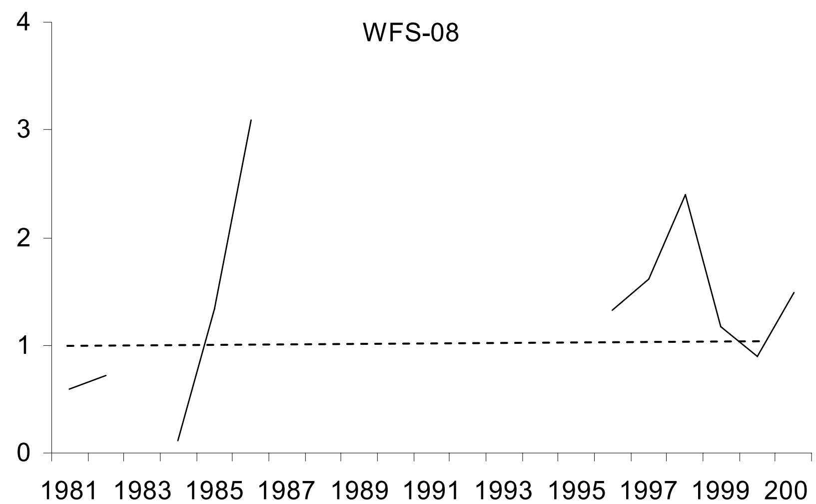

Table 1.—Years and lake whitefish management units included in this analysis for the gill-net and trap-net fisheries of the 1836 treaty-ceded waters of Lakes Superior, Huron, and Michigan.

	Gear Type	
	Gill-net	Trap-net
Management Unit	Years Included	Years Included
WFH-01	1981-2001	1981-1982; 1986-2001
WFH-02	1982-2001	1983; 1986-1987; 1989-2001
WFH-04	1981-2001	1981-1982; 1984-2001
WFM-01	-	1981-1985; 1995-1998; 2000-2001
WFM-02	1986-2001	1986-2001
WFM-03	1986-2001	1986-2001
WFM-04	1981-2001	1989-2001
WFM-05	1981-2005	1981-2001
WFM-06	1985-1989; 1993-2001	-
WFS-05	1986-2001	-
WFS-06	1985-2001	-
WFS-07	1981-2001	1981; 1985-2001
WFS-08	1981-2002	1981-1982; 1984-1986; 1996-2001

Table 2.—Differences between AICc values between final models and a means model (i.e., model with only a year effect) for the lake whitefish gill-net and trap-net fisheries in the 1836 treaty-ceded waters in the management units of Lakes Superior, Huron, and Michigan included in these analysis. Differences are reported as Δ AICc = AICc from means model – AICc from final model.

	Gear Type	
	Gill-net	Trap net
Management Unit	Δ AICc	Δ AICc
WFH-01	536.1	281.3
WFH-02	173.9	324.8
WFH-04	508.1	121.9
WFM-01	-	95.1
WFM-02	93.5	28.4
WFM-03	677.7	478.2
WFM-04	556.4	212.4
WFM-05	320	2.2
WFM-06	-10.2	-
WFS-05	61.1	-
WFS-06	118.2	-
WFS-07	993.5	111.8
WFS-08	322.1	44.4

Table 3.—Average variance component estimates for residual error (σ^2_{iymbgl}), license holder (σ^2_{l}), and month and year (σ^2_{my}) for the lake whitefish gill-net fishery, and random effect estimates of residual error (σ^2_{iyml}), year and license holder (σ^2_{yl}), month and year (σ^2_{my}), and month and year and license holder (σ^2_{myl}) for the lake whitefish trap-net fishery of the 1836 treaty-ceded waters of Lakes Superior, Huron, and Michigan. Variance component estimates were averaged across lake whitefish management units included in these analyses.

Gear Type			
Gill-net		Trap-net	
Variance Component	Mean Estimate	Variance Component	Mean Estimate
σ^2_{iymbgl}	0.47	σ^2_{iyml}	0.17
σ^2_{l}	0.22	σ^2_{yl}	0.29
σ^2_{my}	0.05	σ^2_{my}	0.09
-	-	σ^2_{myl}	0.09

Table 4.—Average estimates of the coefficients for different size classes of boat for the gill-net fishery for lake whitefish on the 1836 treaty-ceded waters of Lakes Superior, Huron, and Michigan. Boats were classified as small ($\leq$ 20 ft), medium (20-30 ft), and large ($\geq$ 30 ft). Coefficients were averaged across lake whitefish management units included in these analyses for each lake.

Boat size	Lake Superior	Lake Huron	Lake Michigan
Large	0.03	0.11	-0.28
Medium	0.05	-0.03	0.09
Small	0.00	0.00	0.00

CHAPTER 2

Deroba, J.J. and J.R. Bence. 2008. A review of harvest policies: Understanding relative performance of control rules. Fisheries Research: 94: 210-223.

The content of this chapter is intended to be identical to the cited publication and is based on the accepted manuscript with changes that reflect corrections made during copy editing. Any differences should be minor and are unintended.

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, and whether the maximum recruitment level (e.g., the asymptote of a Beverton-Holt stock-recruit function) is varied in an autocorrelated fashion over time. Relative performance of control rules also depends on fishery objectives and the amount of compensation in the stock-recruit relationship. The influence of assessment error on the relative performance of control rules depends upon whether policy parameters are fixed using those that perform best without errors or not. 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.

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 tradeoffs 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; Figure 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 affect 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 to choosing catch levels, fishing mortality rates, or thresholds necessary for implementation of control rules. Finally, we offer conclusions and suggestions for interpreting harvest policy analyses and identify future research needs.

2. Common control rules

We describe common control rules as background for our review of their relative performance. Most rules can be categorized into three main types (Figure 1) or a few modifications of these (Figure 2), and explicitly or implicitly specify a relationship between fishing mortality and stock abundance. We choose to specify control rules in terms of fishing mortality because how this per capita mortality rate varies with abundance summarizes the compensatory or depensatory effect of the rule. A constant catch control rule removes the same number or biomass of fish each year, and is depensatory in that it leads to high fishing mortality at low stock sizes (Figure 1; Quinn and Deriso, 1999). A constant fishing mortality rate (also called a constant harvest rate) uses the same fishing mortality regardless of stock abundance (Figure 1), and hence harvest is proportional to biomass (Quinn and Deriso, 1999). When fishing mortality is assumed to be directly proportional to fishing effort, constant fishing mortality rate rules are also referred to as constant effort. A constant or fixed escapement control rule takes all biomass over some specified target level. Control rules such as this are also referred to as "bang-bang" policies in the resource economics literature, because when modeled in continuous-time, harvest is intense above the threshold and zero otherwise (Figure 1; Nostbakken, 2006). This type of control rule is often used when fishing anadromous fish, where a specified number of fish are allowed to pass a weir or other observation location and the remainder of the run is removed. In open-ocean or lake fishing, such a control rule is usually interpreted as allowing harvest of all fish over a threshold abundance or biomass, so that fishing mortality is zero up to that threshold and then increases thereafter (Figure 1).

Each of these basic control rules has a number of variants, many of which have been suggested to retain what are viewed as positive features of a rule while addressing some of its weaknesses. Here we review some of these important variants (Figure 2). The conditional constant catch (CCC) control rule, a variant of constant catch, removes the same number or biomass of fish each year unless removing that amount would exceed some pre-determined maximum fishing mortality rate. If the constant catch amount would cause fishing mortality to exceed this rate, then the rule reverts to a constant fishing mortality rate at the pre-determined maximum (Figure 2B ; Clark and Hare, 2004). This control rule attempts to avoid the high fishing mortality rates that occur at low stock sizes under a constant catch rule but retains the benefit of stable catches at high stock sizes. Murawski and Idoine (1989) and Hjerne and Hansson (2001) suggest similar control rules where the amount of harvest is reduced to a new low level (potentially zero) when biomass falls below a threshold (Figure 2C).

Threshold control rules are suggested as modifications to constant fishing rate rules and specify a biomass below which no fishing is permitted (the threshold), but a constant fishing mortality rate is used otherwise (Figure 2A; Quinn and Deriso, 1999). Variations of this basic form have also been suggested, such as decreasing fishing mortality gradually below the threshold and increasing fishing mortality gradually above the threshold, to produce compensatory and potentially stabilizing fishing mortality (Figure 2E; Quinn et al., 1990; Eggers, 1993; Sigler and Fujioka, 1993; Quinn and Deriso, 1999; Ishimura et al., 2005). Control rules that scale fishing mortality or catch downward when the population is below a threshold are known as biomass-based or adjustable rate rules, and fishing mortality or catch is usually adjusted in proportion to population size (Figure 2E; Quinn and Deriso, 1999). Whether fishing mortality or catch is adjusted with changes in biomass affects the relationship between fishing mortality and biomass (Figures 2E and 2F) and thus has potentially different performance characteristics. The "40-10" rule, which is used to manage U.S. west coast groundfish, is an example of the latter type of biomass-based rule. Catch is reduced linearly as spawning biomass declines below an upper threshold (40% of the unfished level) so that no harvest is allowed when spawning biomass is below a lower threshold (10% of the unfished level) (Hilborn et al., 2002; Punt, 2003; Punt, this issue). The result is that for a 40-10-like rule fishing mortality decreases nonlinearly (Figure 2F). Engen et al. (1997) suggest a variation of a constant escapement rule called "proportional threshold harvesting", which has been used to manage U.S. west coast pelagic species since the early 1980s (Pacific Fishery Management Council, 1998; Barange et al., in press). With this control rule, only a fraction of the surplus above the threshold is harvested. The resulting nonlinear relationship between fishing mortality rate and biomass can be viewed as a biomass-based control rule, and appears similar to a 40-10-like rule (Figure 2D). Proportional threshold harvesting is a special case of a 40-10-like rule with the upper threshold set infinitely high (e.g., a "∞-10" rule). So, for both control rules catch increases linearly with biomass above a lower threshold, but for a 40-10-like rule the slope of the relationship changes above an upper threshold.

3. Common fishery objectives

Fishery objectives are represented in harvest policy analyses using objective functions, and these are used to compare the relative performance of control rules. A frequently-used objective function is cumulative harvest over some fixed time horizon, or the sum of annual values of a utility function over a time horizon, where the utility function relates annual harvest to some economic, biological, or social construct (Quinn and Deriso, 1999). Maximizing cumulative harvest is considered a risk neutral approach, because performance is measured only by the total over the time horizon, with the frequency of low and high annual values playing no role (Reed, 1979; Quinn and Deriso, 1999). More risk-averse objective functions penalize for extreme harvests in an effort to avoid boom-or-bust fisheries (Walters and Pearse, 1996; Lande et al., 1997; Quinn and Deriso, 1999). One risk-averse objective function is to maximize the long-term logarithm of harvest, and this tends to avoid extreme harvests by placing an infinite penalty on zero harvests (Ruppert et al., 1985). This objective function, however, is criticized as being risk-averse only in terms of economic risk to the industry, and not biological risk to the resource (Lande et al., 1997). Another risk-averse objective function is to maximize a linear combination of average yield ($\overline{Y}$) and the negative of the standard deviation (SD) of yield over a given planning horizon (e.g., max[(1- λ)$\overline{Y}$ - λSD]; Quinn et al. 1990; Collie and Spencer 1993). This approach is relatively flexible in that the relative influence of average yield and the standard deviation of yield can be controlled using the weighting term, λ. An alternative, but less commonly used type of risk averse objective accounts for how frequently or over what duration biomass or harvests have been at or below a threshold (Enberg, 2004; Irwin et al., this issue)

Other objective functions have been formulated to maintain biomass or harvest at predetermined target levels (Hightower and Grossman, 1987). This stability can be accomplished by minimizing the sum of squared deviations between biomass or harvest and the predetermined target levels. However, Hightower and Grossman (1987) criticize objective functions that only consider maintaining harvest near a target because two values of fishing mortality could result in the same equilibrium harvest. When rebuilding a stock from a depleted state, the optimal fishing mortality is the higher of the two equilibrium points, which also results in maintaining lower equilibrium abundance. Another criticism of only considering harvest is that, for an age-structured population, the same harvest is obtained for multiple age-structures. Consequently, when stock sizes decline, maintaining harvest near the target requires increasing fishing mortality, which can be destabilizing in terms of abundance and yield, creating a negative feedback (Beddington and May, 1977; Lowe and Thompson, 1993). To remedy these problems, Hightower and Grossman (1987) suggest using an objective function that simultaneously minimizes the deviations of both harvest and biomass from target levels. Similarly, the maximum harvest objective can also be combined with a constraint that requires the biomass at the end of the planning horizon to be near a target level (Hightower and Grossman, 1987). More generally, objective functions can be defined as even more complex functions of multiple performance measures (e.g., Katsukawa, 2004).

Bioeconomic objective functions that aim to maximize profits have also been developed (Clark, 1973). In a simple bioeconomic model, revenue R is assumed to be a linear function of harvest and is found as the product of price (amount paid per unit fish) P and harvest H:

$$R=PH;$$

(Clark, 1973; Reed, 1979; Quinn and Deriso, 1999). Costs C are incorporated into the model as the product of the cost per unit of fishing effort L and total effort E:

$$C=LE.$$

Net profit Q is the difference of the revenues and costs:

$$Q=R\text{-}C.$$

Costs can also be modeled as a function of stock size (Reed, 1979). Costs are most often modeled as a decreasing function of abundance, which requires the assumption that catch per effort (CPE) increases with abundance (Clark, 1973; Reed, 1979). Whether the decrease in cost as abundance increases is linear will depend upon whether catchability also varies with abundance (Reed, 1979). Bioeconomic objective functions can also incorporate discount rates, where the value of capital invested in the current time diminishes in the future due to inflation (Clark, 1973; Reed, 1979; Quinn and Deriso, 1999; Quinn and Collie, 2005). Objective functions incorporating discount rates are referred to as maximizing the expected present value (Reed, 1979). "High" discount rates have been blamed for the demise of some fish stocks, where the future value of capital approaches zero, so that economically, the optimal course of action is to fish the stock quickly to collapse (Clark, 1973). The use of negative discount rates is suggested by some conservation groups as a way to conserve stocks because capital actually increases in value in the future (Quinn and Deriso, 1999). Bioeconomic objective functions that maximize profits also tend to favor larger stock sizes than maximum yield objective functions (Clark, 1973; Deriso, 1987). Consequently, increasing effort beyond the point that attains maximum profits in order to achieve maximum yield is not only inefficient but can also incur other risks associated with smaller population sizes.

4. Relative performance with "perfect" information

4.1. Comparing control rules

Analyses of harvest policies often assume that decisions are made with "perfect" information (i.e., no uncertainty or error), in terms of knowing the underlying dynamic system model and its parameters, in knowing the current state of the system (e.g., biomass), and in being able to implement regulations to achieve a desired result. Assuming perfect information allows for greater ease of computation, and likely reflects the common practice of setting harvest quotas based on a point estimate of abundance (Frederick and Peterman, 1995). Although many would agree that this is an unrealistic assumption for most stocks (e.g., Engen et al., 1997), the results of studies based on perfect information are still used as a guide, because they are viewed as likely to reflect qualitative differences and outcomes that can be expected from the application of various control rules under situations of "imperfect" information.

Assuming perfect information, constant escapement rules generally perform best for maximizing cumulative yield, mean annual yield, or profits, usually followed in performance by threshold or biomass based rules, constant fishing mortality rate rules, and lastly constant catch rules, although this general conclusion may also depend on assuming that maximum recruitment levels (i.e., the asymptote of a Beverton-Holt stock-recruit function) are temporally independent (Table 1; Table 2). For semelparous stocks (e.g., pacific salmon *Oncorhynchus tshawytscha*), Ricker (1958) shows that constant escapement control rules produce 24-57% higher long-term average harvest than constant fishing mortality rate rules, depending on the shape of the stock-recruitment curve, when both the escapement level and fishing mortality rate are set to attain the maximum average yield. This general result is also supported by additional research on iteroparous species and for a broad range of conditions (e.g., various stock-recruit relationships)

(Table 2). With surplus production models, a type III functional response, and autocorrelated consumption rate, threshold rules can produce greater than 100% higher average yield, higher sum of discounted yields, and higher sum of discounted rents than constant fishing rate control rules, depending on the level of autocorrelation in consumption rates (Collie and Spencer, 1993; Spencer, 1997). Constant fishing mortality rate control rules, however, can outperform constant catch rules in terms of yield by 29% or more (Jacobson and Taylor, 1985). Furthermore, even with catch set at maximum sustainable yield (MSY) or the level that maximizes net revenue, several other studies show that constant fishing mortality rate and biomass based control rules provide higher long-term yield and profits (Table 2). Similarly, constant harvest rate rules can produce the same or modestly higher average yield than the various CCC control rules (Hjerne and Hansson, 2001; Clark and Hare, 2004).

In contrast to some of these studies, Walters and Parma (1996) show, using stochastic optimal control methods, that constant escapement control rules are inferior to constant fishing mortality rate control rules in terms of maximizing yield when the asymptote parameter (maximum level of recruitment) of a Beverton-Holt stock-recruit model is autocorrelated. This discrepancy likely occurs because optimal constant escapement control rules are highly sensitive to the maximum level of recruitment (Lande et al., 1997). When maximum recruitment is autocorrelated, controls on spawning biomass exert imperfect control on expected recruitment. Walters and Parma (1996) also report that with autocorrelated maximum recruitment, constant fishing mortality rate control rules attain at least 85% of the theoretical maximum long-term yield (not constrained by a constant control rule) for most populations. This result also holds true when other stock recruitment parameters (i.e., slope near the origin) are simultaneously autocorrelated with the asymptote parameter, but does not hold true when other stock-recruitment parameters are autocorrelated by themselves. Few other studies evaluate the effect of autocorrelated recruitment on the relative performance of harvest policies (Table 2), and none systematically evaluate the influence of additional alternatives for the form of such autocorrelation.

Escapement and threshold control rules were developed to prevent over-exploitation and maintain spawning biomass, and so such rules often maintain higher biomass, lower variation in biomass, and result in less chance of over-exploitation than other control rules (Table 1; Getz and Haight, 1989). Escapement and threshold control rules maintain more consistent levels of biomass than other control rules, because other rules allow some harvest regardless of the level of stock biomass, which can be destabilizing in terms of abundance and yield (Beddington and May, 1977; Lowe and Thompson, 1993). The destabilizing nature of continued fishing as abundance declines is also made worse with depensation at low abundance (Collie and Spencer, 1993; Eggers, 1993; Walters and Parma, 1996), and this is one reason why some authors argue against control rules like constant fishing mortality rates (Lande et al., 1997). Several studies show that constant catch control rules consistently result in the maintenance of less biomass and more instances of stock collapse than other rules that provide the same or higher average harvest, likely because a constant catch control rule leads to high levels of fishing mortality at low abundance (Figure 1; Table 2). Potter et al. (2003) conclude that if maximizing revenues or yield are not high priorities, as in a recreational fishery, a constant catch control rule may be useful to meet other fishery objectives (e.g., high recreational catch rates), but the catch level should be set low to prevent stock collapse. Alternatively, the CCC control rule of Clark and Hare (2004) can maintain higher average spawning stock biomass than a constant harvest rate control rule, but this depends on the constant catch level and ceiling harvest rate. Thus, the CCC control rule may be effective at preventing the high fishing mortality rates at low stock sizes that occur with a strict constant catch control rule.

As a consequence of fishery closures, threshold and biomass based control rules are also usually the optimal rule for quick rebuilding of depleted stocks (Table 1; Quinn et al., 1990). Median rebuilding times to equilibrium biomass under a threshold control rule are shorter than a constant fishing mortality rate control rule (Quinn et al., 1990). Hightower and Grossman (1987) also show that the optimal rebuilding strategy is to cease fishing until the threshold biomass level is reached, and use constant fishing mortality above the threshold.

Relatively high yields and stable biomass almost always appear to come at the cost of higher variability in yield (Ricker, 1958; Gatto and Rinaldi, 1976; Reed, 1979; Lande et al., 1995; Lande et al., 1997). Constant escapement control rules usually result in the highest variability in yield, followed by threshold and biomass based control rules, constant fishing mortality rates, and then constant catch (Table 1; Table 2, but see Enberg, 2004). The high variability of yield in constant escapement and threshold control rules is caused by fishery closures in years when biomass is not above the predetermined level (Lande et al., 1997; Lillegard et al., 2005). Constant fishing mortality rate control rules do not require fishery closures, and so usually have less variability in yield than constant escapement and threshold control rules, but also lead to greater variability in population abundance. Constant fishing mortality rate control rules also perform best at maximizing logarithm of yield, an objective function that places in infinite penalty on zero harvest (Walters and Parma, 1996; Walters and Pearse, 1996; Lande et al., 1997). Intuitively, a constant catch control rule will have zero variability in catch, except in cases when abundance drops below the predetermined level of catch and requires closing the fishery, or management cannot react quickly enough to close the fishery after the catch limit has been attained (Koonce and Shuter, 1987; DiNardo and Wetherall, 1999). However, the stability in yield of the constant catch control rule comes at the cost of foregoing high yields at times when abundance is high, and the highest variability in population abundance and hence risk of fishery collapse (Beddington and May, 1977; Jacobson and Taylor, 1985; Quiggin, 1992; Potter et al., 2003). If consistent yields and a stable market have a "much higher priority" than maximizing revenue, yield, or minimizing risk of fishery collapse, then a constant catch control rule will be a competitive option (Quiggin, 1992; Steinshamn, 1993; Potter et al., 2003).

The differences among control rules in catch/yield variability can be substantial. In a simulation based on the northwestern Hawaiian Islands lobster fishery, mean yearly percentage change in catch was less for a constant catch control rule (yearly variation in catch for the constant catch rule was caused by fishery closures) than a constant fishing mortality rate control rule (about 43% and 156%, respectively) across a range of catch and fishing mortality rate levels (DiNardo and Wetherall, 1999). The various CCC control rules maintain some of the benefits of a constant catch control rule; they can produce less yearly variability in catch than a constant harvest rate strategy, with the relative difference in variability depending on the values used for the CCC control rule parameters (i.e., constant catch level and maximum harvest rate) (Hjerne and Hansson, 2001; Clark and Hare, 2004). Constant fishing mortality rate control rules can also produce standard deviations in annual yield half that of threshold control rules (Collie and Spencer, 1993), and Walters and Parma (1996) show that the advantage of constant fishing mortality over constant escapement in terms of yield constancy is enhanced when maximum recruitment is autocorrelated. The biomass-based “40-10” control rule also maintains much lower standard deviation of average annual catch than an optimal constant escapement control rule (Ishimura et al., 2005).

4.2. Effect of the stock-recruit relationship

The relative performance of harvest policies, and the results of some studies discussed above, can depend on the form of stock-recruit relationship used, and particularly the extent of compensation in the relationship, particularly for threshold control rules. Consequently, caution should be used when interpreting analyses that compare various harvest policies because the results may depend on the amount of compensation assumed to exist in the stock-recruit relationship. When recruitment is highly compensatory (i.e., recruitment is weakly dependent on stock size), the potential benefits of a threshold control rule (i.e., maximum yield or revenue) fail to materialize because maintaining a given level of spawning stock no longer produces benefits in terms of recruitment, but yield is generally still more variable than other control rules due to fishery closures. Hightower and Lenarz (1989) assume recruitment decreases by 10% when the spawning stock is reduced by 50% from the pristine level, making recruitment highly compensatory, and show that a constant escapement control rule produces only 2% greater mean harvest than a constant effort control rule, but CV of harvest is 49%

higher. For South African anchovy *Engraulis capensis*, Butterworth and Bergh (1993) assume recruitment varies around a constant level independent of stock size and show that a constant fishing mortality rate control rule produces the same yield as a constant escapement control rule, but with less yearly variability in yield and less risk of the stock falling below 20% of unfished biomass. Other studies that assume highly compensatory stock-recruit relationships, where recruitment is independent of stock size over a broad range, also report similar results for "40-10", constant catch, and constant fishing mortality rate control rules relative to threshold control rules (Steinshamn, 1998; Ishimura et al., 2005). If these analyses had included a weaker compensatory response in the stock-recruit relationship, the results likely would have been different, and the benefits of threshold control rules (maximum yield or revenue) may have been preserved.

5. Relative performance with "imperfect" information

In reality, management must be conducted with "imperfect" information (i.e., uncertainty), and intuitively, this uncertainty should dictate more conservative or robust harvest policies (Parma, 1993; Frederick and Peterman, 1995; Punt et al., 2002b; Quinn and Collie, 2005). Most work on the effect of such uncertainty on harvest policy performance is focused on the influence of errors in stock biomass estimates. Estimates of biomass that are too high will often result in catch levels that are too high, placing the stock at risk of overexploitation, or alternatively, increased catch may be sacrificed or the fishery may be closed unnecessarily when population estimates are too low (Parma, 1993; Engen et al., 1997; DiNardo and Wetherall, 1999; Milner-Gulland et al., 2001). Uncertainty in estimates of biomass can affect various performance measures used in comparing control rules used in harvest policy analyses, including yield, variability in yield, logarithm of yield, and probability of stock collapse. Generally, uncertainty in estimates of biomass causes decreased yield (or logarithm of yield), increased variability of yield, and increased probability of stock collapse for most control rules (Eggers, 1993; Walters and Parma, 1996; Walters and Pearse, 1996; Lande et al., 1997; Engen et al., 1997; Hilborn et al., 2002; Punt, 2003; Vasconcellos, 2003). Consequently, the sensitivity of different control rules to the presence of "imperfect" information can affect their relative performance (Table 1).

5.1. Policy parameters unadjusted for uncertainty.

Most harvest policy analyses that compare control rules and account for uncertainty in stock size estimates do so by first obtaining harvest policy parameters that perform well without this uncertainty. They then compare the performance of control rules for these pre-specified policy parameters. This method essentially mimics a situation where managers are assumed to have chosen the policy parameters for a rule based on an analysis that did not account for stock assessment errors. Here we review studies of this type. In the next section we consider studies where policy parameters were "adjusted" for uncertainty.

With unadjusted policy parameters, the superior relative performance of a constant-escapement control rule for some performance variables is sensitive to errors in estimates of biomass (Table 1). Engen et al. (1997) show that proportional threshold harvesting results in larger expected cumulative yield than a constant escapement control rule when uncertainty in biomass estimates are high, and nearly as large cumulative yield and less variation in yield when uncertainty in biomass estimates are at "lower" levels, a result also supported by more recent research (Milner-Gulland et al., 2001; Lillegard et al., 2005). Proportional threshold harvesting also reduces the frequency of fishery closures, and consequently yield variability (Engen et al., 1997; Lillegard et al., 2005). In contrast, uncertainty in stock size estimates appears to favor constant escapement over constant fishing mortality rate control rules, at least for the majority of studies where recruitment is varied in a temporally uncorrelated fashion about a stationary stock recruitment function; constant escapement control rules (MSY level of escapement) generally produce higher average catch, average run size (i.e., number of spawners), average logarithm of catch, and lower CV of catch than constant fishing mortality rate control rules (i.e., MSY rate), and the disparity increases with increasing error (i.e., the constant rate rule is more sensitive) (Eggers, 1993; Sladek Nowlis and Bollermann, 2002). These results contrast with the results for “perfect information,” where constant fishing mortality rate control rules are optimal for maximizing logarithm of catch and escapement rules typically have higher variability in catch due to fishery closures. The higher variation in catch for constant fishing mortality rate control rules in the presence of stock assessment errors may occur because higher than planned levels of fishing due to errors are not be compensated for by subsequent reductions in fishing mortality. In the short-term, this could produce lower variation than a constant escapement control rule, but in the long-term an increased variation in stock size can lead to increased variation in yield (Eggers, 1993).

A major caveat to the results presented in the previous paragraph is that a constant fishing mortality rate control rule can be favored over a constant escapement control rule in terms of yield, regardless of the level of uncertainty in biomass estimates for at least one type of autocorrelated recruitment. Walters and Parma (1996) show that a constant fishing mortality rate control rule performs better in terms of yield when the asymptote parameter of a Beverton-Holt stock-recruit model is autocorrelated, even with uncertainty in biomass estimates. This result also holds true when other stock recruitment parameters (i.e., slope near the origin) are simultaneously autocorrelated with the asymptote parameter, but does not hold true when other stock-recruitment parameters are autocorrelated by themselves.

In contrast with the studies described above, Butterworth and Bergh (1993) and Polacheck et al. (1999) show that the relative performance of constant catch, constant fishing mortality rate, and constant escapement control rules generally remain similar to situations of perfect information when uncertainty is added through the use of management strategy evaluations. These studies suggest that under some circumstances the relative performance of these control rules may be robust to the inclusion of uncertainty.

5.2. Uncertainty adjusted policy parameters

An alternative to using policy parameters that work best for a control rule without errors in stock size, is to select them so as to maximize the expected value of an objective function averaged over these (or other) errors (e.g., over simulations). The relative performance of various harvest policies can then be compared based on which policy produces a larger expected value of the objective function. Such studies mimic a situation where it is assumed that managers are taking into account uncertainty (e.g., in stock assessment) when they decide on policy parameters.

When this approach has been compared with the case of perfect information, more conservative fishing within a policy is again favored, and the relative performance of different types of control rules is changed. For example, Frederick and Peterman (1995) show that a constant fishing mortality rate control rule outperforms a constant escapement control rule in terms of maximizing expected present value (measured in dollars) and preventing harvest from falling below 10% of the deterministic equilibrium level when uncertainty in the shape of the stock-recruit function (i.e., uncertainty in the parameters of a Shepherd function) and error in biomass estimates were accounted for. Frederick and Peterman (1995) also show that constant fishing mortality is favored in the case of depensatory recruitment, which might be expected to be more favorable to constant escapement control rules (Ricker, 1958; Larkin and Ricker, 1964; Tautz et al., 1969; Collie and Spencer, 1993; Spencer, 1997). Katsukawa (2004) considers a wide range of policy parameters for a biomass based control rule (Figure 2), which includes constant fishing mortality rate and threshold control rules as limiting cases. The study shows that substantial errors in stock assessments favors control rules more like constant fishing mortality rate, whereas perfect information favors control rules that resemble threshold rules. That is, such control rules tend to produce as much yield while maintaining similar levels of biomass. Similarly, Sethi et al. (2005) uses stochastic optimal control methods to show that assessment error favors control rules that more closely resemble a biomass-based policy than a constant escapement control rule, when the objective is to maximize discounted yield. Similar results have previously been reported by Clark and Kirkwood (1986). Vasconcellos (2003) also report higher and less variable yields for constant fishing mortality rate rules than for constant escapement rules, although to some extent this could be partly due to probabilistically incorporating an autocorrelated asymptote to recruitment as in Walters and Parma (1996). Sethi et al.

(2005) show that implementation error alone does not influence the form of the control rule, but it does appear to have an interactive effect with assessment error. These limited studies that consider uncertainty adjusted results contrast in an important way with the unadjusted results of the previous section; suggesting that accounting for uncertainty when estimating policy parameters is warranted.

6. Selecting catch, fishing mortality, and threshold levels

6.1. Available options – simulations or biological reference points

Once a general family of control rule is chosen, managers must then decide on policy parameters; the level of catch, fishing mortality, or threshold to apply. Ideally, this decision is made through a management strategy evaluation that uses stochastic simulation to incorporate uncertainty in stock assessments (e.g., parameter values and biomass estimates), population dynamics (e.g., stock-recruit function), and implementation (Annala, 1993; Francis, 1993; Frederick and Peterman, 1995, Polacheck et al., 1999). This approach evaluates the robustness of control rules and policy parameters to uncertainty, and prevents the need for selecting an arbitrary level or basing the harvest policy on some biological reference point (BRP) that may be too conservative or too aggressive depending on the stock. Furthermore, optimum levels of catch, fishing mortality, or thresholds often become more conservative as uncertainty in assessments increase, suggesting that estimates from deterministic simulations may be risk-prone (Lowe and Thompson, 1993; Gibson and Myers, 2004; Lillegard et al., 2005).

Although constructing a stochastic simulation is ideal, this is not always feasible due to data requirements and time and effort demands (Annala, 1993; Caddy and Mahon, 1995). Consequently, levels are often selected based on BRPs or historical experience

(Caddy and Mahon, 1995). The use of BRPs requires defining the various reference points as targets or limits, but what qualifies as a target or limit can be confusing. Here we propose similar definitions for targets and limits as those of Caddy and Mahon (1995) and Caddy and McGarvey (1996). A target is a desirable state of the fishery (e.g., fishing mortality) or resource (e.g., biomass) at which management action should aim, so that on average the target is attained. A limit is a "dangerous" state of the fishery or resource that should be avoided or exceeded with only a "low" level of probability or frequency. In order to be effective, a limit must also be accompanied by some pre-defined management actions that are to be taken based on specific evidence that the limit is likely to have been exceeded, which would allow the fishery to rebound. Interpreting a limit as requiring that there is some pre-determined "low" probability that the state of the fishery or resource will exceed the limit can be problematic. Estimating such probabilities would usually require a stochastic simulation model that considers key uncertainties, and often reference points are being used because such a model is not available. Managers can still make informed decisions, however, based on the historical performance of various BRPs, and whether those BRPs seem better suited as a target or limit, given characteristics of the fishery. Below we provide an overview of some of the reference point literature. For a more detailed description and evaluation of each BRP consult the references in Table 3.

6.2. Constant catch levels

MSY has historically been used as a target for constant catch control rules, but the pitfalls of MSY as a target are well known (Clark, 1973; Larkin, 1977; Sissenwine, 1978; Hilborn and Walters, 1992; Caddy and Mahon, 1995 Quinn and Deriso, 1999; Quinn and Collie, 2005). MSY now most often serves as a limit catch level or a starting point from which constant catch levels are scaled downward to more conservative targets (Hilborn and Walters, 1992; Annala, 1993; Overholtz, 1999; Mace, 2001). Maximum constant yield (MCY) is one example of a catch level conceptually similar to MSY, but considers random fluctuations in production, as opposed to assuming deterministic dynamics following a Schaefer surplus production model (Sissenwine, 1978; Murawski and Idoine, 1989). A critical feature of MCY is that as variation (and possibly autocorrelation) in production increases, given stock size, MCY decreases below MSY (Sissenwine, 1978; Getz et al., 1987). Sissenwine (1978), however, warns against using estimates of MCY as target levels because the fishing mortality rate associated with that level of catch can be high, and cause declines in spawning stock biomass and subsequent recruitment. In New Zealand during the 1990s, developed fisheries for which a population model was available to estimate MSY were managed with a constant catch level of 2/3 MSY (Annala, 1993). This level was selected based on stochastic simulation results that found that MCY can be as low as 60% of the deterministic MSY for some stocks (Annala, 1993). Constant catch levels in New Zealand have also been selected using other proxies for MSY, with the exact method of estimation depending on data availability and exploitation history of the fishery (Annala, 1993).

6.3. Constant fishing mortality rate F levels

Various BRP F values, for use in control rules that apply a constant F over all or some range of biomass levels, have been suggested as either targets or limits. F_{msy} was often used as a target, but has been criticized as being economically inefficient and difficult to estimate reliably, and so should likely be treated as a limit or benchmark from which more conservative fishing strategies are developed (Larkin, 1977; Koonce and

Shuter, 1987; Sissenwine and Shepherd, 1987; Hilborn and Walters, 1992; Overholtz, 1999; Quinn and Deriso, 1999; Mace, 2001; Brodziak and Legault, 2005). Setting F equal to M was also suggested as a means to attain MSY, but this rarely holds true (Alverson and Pereyra, 1969; Francis, 1974; Deriso, 1982; Quinn and Deriso, 1999). Furthermore, the relationship between yield and fishing mortality rate is generally flat over a broad range of fishing mortality values, and so setting target fishing mortality rates below F_{msy} will often lose little in yield while maintaining a disproportionately higher amount of biomass (Deriso, 1987; Hilborn and Walters, 1992; Ralston et al., 2000; Dichmont et al., 2006b). Yield per recruit (YPR) analyses are used to formulate two common BRPs, $F_{\max}$ and $F_{0.1}$ (Deriso, 1987). Although sometimes used as targets, these reference points cause stock declines over a broad range of conditions and should likely be used as limits (Sissenwine and Shepherd, 1987; Clark, 1991; Jakobsen, 1992; Goodyear, 1993; Leaman, 1993; Campana et al., 2002; Rahikainen and Stephenson, 2004; Quinn and Collie, 2005). $F_{\mathrm{x}\%}$ BRPs are based on spawning stock biomass or egg production per recruit (SSBR) analyses. These BRPs have the advantage that stocks with similar levels of compensation in the stock-recruit relationship can be cautiously managed with the same $F_{x\%}$ rate (Dorn, 2002). Combined with meta-analyses of stock-recruit data (e.g., Myers et al., 1999; Dorn, 2002), appropriate $F_{x\%}$ rates can be estimated where stock specific estimates of productivity are lacking. However, levels of $F_{\mathrm{x}\%}$ (usually in the range of 20%-40%) have historically been chosen based on yield objectives and were treated as targets (Clark, 1991; Ralston et al., 2000; Brodziak, 2002;

Clark, 2002; Quinn and Collie, 2005). Because these levels of fishing were set without incorporating recruitment and biomass as part of the objective, it is not surprising that the selected $F_{x\%}$ levels have proved inconsistent with an objective of maintaining stock biomass above a specified threshold (Ralston et al., 2000). Several other BRPs have been developed using SSBR analyses and a plot of stock-recruit data. F_{ro} (for recruitment overfishing) is intended for use as a limit rate that explicitly avoids recruitment overfishing (Sissenwine and Shepherd, 1987). F_{rep} (for replacement), and similarly F_{med}, are suggested as targets to maintain current levels of biomass, but will only do so in the absence of density dependence in the stock-recruit relationship (Sissenwine and Shepherd, 1987; Mace and Sissenwine, 1993; Maguire and Mace, 1993; Quinn and Deriso, 1999). F_{low} and F_{high} are set relative to F_{rep} and would likely lead to rebuilding or stock declines, respectively (Jakobsen, 1993). F_{st} (for steady) is a BRP based on a Leslie matrix model that is conceptually similar to F_{rep}. (Quinn and Szarzi, 1993; Hayes, 2000).

6.4. Threshold levels

Threshold levels, for use in threshold and biomass-based control rules, have been selected in a variety of ways. Perhaps the simplest method is to use a time series of abundance data. Sigler and Fujioka (1993) define sablefish stocks to be overfished whenever biomass falls below the historically lowest observed level. For overexploited stocks, Overholtz et al. (1993) suggest using some percent level of biomass higher than current biomass. When a stock specific threshold cannot be determined, thresholds developed for other species with similar taxonomy and life history parameters can also be applied (Mace and Sissenwine, 1993). Because these methods are somewhat arbitrary, the management action that should be taken when biomass falls below these levels is unclear.

Other less arbitrary biomass thresholds have also been developed. For populations exhibiting compensation, Quinn and Deriso (1999) show how a parameter can be added to a Graham-Schaefer surplus production model to estimate the point where latent productivity becomes zero or negative, providing a threshold level of biomass, which is often expressed as a percentage of unfished biomass. Zheng et al. (1993b) develop a similar methodology generalized to a depensatory surplus production model. When a stock-recruit relationship is taken into account, a more elaborate population model can be developed to estimate biomass at MSY for use as a target (or some other MSY proxy) and some level below MSY for use as a threshold (Quinn and Deriso, 1999). In the case of a depensatory stock-recruit relationship, the inflection point has been suggested as a threshold level of biomass, and assuming that growth and mortality are density-independent, the inflection point usually occurs below 20% of pristine biomass, suggesting that 20% is generally a threshold below which fishing should stop (Thompson, 1993). This conclusion is consistent with other studies that found that spawning biomass should be maintained between 20% and 50% of unfished spawning biomass as a way to ensure replacement and attain a large proportion of MSY (Quinn et al., 1990; Clark, 1991; Fujioka et al., 1997; Booth, 2004). Conversely, Myers et al. (1994) conclude that using 20% of unfished spawning biomass as a threshold may be risky for stocks with “severe” depensation, and recommend using the biomass level that produces 50% of the maximum recruitment as a robust threshold. Zheng et al. (1993b) suggest two methods of estimating thresholds based on life-history parameters called Fowler's method and May's method.

Many of the studies discussed above seek to determine a threshold independently from a target value of fishing mortality. In some cases the fishing mortality rate is set at levels that were determined as best for a constant fishing mortality rate control rule. An alternative is to simultaneously search for the threshold level and level of fishing mortality combination that maximize a given objective function in the framework of a stochastic simulation. Zheng et al. (1993a) and Quinn et al. (1990) use this approach with an objective function that considers both maximizing annual yield and minimizing yearly variations in yield. In accord with simulation results, we expect that the optimal fishing mortality rate at high biomasses would generally be higher for a biomass based control rule than for a constant fishing rate control rule and thus there should be benefits to searching for the best combination. However, results are probably too limited to allow for rules of thumb on how much higher the fishing rate should be for a biomass-based control rule in the absence of an explicit analysis.

7. Summary and conclusions

Harvest policies are a necessary feature of transparent fisheries management because they ensure that the rules for how harvest will vary are evident to all stakeholders. However, the application of an inappropriate harvest policy will result in a failure to meet management objectives or potentially cause stock collapse. Rational management requires that objectives be explicitly stated and that a harvest policy is selected so as to best achieve those objectives. The results of this review provide some guidance on what control rules might be worth considering for given objectives, and what factors might influence their relative performance, and so should be included in analyses of harvest policies.

Most research to date focuses on evaluating harvest policies under the assumption of "perfect information" (i.e., no uncertainty or error; Table 2). These analyses often identify optimal control rules for meeting certain fishery objectives under given conditions, and highlight factors that might affect relative policy performance. Of particular importance seems to be the shape of the stock-recruit relationship (i.e., level of compensation), autocorrelation in recruitment, and whether depensatory mechanisms exist (Ricker, 1958; Larkin and Ricker, 1964; Tautz et al., 1969; Hightower and Lenarz, 1989; Collie and Spencer, 1993; Walters and Parma, 1996; Lande et al., 1997; Spencer, 1997; Steinshamn, 1998; Ishimura et al., 2005). Some research also suggests that variability in other population parameters, such as time-varying catchability, may also have an effect on relative policy performance (Punt, 1997; Punt et al., 2002b; Dichmont et al., 2006a; Dichmont et al., 2006c). We believe more needs to be learned about how temporal variation in parameters, such as those governing the stock-recruitment relationship, influences the performance of harvest policies.

Much less research focuses on comparing harvest policies while considering key uncertainties (e.g., in the recruitment function, error in biomass, error in catch statistics). One result of adding uncertainty is that policy parameters (e.g., a constant fishing mortality rate) are generally shifted in a more conservative direction from those based on treating point estimates of parameters governing population dynamics and fishery behavior as known. Thus, research that assumes perfect information should be interpreted cautiously, since uncertainty is a ubiquitous feature (Punt et al., 2002). Furthermore, the relative performance of control rules depends on whether the policy parameters have been adjusted for uncertainty. In general, we believe managers should adjust parameters for uncertainty as is advocated in the Decision Analysis literature (Peterman and Anderson 1999). This conclusion suggests that much more research on the relative performance of control rules using uncertainty adjusted parameters is needed.

Greater uncertainty clearly reduces sustainable yields and other benefits of fishing. The policy studies reviewed here that incorporate uncertainty in stock status or underlying dynamics treat this as a constant fixture of the system. Additional studies are needed that take an adaptive management view, and consider the interaction between harvest policies and understanding of the fishery system (Walters, 1986).

Many resource economists conclude that constant escapement control rules provide maximum profits, but they also generally do not consider the possibility of autocorrelated recruitment, uncertainty, and they often assume that profits are linearly related to harvest (Gatto and Rinaldi, 1976; Reed, 1979; Lande et al., 1995; Nostbakken, 2006). The linear relationship may not adequately consider the social and political repercussions of a frequently closed fishery. We believe this is why constant escapement control rules are not applied more often. For example, in the South African anchovy fishery, a constant escapement control rule was abandoned for a constant fishing mortality rate control rule within two years of being implemented because it became obvious that fishery closures would be frequent (Cochrane et al., 1998).

Most research focuses on single management objectives (e.g., maximizing yield) and the policies that are optimal for meeting single objectives. However, management often involves competing objectives, and selecting a harvest policy that is optimal for one objective involves a trade-off with some other objective (Quinn et al., 1990). For example, constant escapement control rules that maximize long-term yield also often maximize variability in yield (Walters and Parma, 1996). McGlade (1989) proposes an intensive approach to deal with competing objectives called integrated fisheries management, which explicitly models ecological, socioeconomic, legal, and institutional aspects of a fishery into a single model. Management strategy evaluations can also address uncertainties that occur throughout the management process, including the ecological and socioeconomic aspects (Smith et al., 1999; Punt et al., 2002c; Dichmont et al., 2006a,b,c). These approaches might produce optimal policies that differ from traditional single objective approaches (McGlade, 1989). For example, consideration of how closing a fishery affects the short-term economics and social atmosphere of fishing communities would likely result in a different optimal policy than attempting to maximize long-term profits alone. Generally, little is known about optimal policies for meeting multiple competing objectives, and optimal policies in these situations might be different than has been found for single objective approaches (Fieberg, 2004).

To deal with the trade-offs of competing objectives, some control rules attempt to attain “the best of both worlds.” CCC control rules attempt to combine attractive aspects of constant catch and constant fishing mortality rate control rules, so as to attain stable catch with less risk than strict constant catch (Murawski and Idoine, 1989; Hjerne and Hansson, 2001; Clark and Hare, 2004). Biomass based control rules are an alternative that avoids frequent fishery closures and responds to declining biomass by reducing fishing mortality, and so retains attractive features of constant fishing mortality (i.e., few fishery closures) and constant escapement control rules (i.e., reduced harvest at low stock size). To date, little research has focused on these control rules, particularly in the presence of uncertainty. Furthermore, optimal methods for designing biomass based control rules (i.e., exactly how F should decline with biomass) have not been developed and much work is needed on this and related topics.

Harvest policies are generally developed for single species fisheries, but increased awareness of problems caused with by-catch, increased centralization of fishery control, and increased knowledge of ecosystems may lead to attempts to apply harvest policies to entire food-webs or ecosystems (Walters et al., 2005; Quinn and Collie, 2005; Matsuda and Abrams, 2006). Walters et al. (2005) evaluates the ecosystem impacts of applying constant catch control rules to multiple species simultaneously, with the catch level set at MSY and estimated from single species assessments. They show that the ecosystem changes caused by such a strategy results in MSY being unattainable for several species and top predator populations most often declining. Similarly, Dichmont et al. (2006b) uses a management strategy evaluation for Australia's northern prawn *Penaeus spp.* fishery and shows that when species are caught simultaneously, multiple species cannot be sustainably harvested at individual F_{msy} rates. Matsuda and Abrams (2006) develop models to find the level of fishing effort that maximizes yield or profits from a food-web using simple linear rates of production and density dependence in growth for systems with as many as six species and five trophic levels. In many instances, maximizing yield or profits from the system involves eradicating top-predators in order to increase the production of lower trophic levels, particularly if the species in lower trophic levels are more valued. They conclude that further development of policies for entire food-webs may require preventative measures to ensure top predators are not eradicated for the sake of increased profits from lower trophic levels.

Fishing exerts selective pressures on fish stocks that can lead to the evolution of life-history traits that affect productivity (e.g., growth, age at maturity), and this may also affect relative policy performance (Heino, 1998; Conover and Munch, 2002; Swain et al., 2007). Little is known, however, about how sensitive policy performance is to evolutionary change, or whether such changes might also interact with other characteristics known to effect policy performance (e.g., uncertainty in estimates of biomass). This topic should remain an area of active research, and simulation studies that account for evolutionary change induced through harvest would provide valuable insight (e.g., Heino, 1998).

When an appropriate simulation study cannot be conducted to determine policy parameters (e.g., target constant fishing mortality rate) that best achieve stated objectives, BRPs likely provide the next best method for selecting fishing mortality rates and thresholds. The effectiveness of any BRP will depend on the objectives of the fishery and whether assumptions used in the development of a given BRP have been met. Generally, the shape of the stock-recruit relationship, and whether density-dependence or depensatory mechanisms are active will be of particular importance. Furthermore, if left with no better alternative, BRPs can be cautiously applied to species with similar taxonomy and life history characteristics (Mace and Sissenwine, 1993).

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Table 1. The rank order performance of control rules for meeting each of several different fishery objectives. Results given in columns of the table correspond to cases assuming no error in estimates of stock size, with the inclusion of error in estimates of stock size, with and without policy parameters adjusted for uncertainty, and with and without autocorrelation in the maximum level of recruitment (see text). When errors in stock size estimates were incorporated, studies that compared performance for control rules using the policy parameters that were optimal without these errors are "unadjusted"; studies that sought policy parameters that were optimal over the uncertainty are "uncertainty adjusted." When uncertainty in stock assessments was incorporated, rank order reflects finding for the highest levels of assessment error that were evaluated. When for a given table column there are no studies that evaluated relative performance of a control rule, these policies are missing (-).

	No Error in Stock Size Estimates		**Error in Stock Size Estimates**			
	Uncorrelated Max Recruitment	**Correlated Max Recruitment**	**Uncorrelated Max Recruitment**		**Correlated Max Recruitment**	
			Unadjusted Policy Parameters	**Uncertainty Adjusted Policy Parameters**	**Unadjusted Policy Parameters**	**Uncertainty Adjusted**
Rank	**Objective Function: Maximize Yield or Profits**					
Better	Constant Escapement	Constant-F	Proportional Threshold	Constant-F	Constant-F	-
↓	Threshold/Biomass Based	Constant Escapement	Constant Escapement	Threshold/Biomass Based	Constant Escapement	-
	Constant-F	-	Constant-F	Constant Escapement	-	-
Worse	Constant Catch	-	-	-	-	-
	Objective Function: Minimize Risk of Over-exploitation or Maintain Biomass Above a Threshold					
Better	Constant Escapement	-	Constant Escapement	Constant-F	Constant-F	-
↓	Threshold/Biomass Based	-	Constant-F	Threshold/Biomass Based	Constant Escapement	-
	CCC	-	-	Constant Escapement	-	-
	Constant-F	-	-	-	-	-
Worse	Constant Catch	-	-	-	-	-

Table 1 (cont'd)

	No Error in Stock Size Estimates		Error in Stock Size Estimates			
	Uncorrelated Max Recruitment	**Correlated Max Recruitment**	**Uncorrelated Max Recruitment**		**Correlated Max Recruitment**	
			Unadjusted Policy Parameters	**Uncertainty Adjusted Policy Parameters**	**Unadjusted Policy Parameters**	**Uncertainty Adjusted**
	Objective Function: Minimize Stock Rebuilding Time					
Better	Threshold/Biomass Based	-	-	-	-	-
Worse	Constant-F	-	-	-	-	-
	Objective Function: Minimize Variability in Yield or Profits					
Better	Constant Catch	-	Proportional Threshold	-	Constant-F	-
↓	Constant-F	-	Constant Escapement	-	Constant Escapement	-
	Threshold/Biomass Based	-	Constant-F	-	-	-
Worse	Constant Escapement	-	-	-	-	-

Table 2. Papers that compared harvest policies for meeting common fishery objectives assuming no error in estimates of stock size, with the inclusion of error in estimates of stock size, and with or without autocorrelation in the maximum level of recruitment (i.e., asymptote of a Beverton-Holt stock-recruit function). Specific control rules and characteristics included in each paper are indicated with a X.

	Maximum Recruitment Level		Stock Size Estimates		Control Rules						
Studies	**Uncorrelated**	**Correlated**	**No Error**	**Error**	**CC**	**CF**	**CE**	**Threshold**	**BB**	**CCC**	**40-10**
Objective Function: Maximize Yield or Profits											
Ricker 1958	X		X			X	X				
Larkin and Ricker 1964	X		X			X	X				
Tautz et al. 1969	X		X			X	X				
Gatto and Rinaldi 1976	X		X			X	X				
Reed 1979	X		X				X				
Jacobson and Taylor 1985	X		X		X	X					
Koonce and Shuter 1987	X		X		X	X			X		
Hall et al. 1988	X		X			X	X				
Getz and Haight 1989	X		X			X	X				
Butterworth and Bergh 1993	X			X	X	X	X				
Collie and Spencer 1993	X		X			X	X	X			
Eggers 1993	X		X	X		X	X				
Steinshamn 1993	X		X		X	X					
Lande et al. 1995	X		X		X	X	X				
Walters and Parma 1996		X	X	X		X	X				
Engen et al. 1997	X			X			X		X		
Lande et al. 1997	X		X	X		X	X		X		
Spencer 1997	X		X			X		X			
DiNardo and Wetherall 1999	X		X		X	X					
Polacheck et al. 1999	X			X	X	X					
Hjerne and Hansson 2001	X		X			X				X	
Sladek and Bollermann 2002	X			X		X	X	X			
Vasconcellos 2003		X		X		X	X				

Table (cont'd)

Studies	Maximum Recruitment Level		Stock Size Estimates		Control Rules						
	Uncorrelated	**Correlated**	**No Error**	**Error**	**CC**	**CF**	**CE**	**Threshold**	**BB**	**CCC**	**40-10**
Objective Function: Minimize Risk of Over-exploitation or Maintain Biomass Above a Threshold											
Clark and Hare 2004	X		X			X				X	
Katsukawa 2004	X		X	X		X		X	X		
Lillegard et al. 2005	X			X		X	X	X	X		
Beddington and May 1977	X		X		X	X					
Jacobson and Taylor 1985	X		X		X	X					
Koonce and Shuter 1987	X		X		X	X			X		
Getz and Haight 1989	X		X			X	X				
Quiggin 1992	X		X		X	X					
Butterworth and Bergh 1993	X			X	X	X	X				
Eggers 1993	X		X	X		X	X				
Sigler and Fujioka 1993	X		X			X		X	X		
Steinshamn 1993	X		X		X	X					
Zheng et al. 1993a	X		X			X		X			
Lande et al. 1995	X		X		X	X	X				
Lande et al. 1997	X		X	X		X	X		X		
DiNardo and Wetherall 1999	X		X		X	X					
Polacheck et al. 1999	X			X	X	X					
Sladek and Bollermann 2002	X			X		X	X	X			
Vasconcellos 2003		X		X		X	X				
Clark and Hare 2004	X		X			X				X	
Katsukawa 2004	X		X	X		X		X	X		
Objective Function: Minimize Stock Rebuilding Time											
Hightower and Grossman 1987	X		X		X			X			
Quinn et al. 1990	X		X			X		X			
Polacheck et al. 1999	X			X	X	X					

Table 2. (cont'd)

Studies	Maximum Recruitment Level		Stock Size Estimates		Control Rules						
	Uncorrelated	**Correlated**	**No Error**	**Error**	**CC**	**CF**	**CE**	**Threshold**	**BB**	**CCC**	**40-10**
Objective Function: Minimize Variability in Yield or Profits											
Ricker 1958	X		X			X	X				
Larkin and Ricker 1964	X		X			X	X				
Tautz et al. 1969	X		X			X	X				
Gatto and Rinaldi 1976	X		X			X	X				
Reed 1979	X		X				X				
Jacobson and Taylor 1985	X		X		X	X					
Koonce and Shuter 1987	X		X		X	X			X		
Objective Function: Minimize Variability in Yield or Profits (continued)											
Getz and Haight 1989	X		X			X	X				
Butterworth and Bergh 1993	X			X	X	X	X				
Collie and Spencer 1993	X		X			X	X	X			
Eggers 1993	X		X	X		X	X				
Lande et al. 1995	X		X		X	X	X				
Walters and Parma 1996		X	X	X		X	X				
Engen et al. 1997	X			X			X		X		
Lande et al. 1997	X		X	X		X	X		X		
DiNardo and Wetherall 1999	X		X		X	X					
Hjerne and Hansson 2001	X		X			X				X	
Sladek and Bollermann 2002	X			X		X	X	X			
Vasconcellos 2003		X		X		X	X				
Clark and Hare 2004	X		X			X				X	
Enberg 2005		X	X			X		X	X		
Ishimura et al. 2005	X		X				X				X
Lillegard et al. 2005	X			X		X	X	X	X		

Table 3. Studies that evaluated various biological reference points (BRP)

BRP	References
	Catch Levels
MSY	Clark 1973; Beddington and May 1977; Larkin 1977; Sissenwine 1978; Sissenwine and Shepherd 1987; Hilborn and Walters 1992; Caddy and Mahon 1995
MAY	Sissenwine 1978; Getz et al. 1987; Murawski and Idoine 1989; Annala 1993
MSY proxies	Beddington and Cooke 1983; Annala 1993
	Fishing Mortality Levels
F_{msy}	Larkin 1977; Koonce and Shuter 1987; Hilborn and Walters 1992; Overholtz 1999; Mace 2001; Collie and Gislason 2001; Gibson and Myers 2004; Brodziak and Legault 2005
$F = M$	Alverson and Pereyra 1969; Francis 1974; Deriso 1982
F_{max} and $F_{0.1}$	Ricker 1975; Sissenwine and Shepherd 1987; Deriso 1982; Deriso 1987; Clark 1991; Jakobsen 1992; Goodyear 1993; Leaman 1993; Helser and Brodziak 1998; Collie and Gislason 2001; Campana 2002; Rahikainen and Stephenson 2004
$F_{x\%}$	Sissenwine and Shepherd 1987; Gabriel et al. 1989; Clark 1991; Goodyear 1993; Jakobsen 1993; Mace and Sissenwine 1993; Fujioka et al. 1997; Siddeek and Al-Hosni 1998; Clark 1993; Clark 1999; Collie and Gislason 2001; Clark 2002; Williams 2002; Booth 2004; Rahikainen and Stephenson 2004
F_{ro}	Sissenwine and Shepherd 1987
F_{rep}, F_{med}, F_{high}, F_{low}	Sissenwine and Shepherd 1987; Jakobsen 1993; Mace and Sissenwine 1993; Maguire and Mace 1993; Collie and Gislason 2001;
F_{st}	Quinn and Szarzi 1993; Hayes 2000
	Threshold levels
biomass thresholds	Quinn et al. 1990; Clark 1991; Mace and Sissenwine 1993; Overholtz et al. 1993; Sigler and Fujioka 1993; Thompson 1993; Zheng et al. 1993a; Zheng et al. 1993b; Myers et al. 1994; Fujioka et al. 1997; Quinn and Deriso 1999; Collie and Gislason 2001; Booth 2004

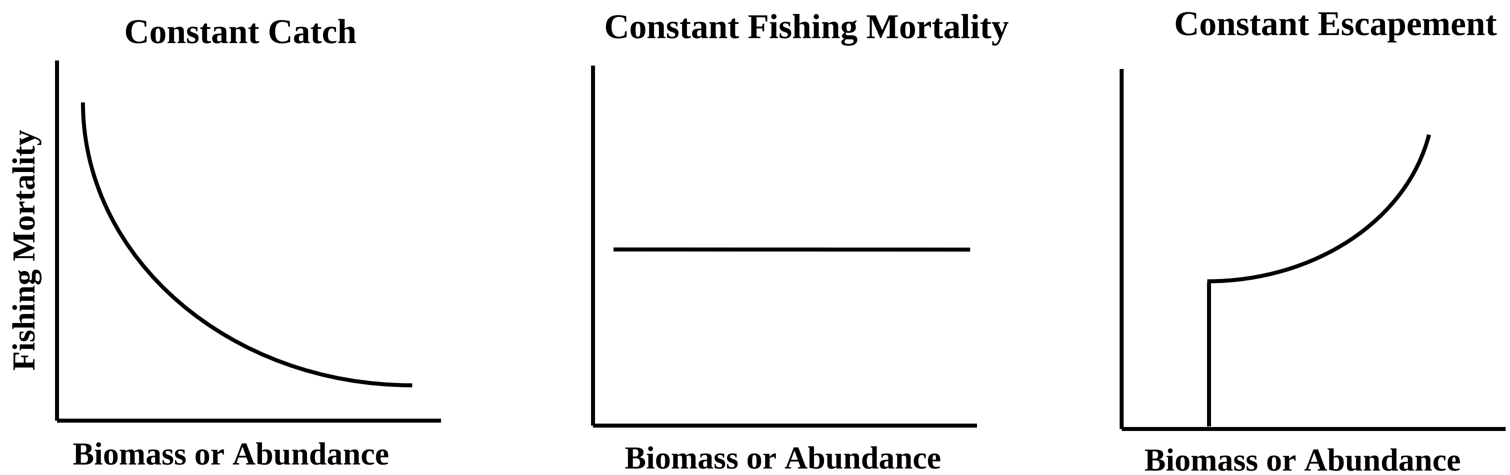

Figure 1.—Basic control rules and how fishing mortality generally changes with biomass or abundance for each type.

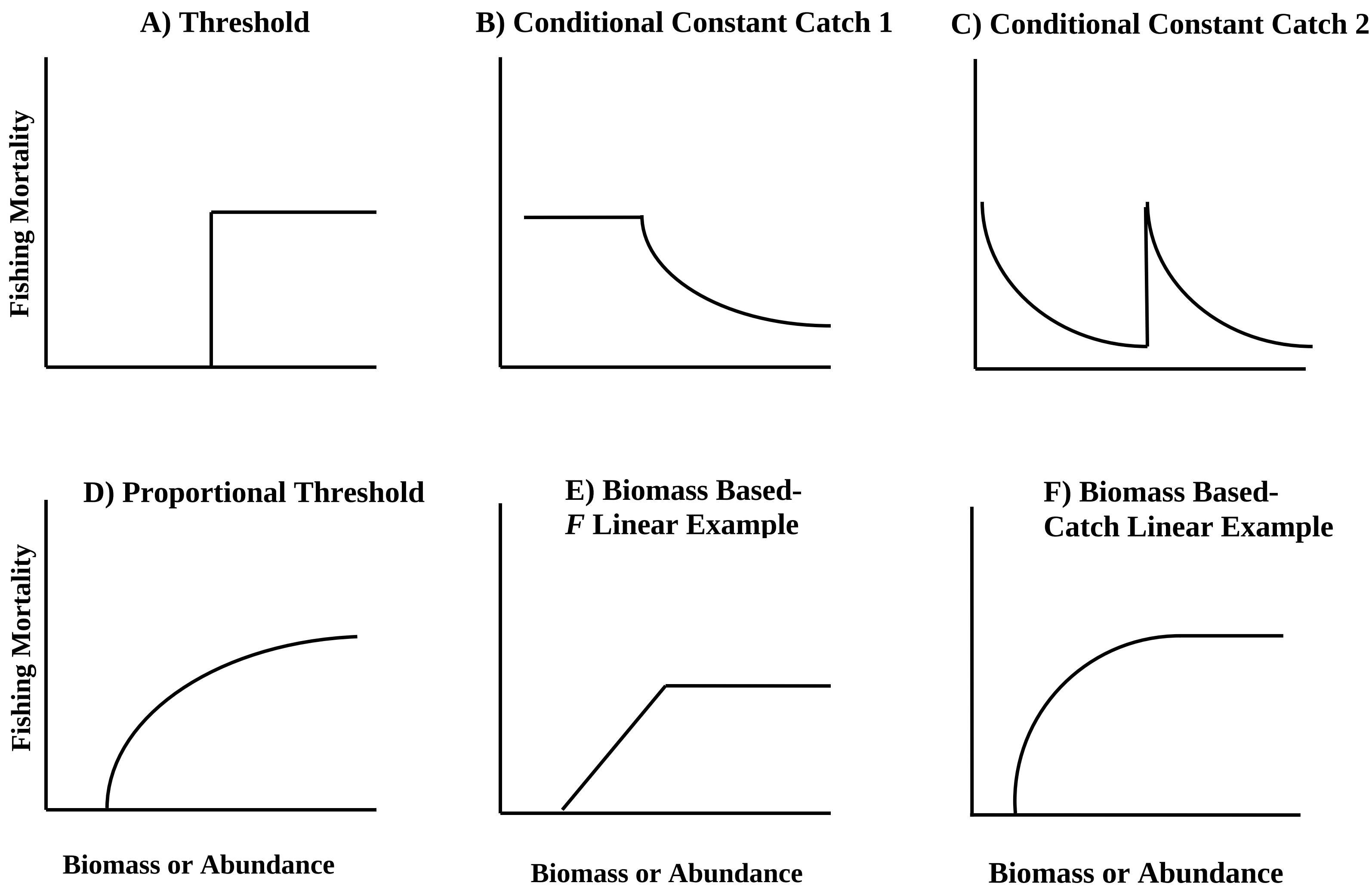

Figure 2.—Variants of basic control rules and how fishing mortality generally changes with biomass or abundance for each type.

CHAPTER 3

EVALUATING HARVEST CONTROL RULES FOR LAKE WHITEFISH IN THE GREAT LAKES: ACCOUNTING FOR VARIABLE LIFE-HISTORY TRAITS

Abstract

Lake whitefish support a commercial fishery in the Great Lakes and experience spatial and temporal variation in life history traits, such as size-at-age. Currently, the fishery is managed by attempting to maintain a constant mortality rate. I used an age-structured simulation model that incorporated stochasticity in life history traits, uncertainty in future lake whitefish growth, and other sources of uncertainty to compare the current strategy with a range of alternative control rules, including conditional constant catch (CCC), constant fishing rate (CF), biomass-based (BB), and CF and BB rules with a 15% limit on the interannual change in the target catch. With appropriate policy parameters, the CF and BB rules can simultaneously attain higher average yield and spawning stock biomass than all other control rules. The CCC rule and limiting the CF or BB rules to a 15% change in target catch had the lowest yearly variability in yield. For control rules using policy parameters that produced the same yield, low biomass levels were attained most frequently for the CF and BB rules with a 15% limit on target catch and least often for the BB rule. The low yearly variability in yield provided by limiting target catch changes to 15% comes at the cost of frequently reducing biomass to low levels, so that in many situations other control rules would be preferred. The sensitivity of results to uncertainty about future lake whitefish growth was control rule specific and depended on whether stock growth was fast or slow.

1. Introduction

1.1. Harvest Control Rules

Harvest control rules are guidelines that specify an amount of catch, fishing effort, or fishing mortality as a specific, and usually simple, function of an estimate of the current system state (e.g, spawning biomass; Deroba and Bence, 2008). Ideally, a harvest control rule is selected based on a management strategy evaluation or simulation analysis that compares control rules for their ability to meet competing fishery objectives (e.g., maximizing yield versus minimizing annual variation in yield), and considers key uncertainties (e.g., shape of the stock-recruit curve) and sources of error in the management process (e.g., assessment error; Smith et al., 1999; Punt et al., 2002; Kell et al., 2006; Deroba and Bence 2008). Often times, however, control rules and the parameters for a control rule are defined in an *ad hoc* manner, and so may not be optimal for meeting given fishery objectives (Deroba and Bence, 2008). Furthermore, many analyses have ignored sources of uncertainty and error that affect relative control rule performance, and so few control rules have been thoroughly examined for their relative ability to meet competing fishery objectives (Deroba and Bence, 2008). Few analyses have also considered the effect of spatial or temporal variation in population parameters, such as growth, maturity, or stock-recruitment relationships, and such factors can affect control rule performance (Deroba and Bence, 2008).

1.2. Lake Whitefish Fishery History and Management

Lake whitefish, *Coregonus clupeaformis*, have supported a historically important subsistence fishery for Native American bands and a highly valued commercial fishery in the upper Great Lakes (Lakes Huron, Michigan, and Superior). Lake whitefish stocks collapsed in each of these lakes in the 1930s and 1940s partially due to overexploitation (Smiley, 1882; Koelz, 1926; Jensen, 1976; Brown et al., 1999; Ebener and Reid, 2005), but have since rebounded to once again become the main commercial species (Mohr and Ebener, 2005). For example, lake whitefish provide about 80% of the total commercial yield from Lake Huron in each year (Mohr and Ebener, 2005).

In 1979, the rights of Native American bands to fish in the Michigan waters of the upper Great Lakes, as reserved in a treaty signed in 1836, were reaffirmed by U.S. federal courts. Since the reaffirmation of treaty fishing rights, periodic stock assessments have been conducted for stocks within spatially defined management units, with the fishery data and harvest from within each management unit treated as applying to a reproductively isolated stock (Figure 1; Ebener et al., 2005).

Lake whitefish stocks are also characterized by spatial and temporal variation in various population parameters. For example, lake whitefish growth in some areas of the Great Lakes has declined in recent years, but similar declines have not occurred everywhere despite similar ecosystem changes (e.g., Hoyle et al., 1999; Pothoven et al., 2001; Cook et al., 2005; Mohr and Nalepa, 2005; Lumb et al., 2007). Growth rates, maturity ogives, natural mortality, and stock-recruit relationships also likely differ spatially among some of the management units due to factors such as different historical exploitation patterns or long-term differences in environmental conditions experienced by distinct stocks occurring across a latitudinal gradient (e.g., Wang et al., 2008).

Since 2000, guidelines for the management of lake whitefish have been set according to a Consent Decree. The 2000 Consent Decree created a Technical Fisheries Committee and its Modeling Subcommittee (MSC) to conduct stock assessments and recommend annual quotas for each individual management unit. Recommended yields are treated as limits in units where yield is allocated between the state and tribal fishery, and targets in units where all yield is allocated to the tribal fishery. The MSC fits statistical catch-at-age (CAA) models to commercial fishery data to estimate population numbers, mortality rates, fishery harvest, and other population parameters of interest. The estimates of the population parameters are then used to project each stock's abundance into the future, and the target or limit quotas are determined so that the total annual mortality rate equals 65% for ages experiencing the highest levels of fishing mortality. The CAA models assume a constant natural mortality rate across ages and time, and so this is equivalent to a constant fishing mortality rate (constant-*F*) control rule.

The constant-*F* control rule and the parameters for the control rule (i.e., 65% total annual mortality rate) are somewhat *ad hoc* and may not be optimal for meeting fishery objectives. The value of 65% was based on the work of Healey (1975) who found that a substantial proportion of lake whitefish stocks with total annual mortality rates in excess of 70% were depleted or precarious, whereas stocks with rates below 65% appeared to have generally fared well. Jacobson and Taylor (1985) compared the relative performance of constant-*F* and constant catch control rules in terms of annual yield and variability in yield for lake whitefish in northern Lake Michigan. Their analyses, however, only evaluated two control rules, did not consider the spatial or temporal variation in lake whitefish population parameters (e.g., growth), and did not include assessment error, which can affect the relative performance of control rules (Deroba and Bence, 2008).

My objective was to evaluate alternative control rules in their ability to meet fishery objectives (e.g., maximizing yield, minimizing annual variation in yield). To address my objective, I developed a simulation model that compared several control rules at meeting fishery objectives and considered key uncertainties (e.g., shape of the stock-recruitment curve) and sources of error (e.g., assessment error).

2. Methods

2.1. Stocks in 1836 Treaty waters

The simulation model developed and used in this study was based upon data and assessments of lake whitefish stocks from 1836 Treaty waters (Figure 1). The 1836 Treaty waters encompass much of the Michigan waters of Lakes Superior, Huron, and Michigan (Figure 1). These waters are stratified into 18 management units with individual surface areas ranging from 69,000 to 733,000 ha, and a total surface area of 5.8 million ha (Figure 1; Ebener et al., 2005).

2.2. Overview of simulations

I developed a stochastic simulation model to project the abundance of hypothetical lake whitefish stocks, based on characteristics of stocks in 1836 Treaty waters. The model included age-3 through an age-12 "plus" group, which was an aggregate group including age-12 and older. Selected performance metrics (section 2.9) were used to compare the performance of various control rules (section 2.8). The simulation model also included assessment and implementation error, and the sensitivity of the results was evaluated to different values for each source of error (section 2.7). For each value of the range of policy parameters searched for each control rule, 1000 simulations were run. Each simulation was a 250 year projection, but results were presented based on a summary of the last 100 years.

Growth and maturity sub-models (sections 2.3 and 2.5) were estimated from biological data based on samples from commercial trap-net catches. Separate sets of growth parameters were estimated and simulations were run for two categories of stocks, fast and slow growth (i.e., stocks with relatively longer or shorter mean lengths at age, respectively). In some areas of 1836 Treaty waters, and more broadly in some areas of the Great Lakes, lake whitefish size-at-age has varied over time, particularly in recent years (e.g., Hoyle et al., 1999; Pothoven et al., 2001; Mohr and Nalepa, 2005). One possibility is that recent trends are part of longer-term fluctuations, so that similar long-term variation will continue to occur as part of a correlated but stationary process. Alternatively, there may have been a permanent change to the environment and recent growth patterns are now a permanent property of these stocks. I developed two variants of a growth model reflecting these alternatives (autocorrelated versus recent growth patterns) and separate sets of simulations were done for each of these for both the fast and slow growth stocks.

Substantial uncertainty exists regarding the recruitment process for most species (Myers et al., 1997; Myers et al., 1999). To acknowledge this, stock-recruitment parameters used in each simulation were drawn randomly from a set of possible values, which were based on fitting the recruitment sub-model (section 2.4) to stock and recruitment time series developed for each management unit from the assessments for that unit.

2.3. Growth sub-models

As indicated in section 2.2, models were parameterized and simulations were run for four growth scenarios: 1) autocorrelated, fast growth, 2) autocorrelated, slow growth, 3) similar to more recent years, fast growth, 4) similar to more recent years, slow growth. Management units were categorized as fast or slow growing, and the models described in sections 2.3.1 and 2.3.2 were parameterized separately based on data for stocks of each category. Because growth is likely linked to maturity (e.g., Beauchamp et al., 2004), the maturity sub-model was also fit separately for fast and slow growth categories (section 2.5). Management units were classified as fast or slow based on pairwise comparisons of mean length at age between management units, and expert opinion (see Appendix A).

2.3.1. Growth autocorrelated

My approach to allowing longer-term fluctuations in size-at-age was to model length at age-3 in each year *y* by:

$$L_{3,y} = \bar{L}_3 e^{\phi_y} e^{\varepsilon_{Ly}} ; \quad (1)$$

where $\bar{L}_3$ was the mean length of an age-3 fish, ϕ_y and ε_{Ly} were, respectively, the autocorrelated and uncorrelated contributions to temporal process error:

$$\varepsilon_{Ly} \sim N\left(0;\sigma_L^2\right); \quad (2)$$

$$\phi_y = \rho_\phi \phi_{y-1} + \gamma_y ; \gamma_y \sim N\left(0;\sigma_\phi^2\right); \quad (3)$$

ρ_ϕ was the level of autocorrelation, and σ_ϕ^2 and σ_L^2 were the variances associated with the process errors. The parameters of this portion of the growth sub-model were estimated based upon analysis of time-series of mean length-at-age data (see Appendix A).

For ages greater than age-3, length in each age *a* and year *y* was simulated using an incremental form of the von Bertalanffy model similar to that of Irwin et al. (2008):

$$L_{a,y} = L_{a-1,y-1} + \Delta L_{a,y}; \quad (4)$$

where

$$\Delta L_{a,y} = \lambda + \theta L_{a-1,y-1} + \omega_y + \varepsilon_{\Delta L,a,y}; \quad (5)$$

and λ and θ were interecept and slope parameters, respectively. The growth increment was influenced by ω_y, a year-specific process error common to all ages, and $\varepsilon_{\Delta L,a,y}$ a process error specific to each year and age combination, where:

$$\omega_y \sim N\left(0;\sigma_\omega^2\right);\ \varepsilon_{\Delta L,a,y} \sim N\left(0;\sigma_{\Delta L}^2\right). \quad (6)$$

The parameters of this portion of the growth sub-model were again estimated from observed mean length at age data by relating increments in mean length for a cohort to current mean length (see Appendix A).

Weight at each age and year was modeled as a power function of length and mean length at age-3 in years *y*+1 and *y*+2, $\overline{L}_{3,y+1,y+2}$:

$$W_{a,y} = \tau L_{a,y}^{\chi} \overline{L}_{3,y+1,y+2}^{\varphi}; \quad (7)$$

where τ is the condition factor parameter, and χ and φ are curvature parameters (Quinn and Deriso, 1999). I included average length at age-3 to allow weight at length to respond to growth conditions. Length at age-3 represents a measure related to relatively recent growth conditions (over the previous two to three years). Consequently mean length at age-3 averaged over years y+1 and y+2 represents a measure of growth conditions during a window roughly centered on year y. This modeling choice was motivated in part by moderately large changes in the weight versus length relationship so that weight at length tended to be positively correlated with length at age-3 in recent years. The parameters of this portion of the growth sub-model were estimated using multiple linear regression relating log transformed mean weight at age to log transformed mean length at age and log transformed mean length at age-3 (see Appendix A).

2.3.2. Growth remained similar to recent levels

For the case of growth remaining similar to more recent levels, the growth sub-models of section 2.3.1 were modified as follows. First, length at age-3 was simulated as above (equation 1), except that ρ_{ϕ} was zero so that ϕ_y (equation 3) were uncorrelated. Second, weight was determined solely as a power function of length (i.e., the power term involving $\overline{L}_{3,y+1,y+2}$ was dropped from equation 7):

$$W_{a,y} = \tau L_{a,y}^{\chi}.$$

The parameters for the growth sub-model for the recent growth scenarios were also estimated similarly to the case of autocorrelated growth, but only data from the three most recent years available from each management unit were used, with the exact range of years depending on the management unit (see Appendix A).

2.4. Stock-recruitment sub-models

Recruitment was defined as the number of age-3 lake whitefish. Recruitment followed Ricker stock-recruit dynamics for the sth simulation:

$$R_{3,y} = \alpha_s SSB_y e^{-\beta_s SSB_y} e^{\varepsilon_{Ry}}, \quad (8)$$

where R was recruitment, SSB was spawning stock biomass, α was the number of recruits per SSB at low SSB, β was the instantaneous decline in recruitment per SSB as SSB increased, ε_{Ry} was autocorrelated temporal process error:

$$\varepsilon_{Ry} = \rho_{Rs}\varepsilon_{Ry-1} + \varsigma_y;\ \varsigma_y \sim N\left(0; \sigma_{Rs}^2\right), \quad (9)$$

and ρ_{Rs} and σ_{Rs}^2 were the level of autocorrelation and variance. Stock-recruitment parameters (α, β, ρ_R, σ_R^2) were randomly selected with equal probability from a set of possible values and retained for each simulation (hence they are subscripted by simulation). These possible parameters of the stock-recruitment sub-model corresponded to estimates for each assessed lake whitefish stock in 1836 Treaty waters, obtained by applying a general linear mixed model to assessment estimates of recruitment and stock size using methods similar to those of Myers et al. (1999; see Appendix A).

Spawning stock biomass was measured in number of eggs:

$$SSB_y = \sum_{a=3}^{a=12+} N_{a,y} m_{L_a} W_{a,y} Fem \times Eggs; \quad (10)$$

where m_{L_a} was proportion mature (see section 2.5), Fem was the proportion of females, and $Eggs$ was the number of eggs per kilogram of fish. Fem was estimated separately for fast and slow growth simulations as the mean proportion of females used in fitting CAA models in fast and slow growth management units, respectively, and $Eggs$ equaled

19,937/kg for all simulations, which was also the value used in all CAA models (Ebener et al., 2005).

2.5. Maturity sub-models

A separate maturity function was estimated for fast and slow growth simulations, and probability of maturity m_{L_a} was modeled as a logistic function of mean length-at-age, weighted by the probability of being a length L given a mean length-at-age L_a and variance $\sigma^2_{L_a}$:

$$m_{L_a} = \sum_{L_a} \left(\frac{1}{1 + e^{-\kappa(L_a - \eta)}} \right) p\left(L \middle| L_a, \sigma^2_{L_a}\right); \quad (11)$$

where κ was the curvature parameter and η was the length at which the inflection point occurs. The probability of maturity was weighted by $p\left(L \middle| L_a, \sigma^2_{L_a}\right)$ to account for the variation around a mean length at age, and the subsequent variation around the probability of maturity at a mean length at age. That is, fish of a given age class may be more less likely to be mature depending on whether they were longer or shorter than the mean length at age, and the weighting accounts for this variation. The parameters of the logistic portion of the maturity sub-model were estimated using logistic regression using data from only females (see Appendix A). The assumed length distributions, $p\left(L \middle| L_a, \sigma^2_{L_a}\right)$, were based on a single estimated coefficient of variation (0.036) for length at age, which together with mean length, L_a, was the basis for the $\sigma^2_{L_a}$ used in equation 11 (see Appendix A).

2.6. Population abundance sub-model

A vector of initial abundances at age (i.e., in year zero) was randomly selected with equal probability from a set of vectors and retained for each simulation. This method was necessary to scale the initial abundances at age to the set of stock-recruit parameters chosen for each simulation. The suite of possible vectors corresponded to the equilibrium abundances at age for each assessed lake whitefish stock in 1836 Treaty waters under a fishing mortality rate that would reduce spawning stock biomass per recruit to 20% of the unfished level (see Appendix A). The vector of initial abundances at age for each simulation was from the same stock as was used for selecting the vector of stock-recruitment parameters. Abundance N in each age and year was then predicted:

$$N_{a,y} = N_{a-1,y-1} e^{-Z_{a,y}}; \quad (12)$$

where Z was the total instantaneous mortality rate and equaled the sum of natural mortality M and fishing mortality. Fishing mortality F was the product of fully-selected fishing mortality and selectivity:

$$F_{a,y} = S_{L_a} F_y; \quad (13)$$

where S_{L_a} was selectivity at mean length-at-age. Selectivity was modeled as a gamma function of mean length-at-age (Quinn and Deriso, 1999), and approximated a trap-net selectivity curve, which is a dominant gear used for lake whitefish in these waters. In the simulations, natural mortality was constant across ages and years, but differed between simulations for fast and slow growth stocks, being set equal to the mean natural mortality rate assumed in CAA assessment models for each stock in each growth category (Ebener et al., 2005).

2.7. Assessment and implementation error

The simulation model included assessment and implementation error, following an approach similar to that of Punt et al. (2008). Assessment error was modeled as a year-specific lognormal random deviation common to all ages with first-order autocorrelation:

$$\hat{N}_{a,y} = N_{a,y} e^{\varepsilon_{ny} - \left(\sigma_n^2/2\right)}; \quad (14)$$

where $\hat{N}$ was assessed abundance, ε_{ny} was autocorrelated error:

$$\varepsilon_{ny} = \rho_n \varepsilon_{ny-1} + \sqrt{1-\rho_n^2}\,\delta_y; \;\; \delta_y \sim N\left(0;\sigma_n^2\right); \quad (15)$$

and ρ_n was the level of autocorrelation.

Assessment error affected the target catch set by managers because target catches $\hat{C}_y$ were set by applying a fully selected desired fishing mortality rate $\hat{F}_y$ to assessed abundance rather than actual abundance:

$$\hat{C}_y = \sum_{a=3}^{a=12+} \frac{\hat{F}_{a,y}\hat{N}_{a,y}\left(1-e^{-\hat{Z}_{a,y}}\right)}{\hat{Z}_{a,y}}; \quad (16)$$

where $\hat{F}_{a,y}$ was the product of fully selected desired fishing mortality and S_{L_a}, and $\hat{Z}_{a,y}$ was the sum of $\hat{F}_{a,y}$ and *M*.

The fully selected fishing mortality rates $\tilde{F}_y$ that would result in the target catch being removed when applied to actual abundance were found numerically using Newton-

Raphson iterations. A maximum of 3.0 was set on $\tilde{F}_y$ because $\hat{C}_y$ were sometimes unachievable.

Implementation error was included as a year specific lognormal random deviation:

$$F_{a,y} = S_{L_a} \tilde{F}_y e^{\varepsilon_{Fy} - \left(\sigma_F^2 / 2\right)}; \ \varepsilon_{Fy} \sim N\left(0; \sigma_F^2\right); \quad (17)$$

where $F_{a,y}$ was the actual fishing mortality rate exerted on the actual abundance $N_{a,y}$.

The sensitivity of results was tested using a range of parameter values for assessment and implementation error (Table 1). The effect of different levels of assessment and implementation error was compared to a baseline scenario, which was defined as the middle value for each parameter (Table 1; σ_n^2 = 0.05, ρ_n = 0.7, σ_F^2 = 0.01). Rather than an experimental design that crossed all assessment and implementation error parameters, each parameter was evaluated at a high and low level while holding all other parameters at the baseline level (i.e., seven combinations). The range of parameter values evaluated for assessment and implementation error are similar to those of studies much like this one, including analyses of lake trout *Salvelinus namaycush* in Lake Superior and yellow perch *Perca falvescens* in Lake Michigan (Irwin et al., 2008; Nieland et al., 2008; Punt et al., 2008).

2.8. Control rules

The control rules evaluated were: conditional constant catch (CCC), biomass based (BB), constant-*F*, and BB and constant-*F* with a 15% limit on the interannual change in the target catch, $\hat{C}_y$ (BB-lim, constant-*Flim*, respectively; Clark and Hare, 2004; Deroba and Bence, 2008). The CCC control rule used a constant target catch unless removing that target catch exceeded some predetermined maximum fully-selected fishing mortality rate, and so the CCC control rule was defined by two policy parameters; a constant catch level and maximum fishing mortality rate (Clark and Hare, 2004). The constant catch levels were set as a fraction of maximum sustainable yield (MSY; see Appendix A). MSY was randomly selected from a suite of values and retained for each simulation. The suite of possible values corresponded to values for each assessed lake whitefish stock in 1836 Treaty waters, and the value of MSY for each simulation was for the same stock as was used for selecting the vector of stock-recruitment parameters. The fully-selected fishing mortality rate that would result from removing the target constant catch amount from the assessed abundance ($\hat{N}$), for comparison to the predetermined maximum fishing mortality rate, was calculated numerically using Newton-Raphson iterations. The BB control rule was similar to that of Katsukawa (2004) and was defined by three policy parameters; a lower *SSB* threshold SSB_{LT} below which $\hat{F}_y$ was set to a low level, an upper *SSB* threshold SSB_{HT} above which $\hat{F}_y$ was set to a maximum rate F_{sat}, and F_{sat}. As assessed spawning stock biomass $S\hat{S}B_y$ decreased from SSB_{HT}, $\hat{F}_y$ decreased linearly with $S\hat{S}B_y$ until $\hat{F}_y$ equaled 0.05:

$$\text{If } S\hat{S}B_y < SSB_{LT} \text{ then } \hat{F}_y = 0.05$$

If $SSB_{LT} < S\hat{S}B_y \leq SSB_{HT}$ then $\hat{F}_y = \max(F_{sat} \dfrac{S\hat{S}B_y - SSB_{LT}}{SSB_{HT} - SSB_{LT}}, 0.05)$

If $SSB_{HT} \leq S\hat{S}B_y$ then $\hat{F}_y = F_{sat}$. (18)

(Figure 2). All other control rules were also restrained to have a target fishing mortality rate of at least 0.05 because I assumed some amount of fishing would always take place. Preliminary analyses showed that results were not sensitive to this assumption. SSB_{LT} and SSB_{HT} were set as a fraction of unfished *SSB*, $SSB_{\mathrm{F=0}}$ (see Appendix A). $SSB_{\mathrm{F=0}}$ was randomly selected from a suite of values and retained for each simulation, which was necessary to scale the policy parameters that depended on a measure of *SSB* to the set of stock-recruit parameters chosen for each simulation. The suite of possible values corresponded to values for each assessed lake whitefish stock in 1836 Treaty waters, and the value of $SSB_{\mathrm{F=0}}$ for each simulation was for the same stock as was used for selecting the vector of stock-recruitment parameters. $S\hat{S}B_y$ was estimated in the same way as SSB_y (equation 10) except with $N_{a,y}$ replaced with $\hat{N}_{a,y}$ (equation 14). The constant-*F* control rule was a special case of the BB control rule with SSB_{LT} and SSB_{HT} both set to zero, and was defined by one policy parameter; a level of fishing mortality. The BB-lim and constant-*Flim* control rules worked in the same way as the BB and constant-*F* rules except with the specified restriction on the target catch. For each control rule, a range of values was evaluated for each policy parameter. The constant catch parameter of the CCC rule was varied from 0.1MSY to 1.4MSY in increments of 0.1, while the maximum fishing mortality rate parameter was varied from

0.2 to 3.0 in increments of 0.2. For the BB control rule, with and without the restraint on interannual catch, SSB_{LT} and SSB_{HT} were varied from $0.0SSB_{F=0}$ to $1.0SSB_{F=0}$ in increments of 0.1, while F_{sat} was varied from 0.05 to 3.0 in increments of 0.05. The constant-*F* strategy, with and without the restraint on interannual catch, was evaluated over the same range of values as F_{sat}.

2.9. Performance metrics

Plots of *SSB* versus yield *Y,* interannual variability in yield *Yvar* versus the proportion of years that *SSB* fell below 20% of $SSB_{F=0}$, *Y* versus *Yvar*, and *Y* versus the proportion of years that *SSB* fell below 20% of $SSB_{F=0}$ were used to examine the trade-offs among potential competing fishery objectives and compare the performance of control rules. In sections below, I refer to the proportion of years that *SSB* fell below 20% of $SSB_{F=0}$ as "risk" because levels of *SSB* near this value have been used as a biological reference point below which recruitment overfishing was likely to occur and so should be avoided (Quinn et al., 1990; Clark, 1991; Thompson, 1993; Fujioka et al., 1997; Booth, 2004). Mean *Y* and *SSB* over the last 100 years, the proportion of the last 100 years with *SSB* less than 20% of $SSB_{F=0}$, and *Yvar* over the last 100 years were recorded for each simulation. The interannual variability in yield, defined as in Punt et al. (2008) was calculated over the last 100 years for each simulation:

$$Y\,\text{var} = \frac{\sum_{y>150} \left| Y_y - Y_{y-1} \right|}{\sum_{y>150} Y_y}; \quad (19)$$

where

$$Y_y = \sum_{a=3}^{a=12+} \frac{F_{a,y} N_{a,y} \left(1 - e^{-Z_{a,y}}\right)}{Z_{a,y}} W_{a,y} \,. \quad (20)$$

The trade-off plots described above were then constructed for each of three percentiles calculated among simulations: the median, the percentile value less than 75% of the values among simulations (i.e., 25th percentile for *SSB* and *Y*, 75th percentile for risk and *Yvar*), and the percentile value less than 90% of the values among simulations (i.e., 10th percentile for *SSB* and *Y*, 90th percentile for risk and *Yvar*).

The rank order performance of the control rules was evaluated for each growth scenario and trade-off plot by examining the combination of policy parameters that resulted in the best performance for each control rule. This method equates to determining the optimal control rule as if future growth (i.e., autocorrelated versus recent growth patterns) was a known certainty.

To evaluate the sensitivity of control rule performance to uncertainties about future growth, an optimal set of policy parameters (see below) was chosen for each control rule, trade-off plot, and growth scenario. The optimal set of policy parameters for each future growth scenario was then applied to the alternative future growth scenario (i.e., autocorrelated versus recent growth patterns), but for the same type of stock growth (i.e., fast or slow growing). The difference in performance between the optimal set of policy parameters and the set of policy parameters being applied under the wrong future growth scenario was used as the measure of sensitivity. This method equates to evaluating how well a control rule would perform if policy parameters were chosen assuming one type of future growth was true, when in fact the alternative growth future was true. The optimal set of policy parameters for each trade-off plot was defined as the set that: maximized yield and maintained *SSB* above 50% of $SSB_{F=0}$, minimized variability in yield and produced risk less than 0.40, maximized yield and produced variability in yield less than 0.4, and maximized yield and produced risk less than 0.40. This method of selecting optimal policy parameters was only used to illustrate the sensitivity of control rule performance to uncertain future growth, and because this does not necessarily reflect desired tradeoffs, should not be used for management without careful consideration of fishery objectives.

3. Results

3.1. Overview of results

Varying the level of implementation error had little effect on the relative or absolute performance of the control rules, and consequently, all the results below are for the baseline level. Varying the parameters related to assessment error affected the relative performance of some control rules, but only for trade-off plots that included variability in yield (Section 3.4). For the other performance metrics, the relative and absolute performance of the control rules varied little among the different levels of assessment error parameters (see Appendix B), and this was consistent among growth scenarios. Thus, the choice of optimal parameters would also generally be robust to the level of assessment error. As a consequence, results for the sensitivity of the control rules to varying assessment error parameters (Section 3.4) include example graphs based on simulations of fast growth similar to more recent levels, and the results in all other sections are for baseline levels of assessment error. Results for the different percentiles showed similar trade-offs among performance metrics and relative differences among control rules; so only results for the median are considered further. The rank order performance of the control rules for each trade-off plot was also the same for all levels of each source of uncertainty (see Appendix B), and these rank orders are presented in Section 3.2 with example graphs based on simulations of fast growth similar to more recent levels.

3.2. Rank-order performance of control rules

For the plot of *SSB* versus *Y*, the BB control rule performed best, providing more *Y* at a given level of *SSB* and higher *SSB* at a given level of *Y* than other control rules (Figure 3). The BB control rule was followed in performance by constant-*F*, CCC, and the BB-lim and constant-*Flim* control rules (Figure 3).

For the plot of *Yvar* versus risk, the CCC, BB-lim, and constant-*Flim* control rules provided less *Yvar* at a given level of risk than other control rules (Figure 3). These same control rules, however, were also more risky at a given level of *Yvar* than other control rules (Figure 3).

For the plot of *Y* versus *Yvar*, the CCC, BB-lim, and constant-*Flim* control rules provided less or similar *Yvar* at a given level of *Y* than other control rules (Figure 4). The BB control rule, however, attained more *Y* at a given level of *Yvar*, and was followed in performance by the constant-*F*, CCC, and the BB-lim and constant-*Flim* control rules (Figure 4).

For the plot of *Y* versus risk, the BB control rule performed best, providing more *Y* at a given level of risk and less risk at a given level of *Y* (Figure 4). The BB control rule was followed in performance by constant-*F*, CCC, and the BB-lim and constant-*Flim* control rules (Figure 4).

3.3. Sensitivity to future growth uncertainty

3.3.1. Fast growth stocks

For *SSB* versus *Y*, yield was generally insensitive to future growth, and the BB and constant-*F* control rules were less sensitive than other control rules. All of the percent changes in yield from the optimum were less than 6%, as were the changes in *SSB* for the BB and constant-*F* control rules (Table 2). For the CCC, BB-lim, and constant-*Flim* control rules, the percent changes in *SSB* were at least 10%, and *SSB* decreased from the optimum and below 50% of $SSB_{F=0}$ (i.e., the level used to define optimal) when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future, but increased from the optimum for the opposite situation (Table 2). So, control rules and policy parameters chosen by incorrectly assuming future growth will be autocorrelated cost little in yield and produced more *SSB* than the optimum, relative to incorrectly assuming future growth will be similar to recent levels, which produced less *SSB* than the optimum.

For *Yvar* versus risk, results were insensitive to the future growth scenario. For all control rules, the percent change from the optimal levels was 0.00 (Table 2).

For *Y* versus *Yvar*, results were generally insensitive to the future growth scenario. All of the percent changes in yield were less than 5%, and the changes in variability in yield were all less than 8% (Table 2). Variability in yield increased from the optimum and, for the BB rule, above 0.40, when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future, but decreased from the optimum for the opposite situation (Table 2). So, control rules and policy parameters chosen by incorrectly assuming future growth will be autocorrelated cost little in yield and produced less variability in yield than the optimum, relative to incorrectly assuming future growth will be similar to recent levels, which produced more variability in yield than the optimum.

For *Y* versus risk, yield was generally insensitive to the future growth scenario, but risk was more sensitive. All of the percent changes in yield were less than 5%, but the changes in risk were more variable (Table 2). Risk increased from the optimum and, for the BB-lim and constant-*Flim* rules, to 0.40, when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future, but decreased from the optimum for the opposite situation (Table 2). So, control rules and policy parameters chosen by incorrectly assuming future growth will be autocorrelated cost little in yield and produced less risk than the optimum, relative to incorrectly assuming future growth will be similar to recent levels, which produced more risk than the optimum.

3.3.2. Slow growth stocks

For *SSB* versus *Y*, the CCC, BB, and constant-*F* control rules were less sensitive to the future growth scenario than the BB-lim and constant-*Flim* rules. All of the percent changes in *SSB* and yield were less than 5% for the CCC, BB, and constant-*F* control rules (Table 2). For the BB-lim and constant-*Flim* rules, however, yield decreased and *SSB* increased from the optimum when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future (Table 2). Results for these control rules were less consistent when policy parameters were chosen as though growth would be autocorrelated, but growth similar to recent levels was the true future. For the BB-lim rule, both yield and *SSB* decreased from the optimum, and

SSB was less than 50% of $SSB_{F=0}$ (Table 2). For the constant-*Flim* rule, yield increased but SSB decreased below 50% of $SSB_{F=0}$ (Table 2). So, the costs and benefits of choosing policy parameters based on assuming an incorrect future for lake whitefish growth depended on the control rule.

For *Yvar* versus risk, results were insensitive to the future growth scenario, except for the CCC control rule. For the CCC control rule, variability in yield and risk increased from the optimum when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future (Table 2). When policy parameters were chosen as though growth would be autocorrelated and growth similar to recent levels was the true future, the percent changes were less than 3%, and variability in yield increased while risk decreased from the optimum levels (Table 2). So for the CCC control rule, policy parameters chosen by incorrectly assuming future growth will be autocorrelated cost little in variability in yield and produced slightly less risk than the optimum, relative to incorrectly assuming future growth will be similar to recent levels, which produced more variability in yield and risk than the optimum.

For *Y* versus *Yvar*, sensitivity to the future growth scenario depended on the control rule, but the BB control rule was the most sensitive. For the BB and constant-*F* control rules, yield and variability in yield increased from the optimum (above 0.40 for variability in yield) when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future, but decreased from the optimum for the opposite situation (Table 2). For the other control rules, yield and variability in yield decreased from the optimum when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future (Table 2). When policy parameters were chosen as though growth would be autocorrelated and growth similar to recent levels was the true future, yield decreased and variability in yield increased from the optimum (Table 2). So, the costs and benefits of choosing policy parameters based on assuming an incorrect future for lake whitefish growth will depend on the control rule.

For yield versus risk, results were generally more sensitive to the future growth scenario than other trade-off plots. For all control rules, yield and risk decreased from the optimum when policy parameters were chosen as though growth would be similar to recent levels and autocorrelated growth was the true future, but in the opposite situation, yield decreased or was the same and risk increased from the optimum, and above 0.40 for the BB-lim rule (Table 2). So, control rules and policy parameters chosen by incorrectly assuming future growth will be similar to recent levels produced costs in yield at the benefit of less risk than the optimum, relative to incorrectly assuming future growth will be autocorrelated, which produced costs in yield and risk from the optimum.

3.4. Sensitivity to assessment error parameters

Varying assessment error parameters affected the performance of the control rules for trade-off plots that included *Yvar*. For the plot of *Yvar* versus risk, control rules that performed well at each performance metric increased in superiority over other control rules as ρ_n was decreased (Figure 5) or σ_n^2 was increased (Figure 6). Specifically, the CCC, BB-lim, and constant-*Flim* control rules increased in superiority in terms of *Yvar* at a given level of risk, and the BB and constant-*F* rules increased in superiority in terms of attaining less risk at a given level of *Yvar*. For the plot of *Y* versus *Yvar*, the CCC, BB-lim, and constant-*Flim* control rules increased in superiority in terms of *Yvar* at a given level of *Y* as ρ_n was decreased (Figure 7) or σ_n^2 was increased (Figure 8), but an increase in the superiority of the BB and constant-*F* control rules in terms of *Y* at a given level of *Yvar* did not materialize.

4. Discussion

In this study, the BB control rule provided more yield and less risk than other control rules with all else being equal, and was followed in rank-order by constant-*F*, CCC, and the BB-lim and constant-*Flim* control rules, which is consistent with similar research (Irwin et al., 2008; Punt et al., 2008). Irwin et al. (2008) used a similar BB control rule for a recreational yellow perch *Perca flavescens* fishery in southern Lake Michigan and found that the BB control rules produced higher yields and less risk than a constant-*F* control rule at given levels of *SSB*. Punt et al. (2008) used a BB control rule that reduced catch (instead of *F*) linearly with *SSB* for groundfish off the U.S. west coast and found that the BB control rules produced higher yield and less risk than a constant-*F* control rule at low levels of productivity, but performance was nearly equal for high productivity.

The CCC, BB-lim, and constant-*Flim* control rules provided less interannual variation in yield than other control rules, but at the cost of yield and risk. Clark and Hare (2004) found that the CCC control rule could produce similar yields and *SSB* than a constant-*F* control rule, but with less variability in yield for Pacific halibut *Hippoglossus stenolepis*. Their simulations, however, did not include parameter uncertainty in the stock-recruit relationship or assessment error. The results of this study suggest that including these sources of uncertainty affects the relative performance of the CCC control rule, as has been shown for other control rules (Deroba and Bence, 2008). For roundfish stocks managed by the International Council for the Exploration of the Sea, limits on the interannual change in target catch that prevented quotas from being decreased often resulted in less yield and greater frequency of low *SSB* than a constant-*F* control rule (Kell et al., 2006), which is consistent with the findings of this study where the BB-lim and constant-*Flim* control rules performed worst in terms of yield and risk of low spawning stock with all else being equal (e.g., constrained to provide some specified level of spawning stock or yield). The relative performance of limiting the interannual change in target catch, however, can depend on how tight the restraint is on the interannual change, productivity, variability in recruitment or growth, and current status of the stock (Punt et al., 2002; Kell et al., 2006).

The rank order performance of the control rules, while treating future growth as known, was robust to the type of autocorrelated growth evaluated in this study, and the growth scenarios in general, but time varying population dynamics have been shown to affect relative performance (Walters and Parma, 1996; Deroba and Bence, 2008). Walters and Parma (1996) showed that a constant fishing mortality rate control rule performed better in terms of yield when the asymptote parameter of a Beverton–Holt stock–recruit model was autocorrelated, and this was counter to when this parameter of the stock-recruit model was constant. Whether catchability is treated as time-varying in stock assessments also has an effect on control rule performance (e.g., Dichmont et al., 2006). Few studies have evaluated the effect of time-varying parameters, but more research is warranted in this area (Deroba and Bence, 2008).

The robustness of control rule performance to uncertainty about future lake whitefish growth, and the most robust future lake whitefish growth to assume for selecting policy parameters, depended on whether stock growth was fast or slow. For fast growth stocks, selecting control rules and policy parameters by incorrectly assuming that future growth will be autocorrelated resulted in little cost from the optimum levels relative to the alternative of incorrectly assuming future growth will be similar to recent levels. For slow growth stocks, however, the robustness of which future lake whitefish growth to assume for selecting policy parameters depended on the control rule and trade-off plot. The decision to select control rules and policy parameters based on some assumption about future lake whitefish growth will ultimately depend on how competing fishery objectives are weighted relative to each other. Generally, however, control rules and policy parameters for fast growth stocks should likely be selected assuming future growth will be autocorrelated, but a universal recommendation for slow growth stocks is less clear (i.e., depends on the control rule and fishery objectives).

The results were generally robust to the level of assessment error. As reported here, Punt et al. (2008) found that assessment error affected results for *Yvar*, but other performance metrics similar to those included in this study were robust to this source of uncertainty. Irwin et al. (2008) did not include a measure of yield variability, but also found that other performance metrics similar to those included in this study were insensitive to varying assessment error. Conversely, Katsukawa (2004) reported that the superiority of BB control rules over constant-*F* control rules in terms of yield, diminished with increasing assessment error variance. This contradiction may have occurred because Katsukawa (2004) did not include other sources of uncertainty (e.g., shape of the stock-recruitment curve) that may outweigh the effect of assessment error on the relative performance of control rules. Alternatively, Katsukawa (2004) summarized tradeoffs in terms of yield versus the minimum biomass over a time-horizon, and stocks managed in the face of greater assessment uncertainty might suffer more extremes in stock size.

In this study, limiting the interannual change in target catch by 15% was inferior or at best similar to other control rules for all performance metrics, and in some cases was more sensitive to uncertainty in future lake whitefish growth. So, using alternative control rules would likely cost little relative to limiting the interannual change in target catch by 15%, and would produce benefits in most situations. This result may not be general, however, as benefits associated with limiting the interannual variability in target catch depend on fishery objectives, the degree to which the interannual change is restrained, stock status, and other population parameters such as growth variability (Kell et al., 2006).

Depending on the relative weight of fishery objectives, a control rule and policy parameters other than the one currently in use (i.e., constant-*F* based on a total annual mortality rate of 65%) may want to be considered for lake whitefish populations in Lakes Huron, Michigan, and Superior. For example, a BB control rule with appropriately selected policy parameters could likely produce nearly the same or more yield, spawning stock biomass, and less risk with little cost in variability in yield relative to the currently used policy. Similarly, the CCC control rule can likely provide less variability in yield, but at the cost of yield. So, if maintaining low variability in yield is more desirable than maximizing yield, a CCC control rule may want to be considered.

Not all dynamics or uncertainties about lake whitefish were included in this study, and unanticipated changes in the future may require periodic reviews of this evaluation (Butterworth, 2008). For example, this study did not include density dependent growth, which has been shown to occur for lake whitefish (Henderson et al., 1983; Kratzer et al., 2005). Density dependence was not included because the recent declines in lake whitefish growth that have occurred in some areas generally happened over a time period when abundance has declined or remained relatively stable, and so could not have been caused by density dependence (e.g., Lumb et al., 2007). Density dependence is, however, a likely compensatory response in lake whitefish and so should be considered if conditions arose to make such dependence important. To address such changes that may be outside the realm of uncertainties included in a management strategy evaluation, Butterworth (2008) recommended scheduling periodic reviews to consider whether evaluations should be updated. If radical unanticipated changes occur, Butterworth (2008) recommended making an *ad hoc* adjustment to the pre-agreed control rule until the management strategy evaluation can be updated and tested for robustness to the recent changes. Alternatively, stakeholders could agree on a pre-determined default management plan that would be applied temporarily until the management strategy evaluation is reviewed (Butterworth, 2008). Such scheduled maintenance of this evaluation would also be prudent given the uncertainties and variability in lake whitefish population dynamics.

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Figure 1.— 1836 Treaty-ceded waters and lake whitefish management units in Lakes Superior, Huron, and Michigan (Ebener et al. 2005).

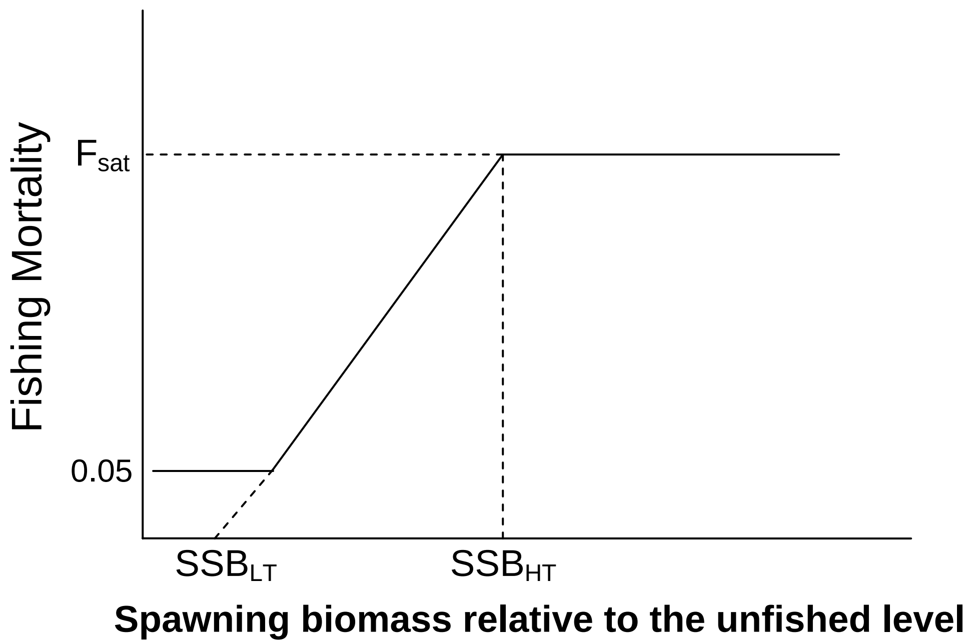
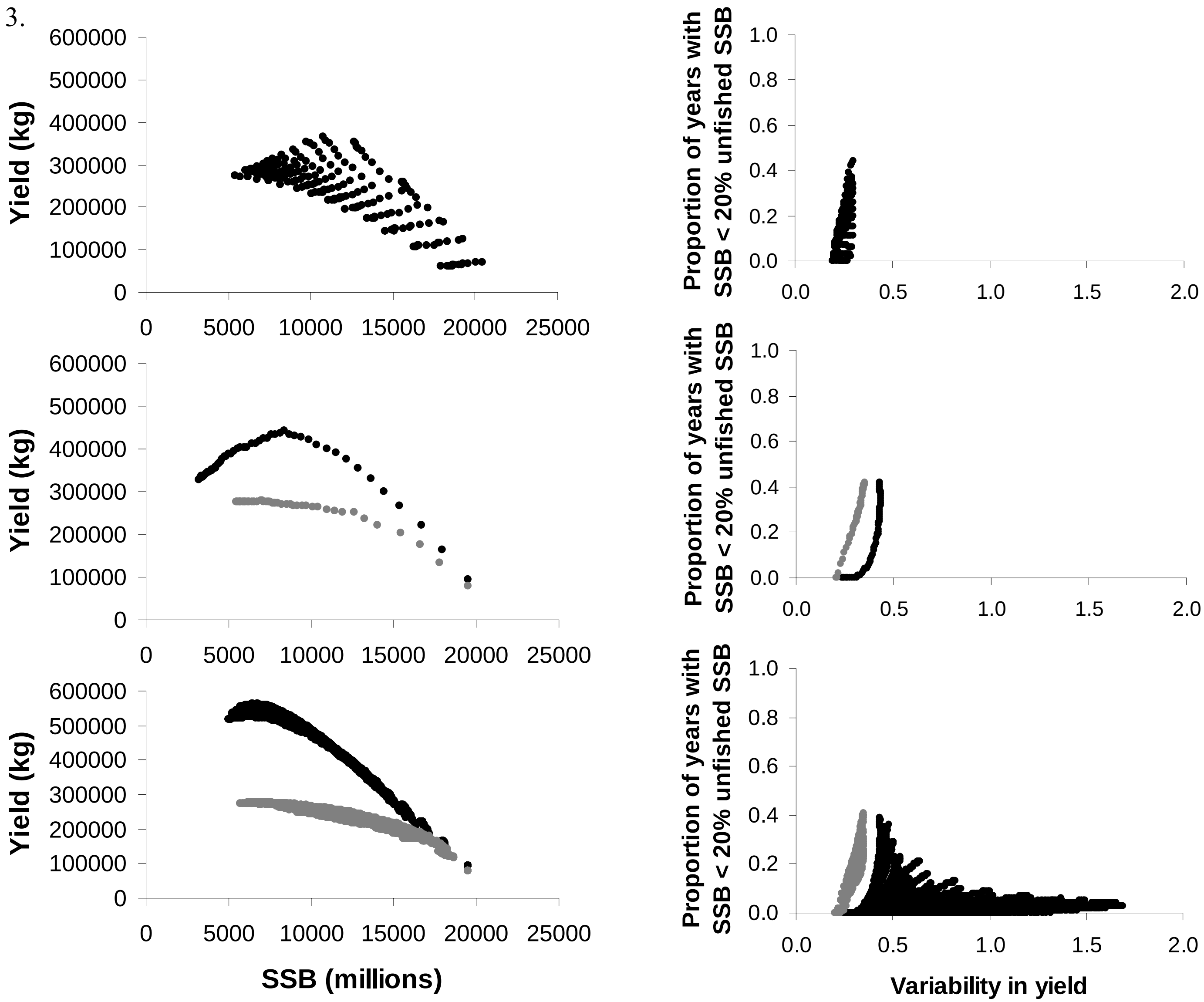


Figure 2.—Example of the biomass based control rule used in this analysis (solid line). Dashed lines are provided as a reference for defining the policy parameters.

Figure 3.—Median spawning stock biomass versus median yield (left column) and median interannual variability in yield versus median proportion of years with spawning stock biomass less than 20% of the unfished level (right column) for baseline levels of assessment and implementation error parameters and fast growth similar to recent levels (see text for details), for the conditional constant catch control rule (top row), constant-*F* (black dots, middle row), constant-*F* with a 15% limit on the interannual change in target catch (grey dots, middle row), biomass based (black dots, bottom row), and biomass based with a 15% limit on the interannual change in target catch (grey dots, bottom row). Each dot corresponds to the medians from 1000 simulations for one combination of policy parameters for the given control rule.

Figure 3.



Yield (kg)
600000
500000
400000
300000
200000
100000
0
0
5000
10000
15000
20000
25000
SSB (millions)
Proportion of years with SSB < 20% unfished SSB
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
Variability in yield

Figure 4.— As in figure 3, except for median yield versus median interannual variability in yield (left column) and median yield versus median proportion of years with spawning stock biomass less than 20% of the unfished level (right column).

Figure 4.

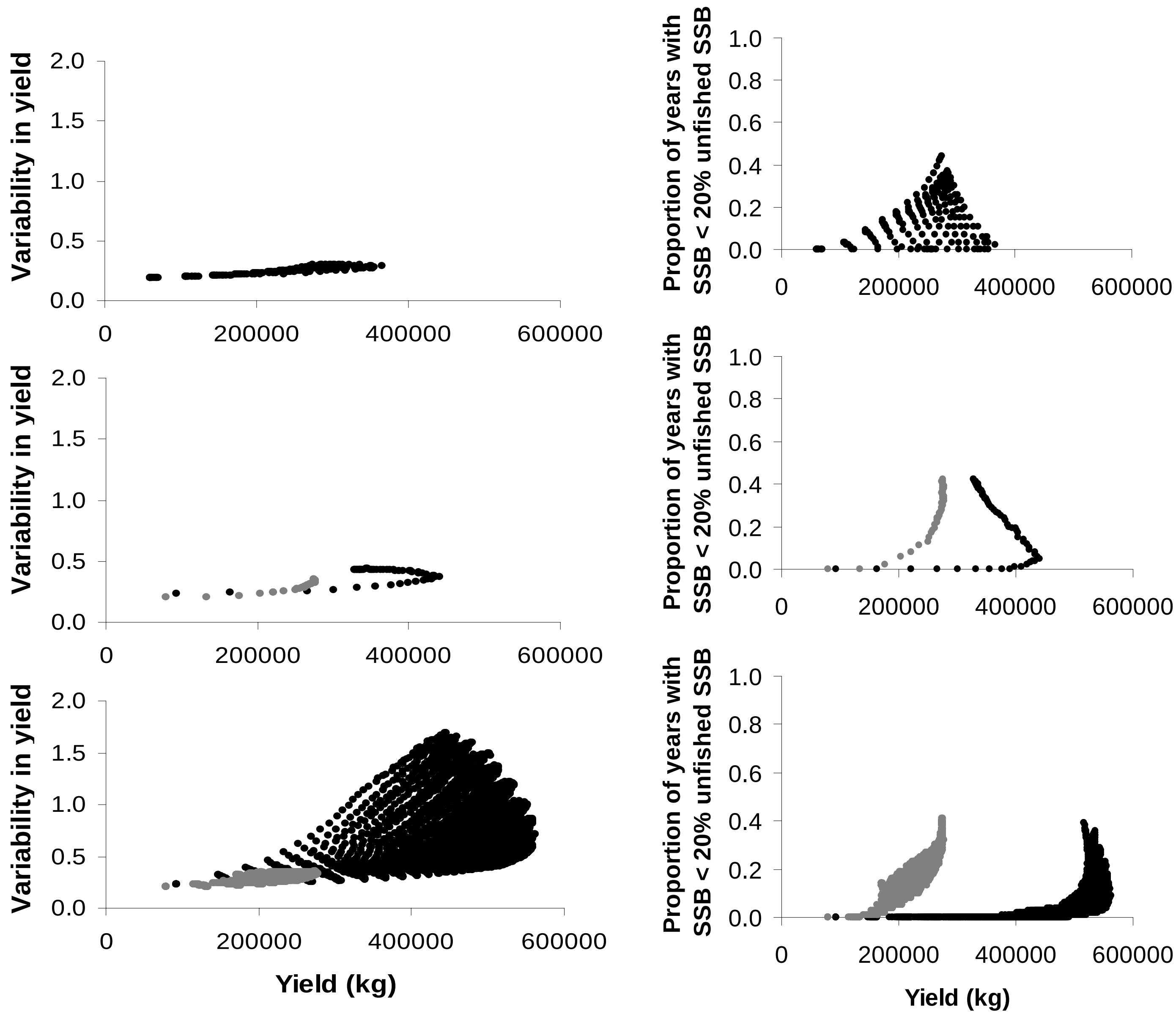
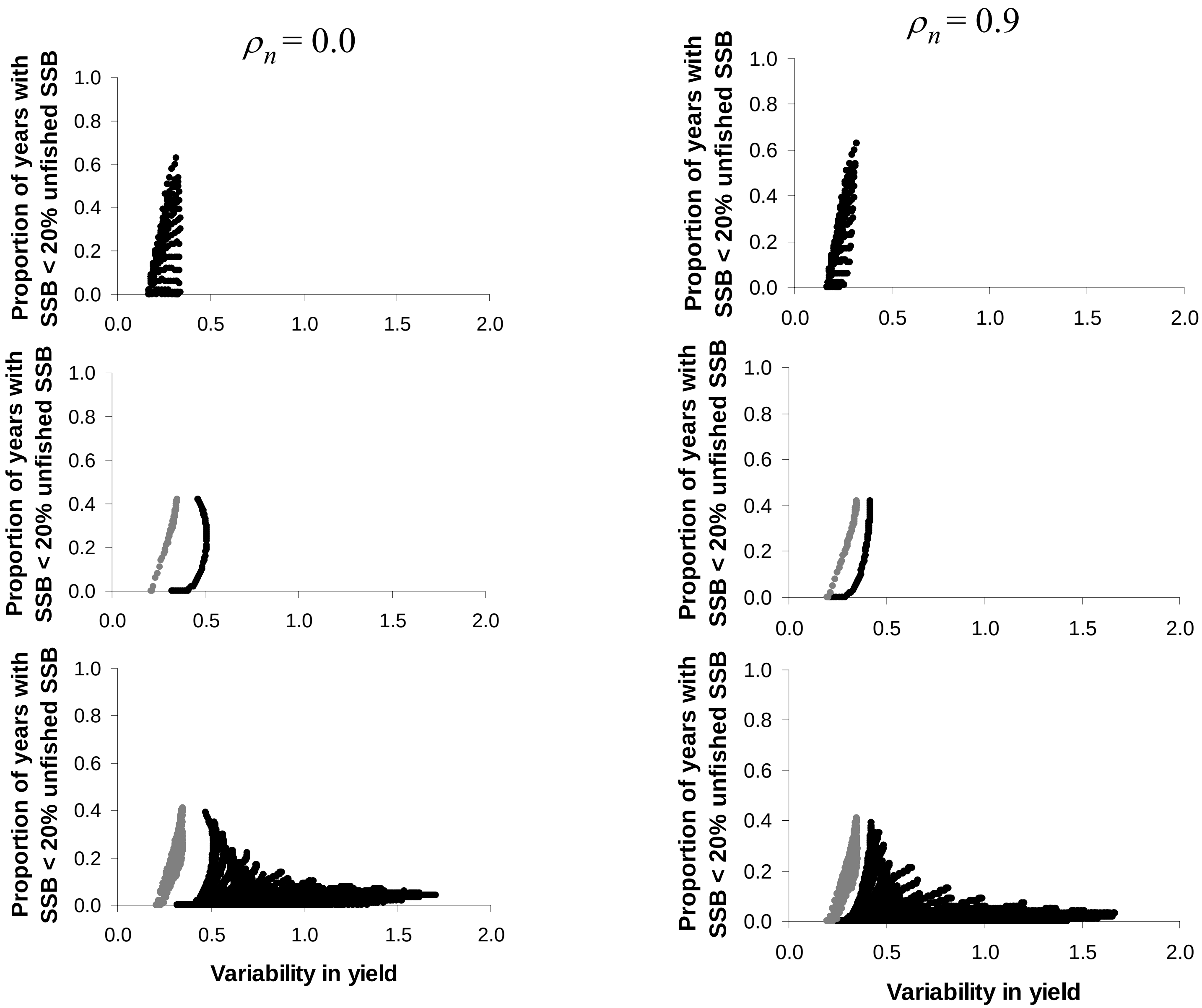

Variability in yield
2.0
1.5
1.0
0.5
0.0
0
200000
400000
600000
Yield (kg)
Proportion of years with
SSB < 20% unfished SSB
1.0
0.8
0.6
0.4
0.2
0.0

Figure 5.—Median interannual variability in yield versus median proportion of years with spawning stock biomass less than 20% of the unfished level for baseline assessment and implementation error variance, the extent of autocorrelation in assessment error set equal to 0.0 or 0.9, and fast growth similar to recent levels (see text for details). Control rules are displayed as in Figure 3.

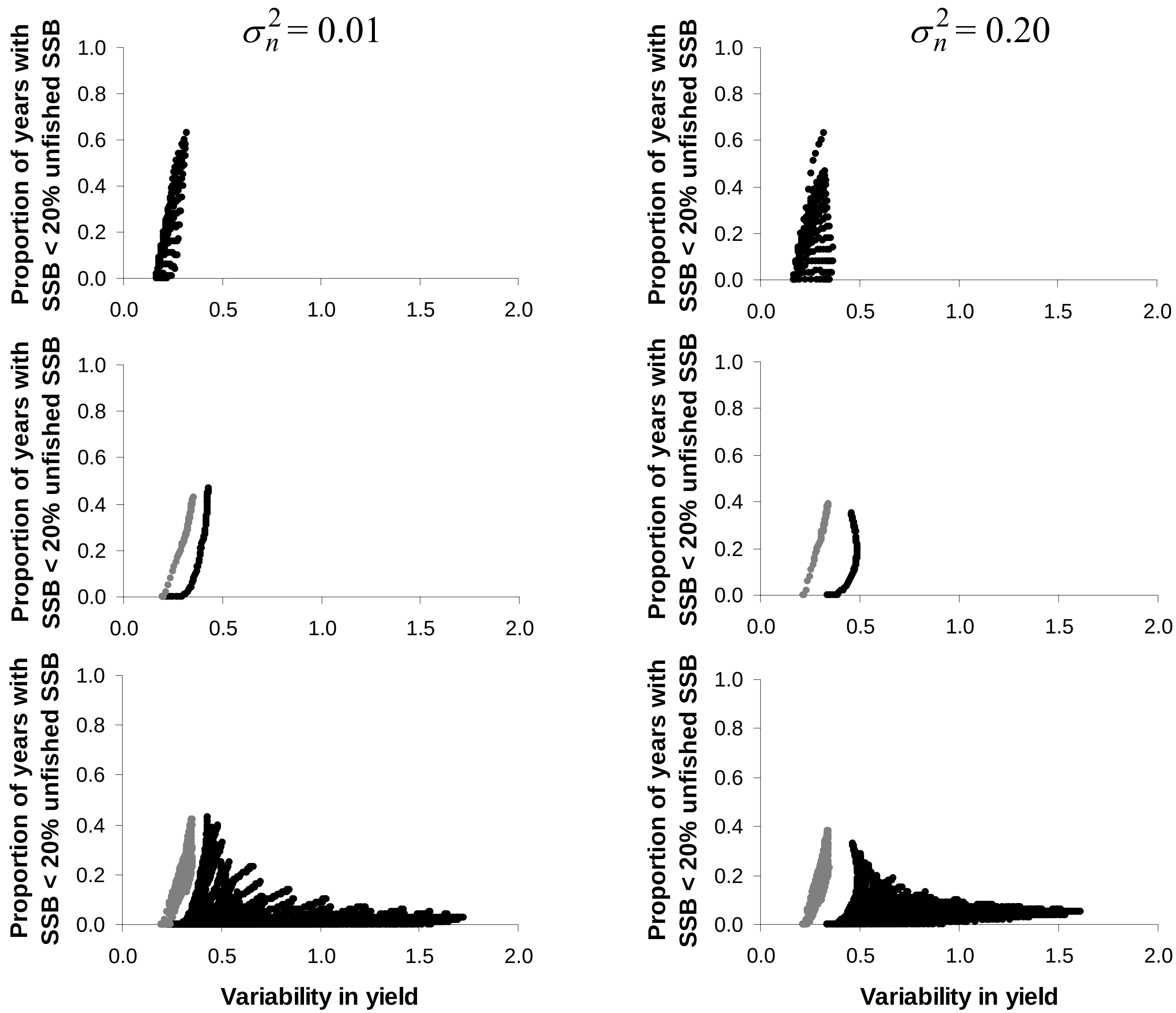
Figure 5.



$\rho_n = 0.0$
$\rho_n = 0.9$
Proportion of years with SSB < 20% unfished SSB
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
Variability in yield

Figure 6.—As in Figure 5, except with the extent of autocorrelation in assessment error set equal to the baseline level (0.7), and for assessment error variance equal to 0.01 or 0.20.

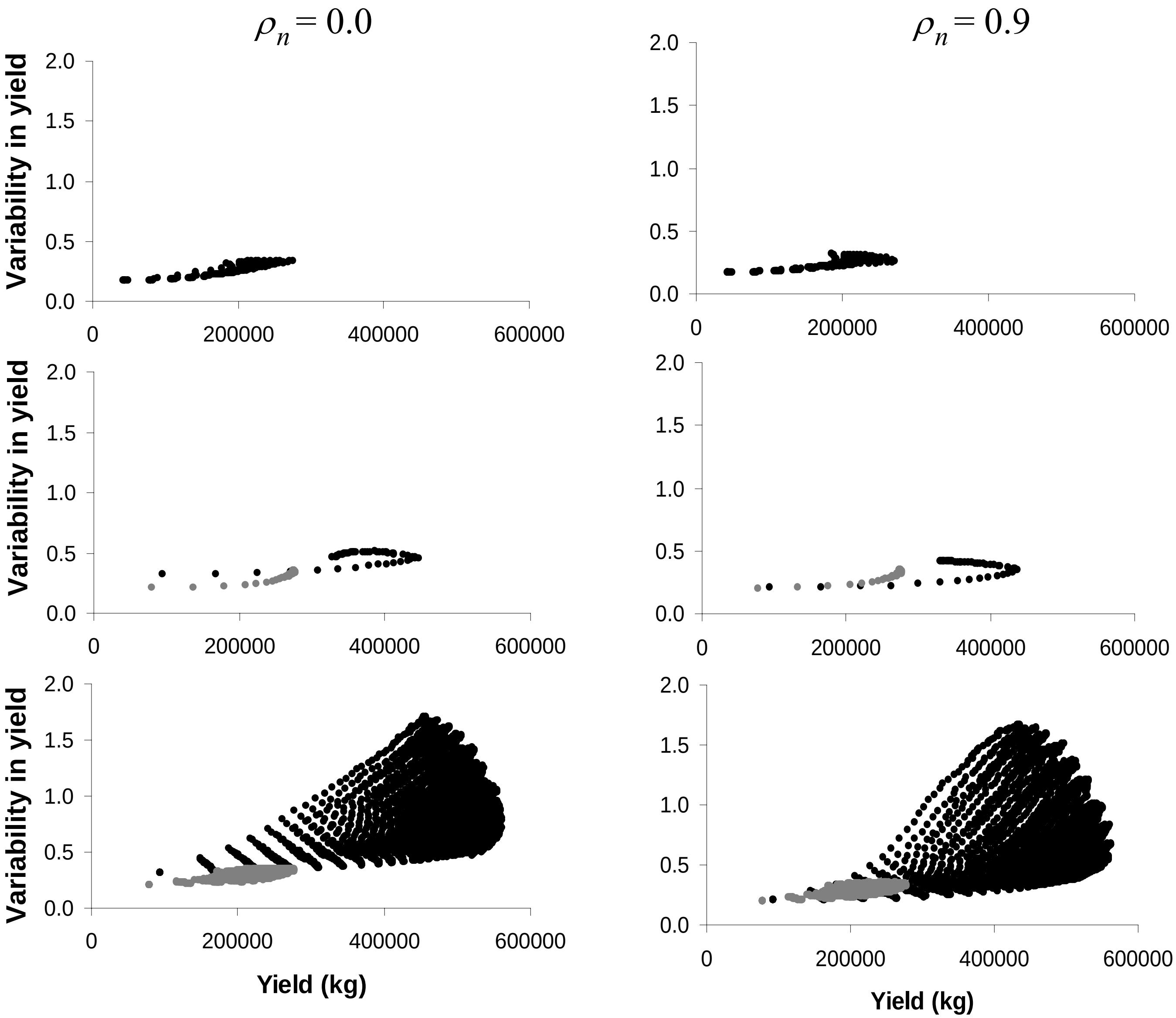
Figure 6.



$\sigma_n^2 = 0.01$
$\sigma_n^2 = 0.20$
Proportion of years with SSB < 20% unfished SSB
Variability in yield

Figure 7.—As in Figure 5, except with median yield versus median interannual variability in yield.

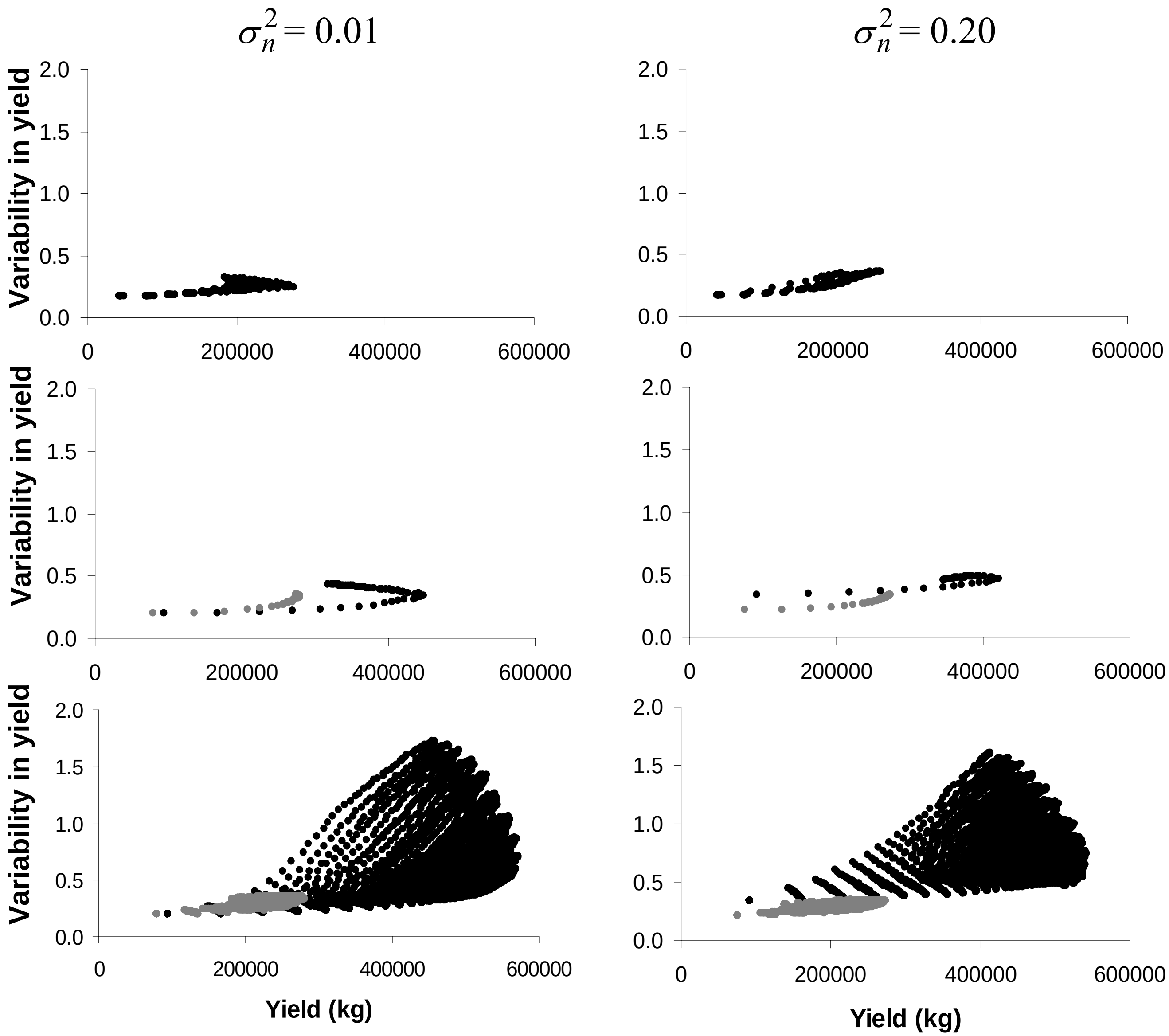
Figure 7.



$\rho_n = 0.0$
$\rho_n = 0.9$
Variability in yield
Variability in yield
Variability in yield
0.0
0.5
1.0
1.5
2.0
0
200000
400000
600000
Yield (kg)
Yield (kg)

Figure 8.—As in Figure 5, except with the extent of autocorrelation in assessment error equal to the baseline level (0.7), for assessment error variance equal to 0.01 or 0.20, and for median yield versus median interannual variability in yield.

Figure 8.



$\sigma_n^2 = 0.01$
$\sigma_n^2 = 0.20$
Variability in yield
2.0
1.5
1.0
0.5
0.0
0
200000
400000
600000
Yield (kg)

154

Table 1.—The different assessment and implementation error parameter values evaluated.

Parameter	**Value**
Assessment error variance, σ_n^2	0.01, 0.05, 0.20
Assessment error autocorrelation, ρ_n	0.0, 0.7 0.9
Implementation error variance, σ_F^2	0.0, 0.01, 0.0625

Table 2.—The performance of optimal policy parameters (see text) chosen assuming the incorrect future about lake whitefish growth (autocorrelated versus recent) for each of four trade-offs in performance metrics and for fast and slow growing stocks in 1836 Treaty-ceded waters. The pairs of values under each growth scenario sub-heading are the performance of the policy parameters chosen assuming the wrong future lake whitefish growth, and are in the same respective order as the performance metrics defined by the trade-off plot for each row. The values in parentheses are the percent change from the optimal set of policy parameters chosen assuming the correct future lake whitefish growth. Spawning stock biomass values are reported as a fraction of the unfished level.

Trade-off Plot	Fast				Slow			
	Actual Future Growth Scenario							
	Autocorrelated		Recent		Autocorrelated		Recent	
	Conditional Constant Catch							
Yield vs. SSB	269437 (-2)	0.47 (-19)	353900 (-3)	0.59 (+18)	233050 (0)	0.54 (0)	151488 (0)	0.52 (0)
Yvar vs. Risk	0.17 (0)	0.00 (0)	0.19 (0)	0.00 (0)	0.16 (+2)	0.06 (+500)	0.15 (+1)	0.00 (-100)
Yield vs. Yvar	269437 (-2)	0.29 (+7)	353900 (-3)	0.27 (-4)	233050 (-3)	0.33 (-5)	148246 (-2)	0.32 (+7)
Yield vs. Risk	269437 (-2)	0.05 (+400)	353900 (-3)	0.00 (-2)	233050 (-3)	0.13 (-46)	148246 (-2)	0.18 (+157)
	Biomass Based							
Yield vs. SSB	372818 (-5)	0.52 (+4)	473026 (+2)	0.48 (-4)	403322 (+1)	0.48 (-4)	242113 (-2)	0.52 (+4)
Yvar vs. Risk	0.29 (0)	0.00 (0)	0.24 (0)	0.00 (0)	0.26 (0)	0.00 (0)	0.25 (0)	0.00 (0)
Yield vs. Yvar	408409 (+1)	0.41 (+3)	491691 (-3)	0.38 (-3)	365127 (+22)	0.51(+28)	202301 (-14)	0.33 (-18)
Yield vs. Risk	449435 (0)	0.13 (+8)	560639 (0)	0.08 (-11)	418417 (-1)	0.18 (-18)	255924 (-1)	0.20 (+43)
	Constant-*F*							
Yield vs. SSB	331577 (0)	0.50 (0)	398959 (0)	0.51 (0)	272807 (0)	0.50 (0)	182210 (0)	0.51 (0)
Yvar vs. Risk	0.29 (0)	0.00 (0)	0.24 (0)	0.00 (0)	0.26 (0)	0.00 (0)	0.25 (0)	0.00 (0)
Yield vs. Yvar	326028 (-4)	0.38 (+6)	426116 (-3)	0.35 (-6)	278940 (+5)	0.42 (+5)	179020 (-2)	0.33 (-6)
Yield vs. Risk	326028 (-4)	0.10 (+67)	426116 (-3)	0.03 (-40)	278940 (-4)	0.14 (-63)	153258 (-16)	0.37 (+362)
	Biomass Based with a 15% Limit							
Yield vs. SSB	201536 (+4)	0.45 (-10)	251255 (-4)	0.57 (+14)	166747 (-7)	0.51 (+2)	117944 (-3)	0.46 (-8)
Yvar vs. Risk	0.20 (0)	0.00 (0)	0.20 (0)	0.00 (0)	0.19 (0)	0.00 (0)	0.19 (0)	0.00 (0)
Yield vs. Yvar	209020 (-1)	0.31 (+4)	273325 (-1)	0.32 (-4)	191478 (-6)	0.33 (-9)	122379 (-5)	0.31 (+13)
Yield vs. Risk	209020 (-1)	0.40 (+21)	273325 (-1)	0.27 (-16)	191478 (-6)	0.33 (-15)	125430 (-2)	0.42 (+35)
	Constant-*F* with a 15% Limit							
Yield vs. SSB	198279 (+5)	0.43 (-14)	250044 (-3)	0.59 (+16)	162228 (-7)	0.56 (+10)	117154 (+4)	0.45 (-10)
Yvar vs. Risk	0.20 (0)	0.00 (0)	0.20 (0)	0.00 (0)	0.19 (0)	0.00 (0)	0.19 (0)	0.00 (0)
Yield vs. Yvar	208611 (-1)	0.31 (+4)	273465 (-1)	0.32 (-3)	194041 (-5)	0.32 (-14)	121763 (-4)	0.31 (+15)
Yield vs. Risk	208611 (-1)	0.40 (+18)	273465 (-1)	0.28 (-12)	194041 (-4)	0.35 (-10)	126186 (0)	0.39 (+22)

APPENDIX A

Appendix A describes the details of how parameters for each sub-model of the simulation were estimated.

A.1. Classifying management units as fast or slow

Two complimentary methods were used to categorize management units as fast or slow growing. Mean length at age of fish was estimated among months for each year and management unit combination $\left(\bar{L}_{a,y,u}\right)$. Multiple linear regressions were then fit by age with $\bar{L}_{y,u}$ as the dependent variable and year $\left(\xi_y\right)$ and management unit $\left(\psi_u\right)$ as categorical explanatory variables:

$$\bar{L}_{y,u} = \varpi + \xi_y + \psi_u + \varepsilon_{y,u};$$

where ϖ was the overall intercept and $\varepsilon_{y,u}$ was residual error. Pairwise comparisons of the least squares means for each management unit were conducted. Generally, WFS07 and WFM05 had significantly larger mean lengths at age than other management units ($P < 0.05$) and so were categorized as fast growth, while all other management units were classified as slow (Table A1). To buttress these categorizations, a lake whitefish biologist familiar with the data was asked to rank the management units as fast or slow, and his categorizations confirmed these analyses (Mark Ebener, personal communication). Not unexpectedly, the growth models parameterized (see the main text and below) using the data from the management units in the slow growth category led to lower expected mean lengths at age than for the fast growth category (Table A2).

A.2. Growth sub-models

Data on growth and maturity were available from nine management units for a varying range of years (Table A1). The parameters for the growth sub-model with autocorrelated length at age-3 were estimated using a general linear mixed model using data from ages 4-8 with $\log\left(\overline{L}_{a,y,u}\right)$ as the dependent variable, a fixed effect of age $\left(\nu_a\right)$, and a random effect for the interaction of year class and management unit $\left(b_{r,u}\right)$ that had an AR(1) error structure:

$$\log\left(\overline{L}_{a,y,u}\right) = \partial + \nu_a + b_{r,u} + \varepsilon_{a,y,u};$$

where ∂ was the overall intercept, *r* denotes year class, *u* denotes management unit, and $\varepsilon_{a,y,u}$ was the residual error $\sim N\left(0;\sigma_L^2\right)$, and:

$$b_{r,u} = \rho_\phi b_{r-1,u} + \gamma_r;$$

where $\gamma_r \sim N\left(0;\sigma_\phi^2\right)$ and other symbols were defined as in the main text. Mean length at age-3 $\overline{L}_3$ was estimated as the exponent of three times ∂ (i.e., log length at age-0). During preliminary analyses, simulated $L_{3,y}$ were sometimes unrealistically high or low. So, $L_{3,y}$ was capped at 10% smaller and 10% larger than the smallest and largest observed age-3 fish in the data, respectively (Table A3). For fast growth simulations, the caps were never hit. For slow growth simulations the upper cap was hit in about 3% of years and the lower cap in about 9% of years.

The parameters of the growth sub-model for ages greater than three were estimated using a general linear mixed model with the increment in mean length for a cohort $(\Delta L_{a,y})$ as the dependent variable, a fixed effect of $L_{a-1,y-1}$, and a random effect for the interaction of year and management unit $(c_{y,u})$:

$$\Delta L_{a,y} = \lambda + \theta L_{a-1,y-1} + c_{y,u} + \varepsilon_{\Delta L,a,y};$$

where $c_{y,u} \sim N(0;\sigma_{\omega}^{2})$, $\varepsilon_{\Delta L,a,y}$ was residual error $\sim N(0;\sigma_{\Delta L}^{2})$, and other symbols were defined as in the main text.

The parameters of the weight portion of the growth sub-model with autocorrelated length at age-3 were estimated using a multiple linear regression with log transformed mean weight at age $(\log(W_{a,y}))$ as the dependent variable and $\log(L_{a,y})$ and $\log(\overline{L}_{3,y+1,y+2})$ as fixed effects:

$$\log(W_{a,y}) = \log(\tau) + \chi\log(L_{a,y}) + \varphi\log(\overline{L}_{3,y+1,y+2}) + \varepsilon_{W,a,y};$$

where $\varepsilon_{W,a,y}$ was residual error $\sim N(0;\sigma_{W}^{2})$ and other symbols were defined as in the main text.

A.3. Stock-recruitment sub-model

The parameters of the stock-recruitment sub-model were estimated using a general linear mixed model, similar to that described in Myers et al. (1999). The model was parameterized using estimates of stock and recruitment from medium and high quality CAA models, ranked by the 1836 Treaty waters modeling sub-committee as of 2007, in each management unit. Each CAA model was changed from penalizing recruitment estimates that deviated from the expectations of a Ricker stock-recruitment curve as described in Ebener et al. (2005), to estimating a series of deviations around a population scaling factor parameter with the deviations being required to sum to zero. That is, the CAA models were changed so that recruitment estimates were not penalized for deviating from some pre-specified stock-recruit relationship. The recruitment estimates in each year for each management unit $(R_{y,u})$ were then standardized as in Myers et al. (1999):

$$\tilde{R}_{y,u} = R_{y,u} SSBR_{F=0,u} (1 - e^{-M_u});$$

where $SSBR_{F=0,u}$ was the spawning stock biomass per recruit at the unfished level for each management unit, and M_u was the natural mortality rate in each management unit estimated using Pauly's equation (Ebener et al., 2005). Parameters of the stock-recruitment model were then estimated for a variation of the log transformed Ricker model (Myers et al., 1999):

$$\log\left(\frac{\tilde{R}}{SSB}\right)_{y,u} = \tilde{\alpha} + g_u + \beta_u SSB_{y,u} + \varepsilon_{R,y,u};$$

where $\tilde{\alpha}$ was the overall intercept, g_u was the random effect of management unit, $\varepsilon_{R,y,u}$ was temporally autocorrelated residual error, and :

$$\varepsilon_{R,y,u} = \rho_{Ru} \varepsilon_{R,y-1,u} + \varsigma_y ; \; \varsigma_y \sim N\left(0; \sigma^2_{Ru}\right);$$

where remaining symbols were defined as in the main text. To estimate each α_u, the units were converted back from the standardized units of recruitment:

$$\alpha_u = \frac{e^{\tilde{\alpha} + g_u}}{SSBR_{F=0,u} (1 - e^{-M_u})}.$$

$SSBR_{F=0,u}$ was calculated for each management unit using parameters used in each unit's CAA model. Weight at age and the proportion of females mature at age were estimated for each unit as the average over years. *M* and the proportion of females in the population were set to the same constant value as was used in the CAA model for each unit, and the number of eggs per kilogram of fish was set to 19,937/kg, which was the value used in all CAA models (Ebener et al., 2005).

A.4. Maturity sub-model

The parameters of the maturity sub-model were estimated using logistic regression on data from females:

$$\log\left(\frac{p(m)}{1-p(m)}\right)=\vartheta+\kappa L;$$

where $p(m)$ was the probability of maturity and ϑ was the intercept. Length at the inflection point (η) was estimated as the quotient of ϑ and -κ (ϑ/-κ).

The $p\left(L \middle| L_a, \sigma^2_{L_a}\right)$ was calculated by assuming that the variability around L_a followed a normal distribution with variance $\sigma^2_{L_a}$. The variance terms, $\sigma^2_{L_a}$, were calculated by multiplying L_a by the mean coefficient of variation (CV; 0.036) of the mean lengths at age estimated among months for each year and management unit combination. A single CV was used because the CVs for the mean lengths at age for each year and management unit combination showed no trend with mean length.

A.5. Maximum sustainable yield and unfished SSB

Maximum sustainable yield, used to define the parameters of the CCC control rule, was calculated for each management unit by finding the fully selected fishing mortality rate that maximized the product of yield per recruit and the equilibrium recruitment for each management unit. Yield per recruit was calculated separately for fast and slow growth stocks using the expected mean lengths, weights, selectivity, and proportion mature for each age predicted by the growth and maturity sub-models described here and in the main text, and the values of natural mortality and proportion of females in the population used in the simulations for each type of stock growth (i.e., fast and slow; see main text). Equilibrium recruitment was calculated for each management unit using the relationship between the spawning stock biomass per recruit curve, calculated using the life history parameters predicted by growth and maturity sub-models for each type of stock growth (i.e., fast and slow), and the stock-recruit relationship for each management unit (Quinn and Deriso; 1999, pg. 475). This relationship was also used to find the equilibrium $SSB_{\mathrm{F=0}}$ used to define the SSB_{LT} and SSB_{HT} policy parameters.

Table A1—Growth category and the range of years for which a random sample of commercial trap-net data were available from lake whitefish management units in the 1836 Treaty-ceded waters of Michigan used in parameterizing growth and maturity sub-models.

Management Unit	Years of Growth and Maturity Data	Growth Category
WFH01	1984-2007	slow
WFH02	1987; 1991-2007	slow
WFH04	1980; 1986; 1988-2006	slow
WFH05	1986; 1988-1990; 2000-2007	slow
WFM01	1992; 1995-1996; 2000-2007	slow
WFM02	1987; 1990-2003	slow
WFM05	1981-1984; 1986-1991; 1993-1995; 1997; 2002	fast
WFS07	1980; 1982-1984; 1986-1988; 1991-2007	fast
WFS08	1966; 1982; 1984-1986; 1996-2007	slow

Table A2—Expected mean length (mm) at age of lake whitefish for four growth models (see text for details).

	AGE									
Growth	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Fast-autocorrelated length at age-3	428	467	503	536	565	592	617	639	659	678
Slow-autocorrelated length at age-3	417	447	474	498	519	537	554	569	582	594
Fast-similar to more recent levels	437	474	511	546	580	613	646	677	708	738
Slow-similar to more recent levels	362	397	427	453	476	496	514	529	543	554

Table A3—Upper and lower caps placed on simulated length (mm) at age-3 lake whitefish for fast and slow growth category simulations.

	Growth Category	
Cap	**Fast**	**Slow**
Upper	539	601
Lower	228	210

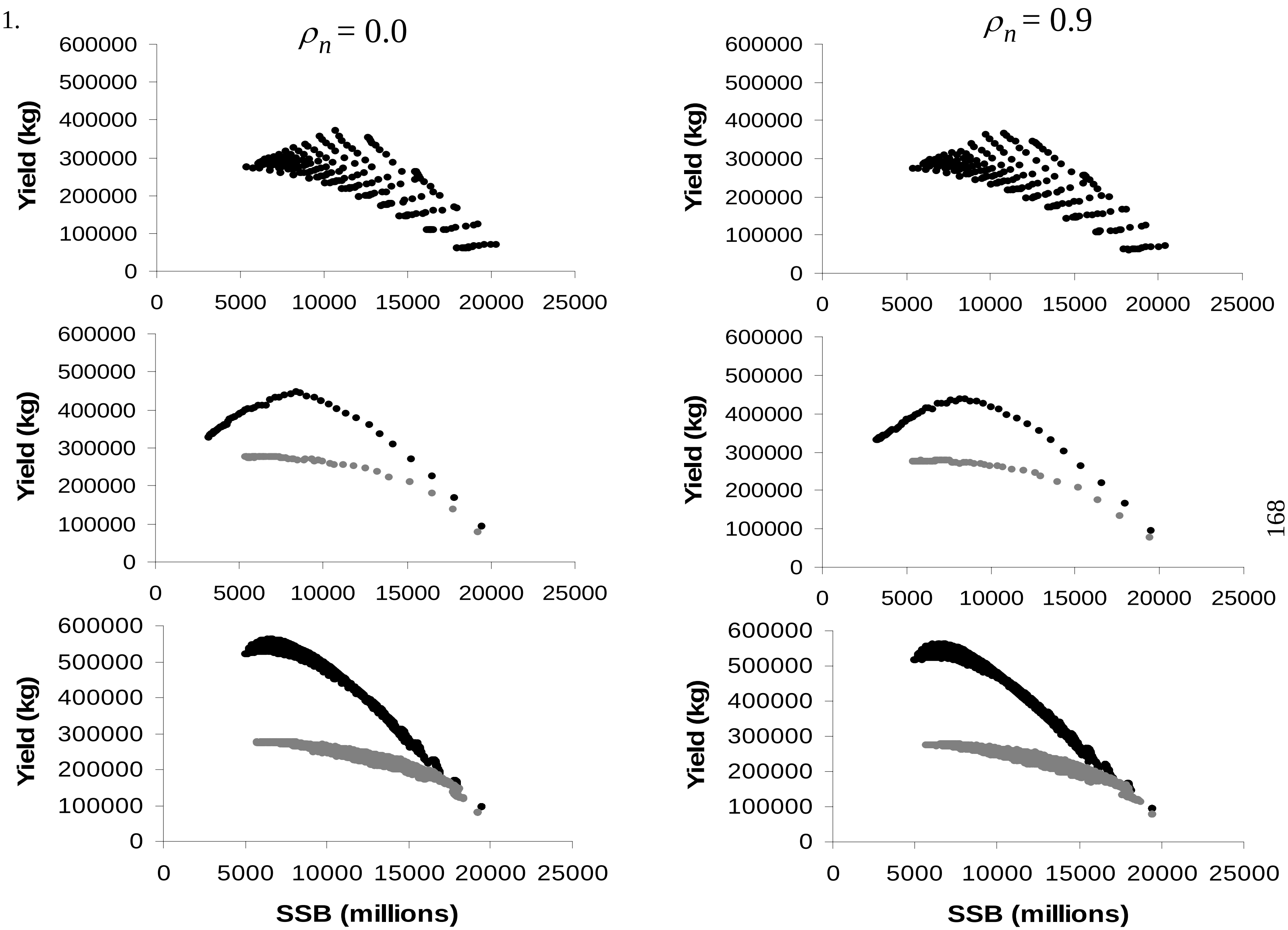
APPENDIX B

This appendix presents additional trade-off plots beyond those presented in the main text. Displaying all the results for four performance metrics, five control rule variants, three levels of productivity, seven levels for the parameters of assessment and implementation error, and four growth scenarios would require 1,512 panels. Displaying all these results in this appendix was not feasible.

The subset of trade-off plots shown here support statements in the main text. Figures B1-B4 illustrate that varying the parameters related to assessment error had little effect on the relative or absolute performance of control rules for trade-off plots not involving variability in yield. Figures B5-B8 illustrate that the rank order performance of the control rules is robust to the growth scenarios.

Figure B1.—Median spawning stock biomass versus yield for baseline assessment and implementation error variance, the extent of autocorrelation in assessment error set equal to 0.0 or 0.9, and fast growth similar to recent levels (see text for details), for the conditional constant catch control rule (top row), constant-*F* (black dots, middle row), constant-*F* with a 15% limit on the interannual change in target catch (grey dots, middle row), biomass based (black dots, bottom row), and biomass based with a 15% limit on the interannual change in target catch (grey dots, bottom row).

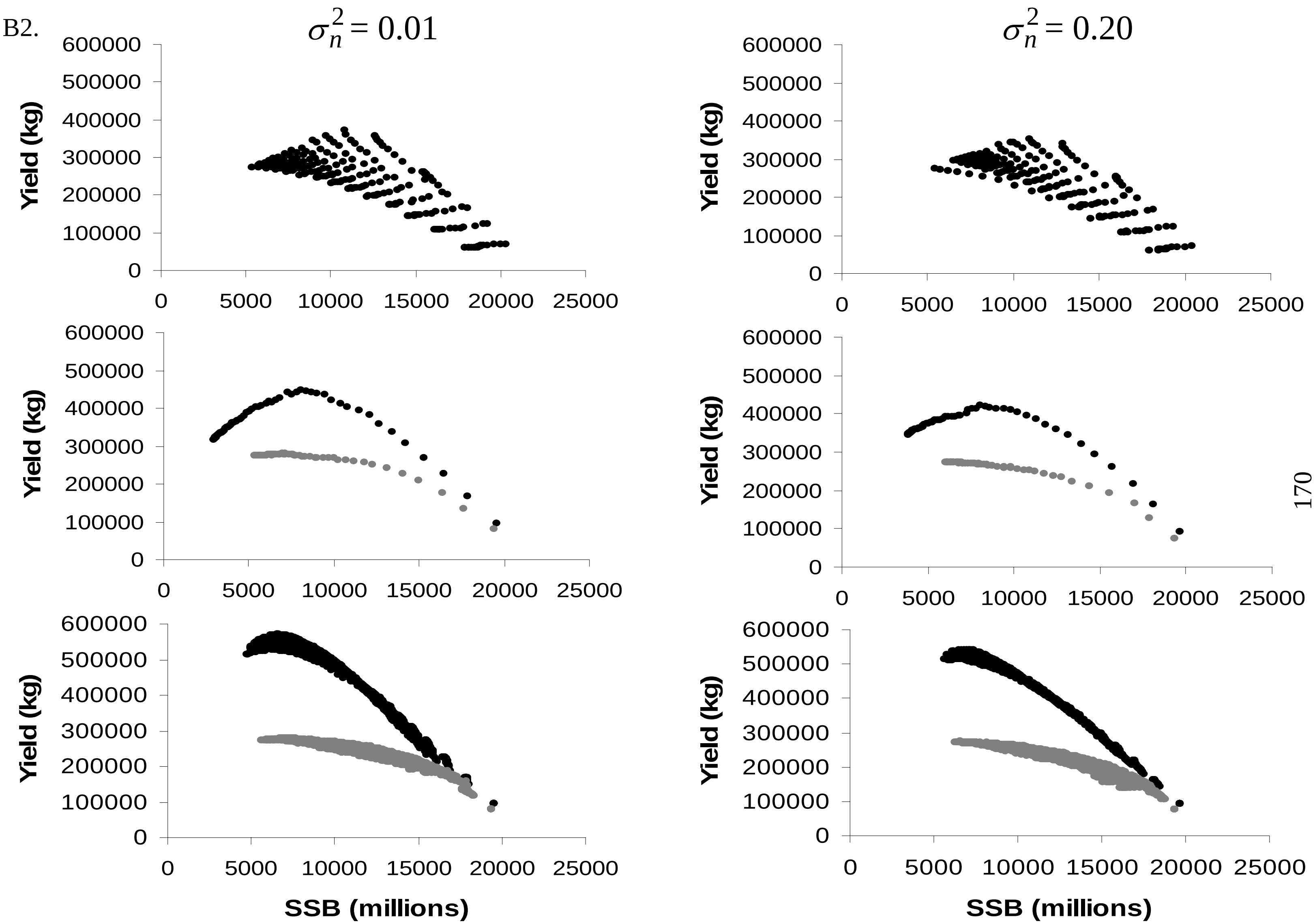
Figure B1.



$\rho_n = 0.0$
$\rho_n = 0.9$
Yield (kg)
SSB (millions)
600000
500000
400000
300000
200000
100000
0
0
5000
10000
15000
20000
25000

Figure B2.— As in Figure 1B, except with the extent of autocorrelation in assessment error set equal to the baseline level (0.7), and for assessment error variance equal to 0.01 or 0.20.

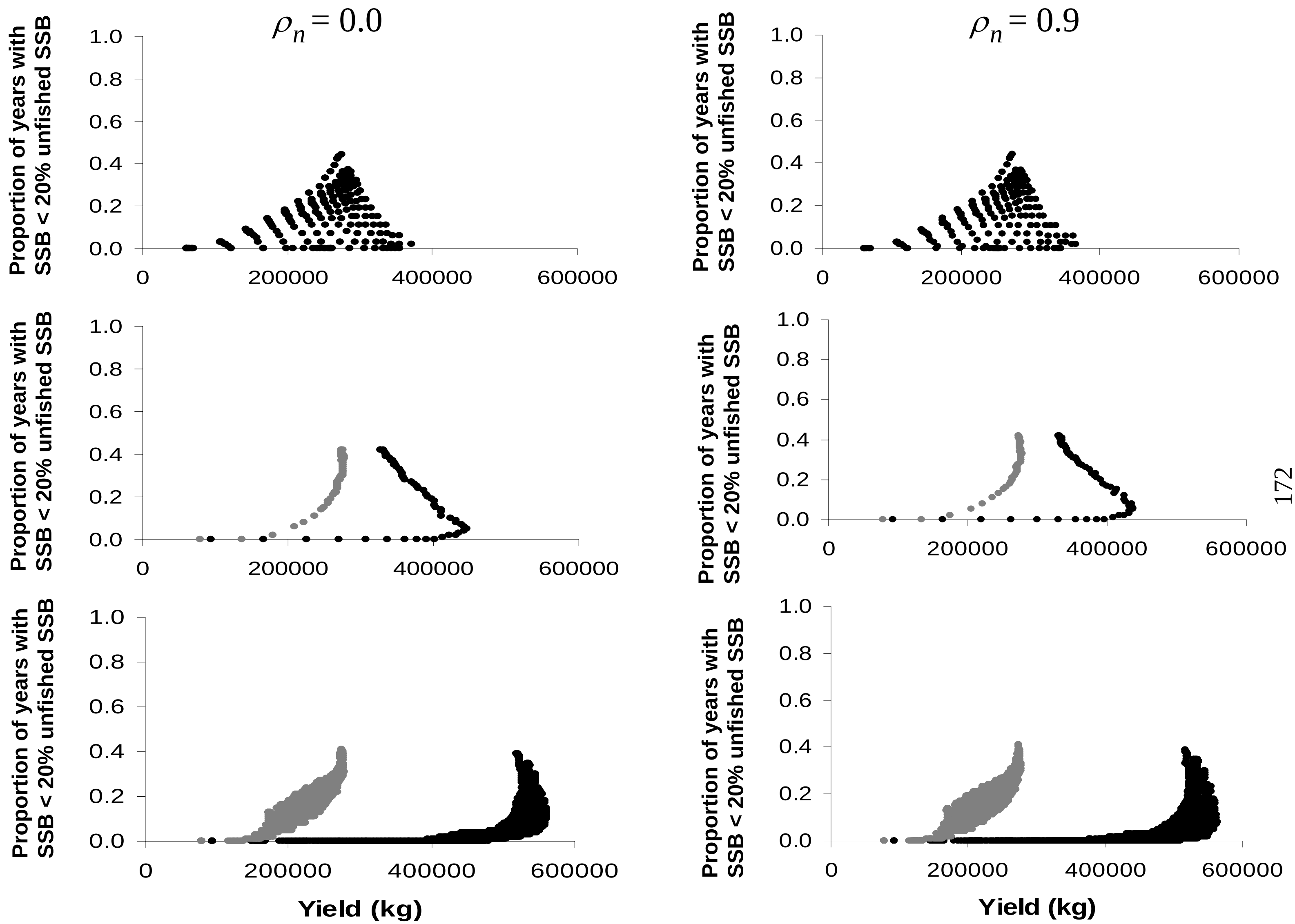
Figure B2.



$\sigma_n^2 = 0.01$
$\sigma_n^2 = 0.20$
Yield (kg)
600000
500000
400000
300000
200000
100000
0
0
5000
10000
15000
20000
25000
SSB (millions)

Figure B3.—As in Figure 1B, except for median yield versus the proportion of years with spawning stock biomass less than 20% of the unfished level.

Figure B3.



$\rho_n = 0.0$
$\rho_n = 0.9$
Proportion of years with SSB < 20% unfished SSB
1.0
0.8
0.6
0.4
0.2
0.0
0
200000
400000
600000
Yield (kg)

Figure B4.— Median yield versus the proportion of years with spawning stock biomass less than 20% of the unfished level with the extent of autocorrelation in assessment error set equal to the baseline level (0.7), for assessment error variance equal to 0.01 or 0.20, and fast growth similar to recent levels (see text for details). Control rules are displayed as in Figure 1B.

Figure B4.

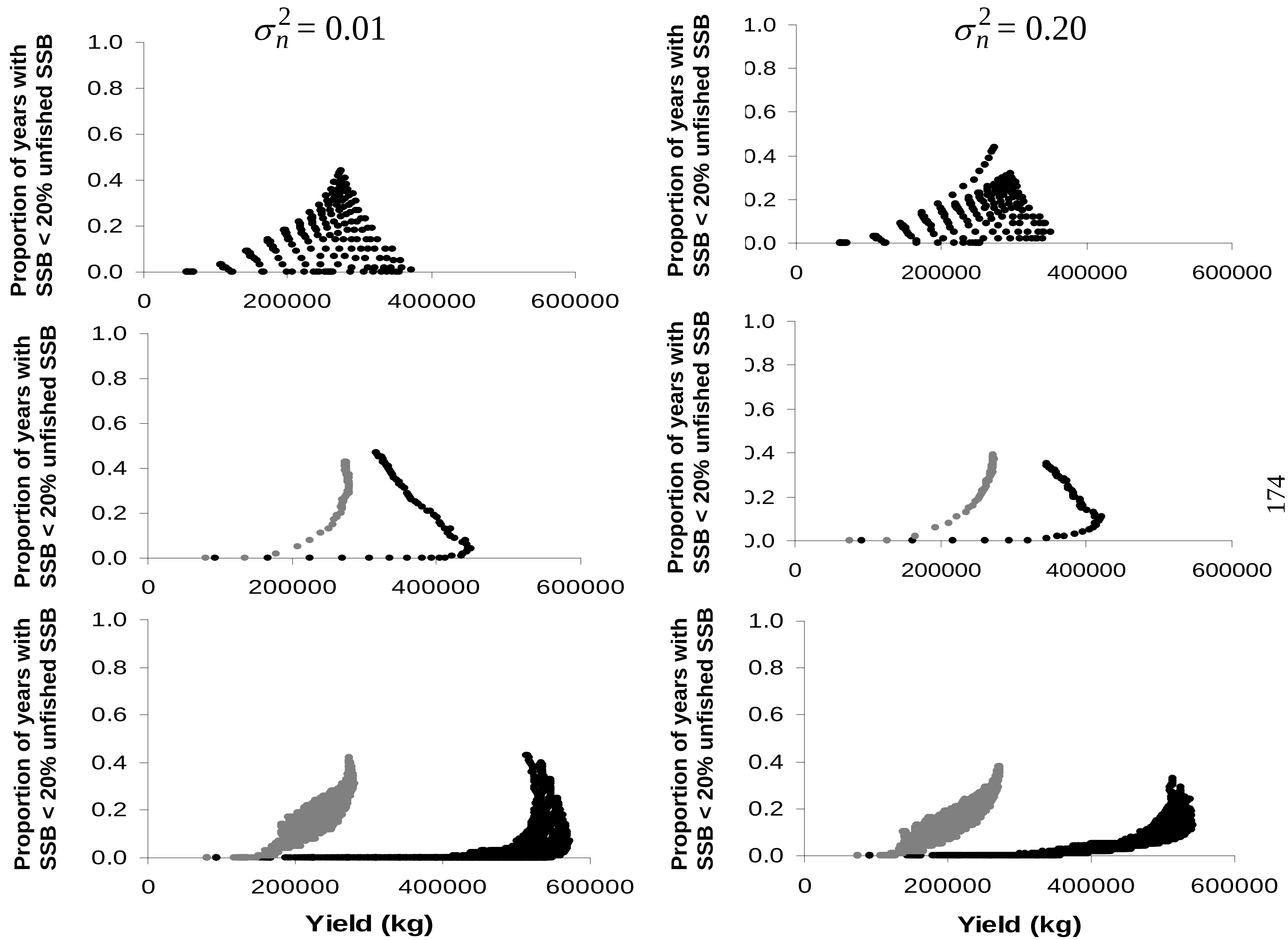
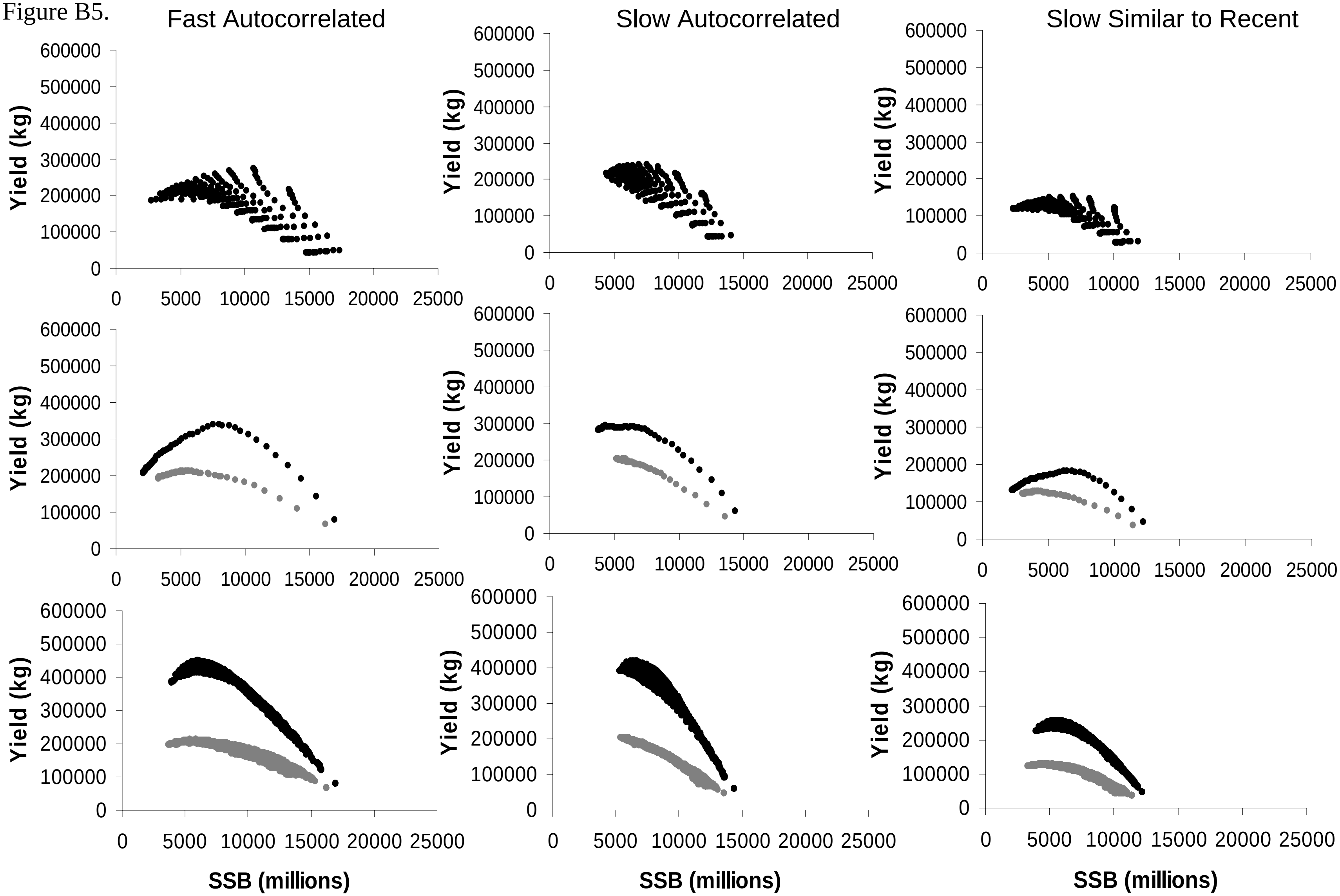

$\sigma_n^2 = 0.01$
$\sigma_n^2 = 0.20$
Proportion of years with SSB < 20% unfished SSB
1.0
0.8
0.6
0.4
0.2
0.0
0
200000
400000
600000
Yield (kg)

Figure B5.—Median yield versus spawning stock biomass for baseline levels of assessment and implementation error parameters and for autocorrelated fast growth, autocorrelated slow growth, and slow growth similar to more recent levels. Control rules are displayed as in Figure 1B.

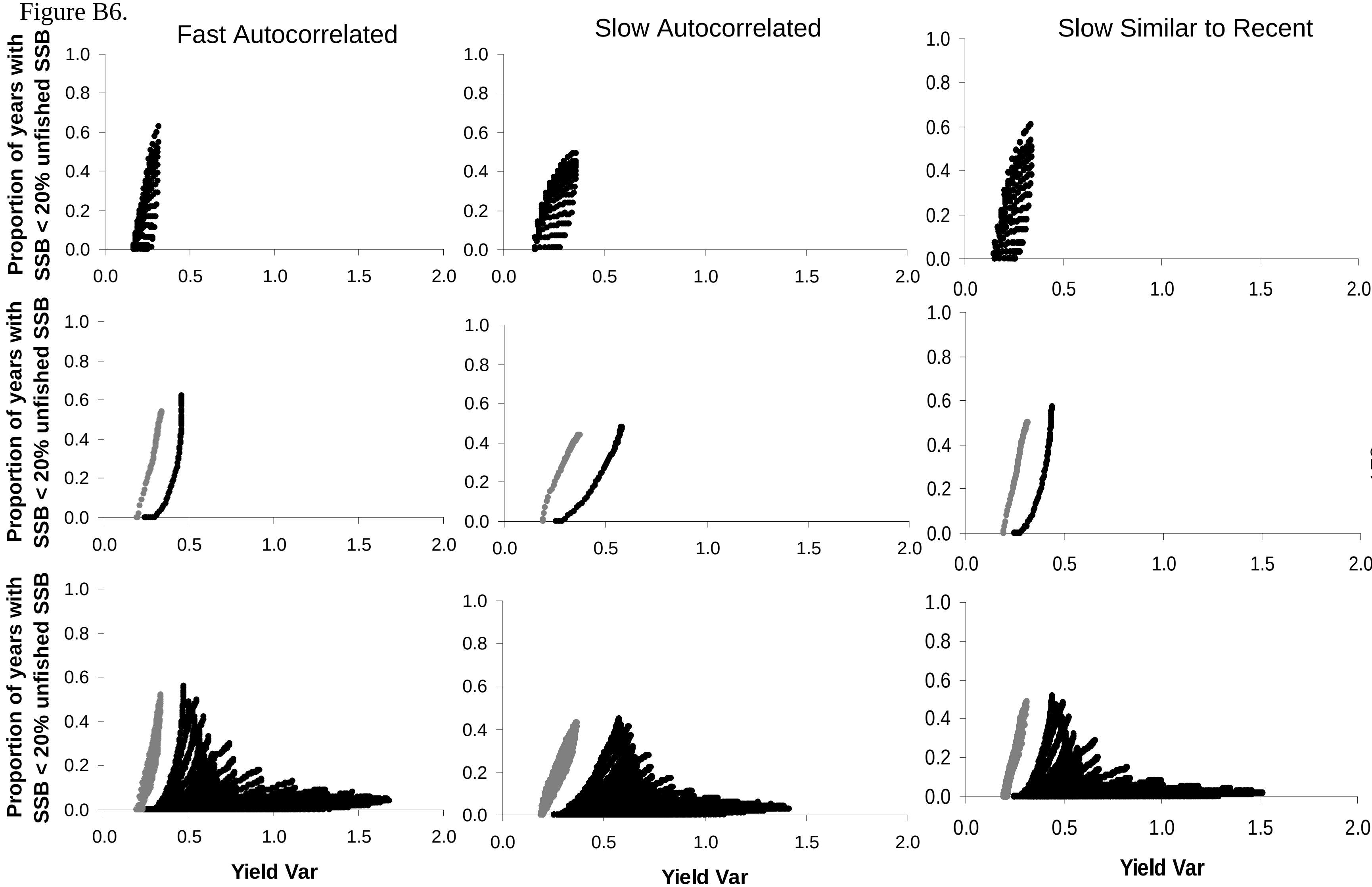
Figure B5.



Fast Autocorrelated
Slow Autocorrelated
Slow Similar to Recent
Yield (kg)
SSB (millions)
0
100000
200000
300000
400000
500000
600000
0
5000
10000
15000
20000
25000

Figure B6.—As in Figure B5, except for variability in yield versus risk.

Figure B6.



Fast Autocorrelated
Slow Autocorrelated
Slow Similar to Recent
Proportion of years with SSB < 20% unfished SSB
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
Yield Var

Figure B7.—As in Figure B5, except for yield versus variability in yield.

Figure B7.

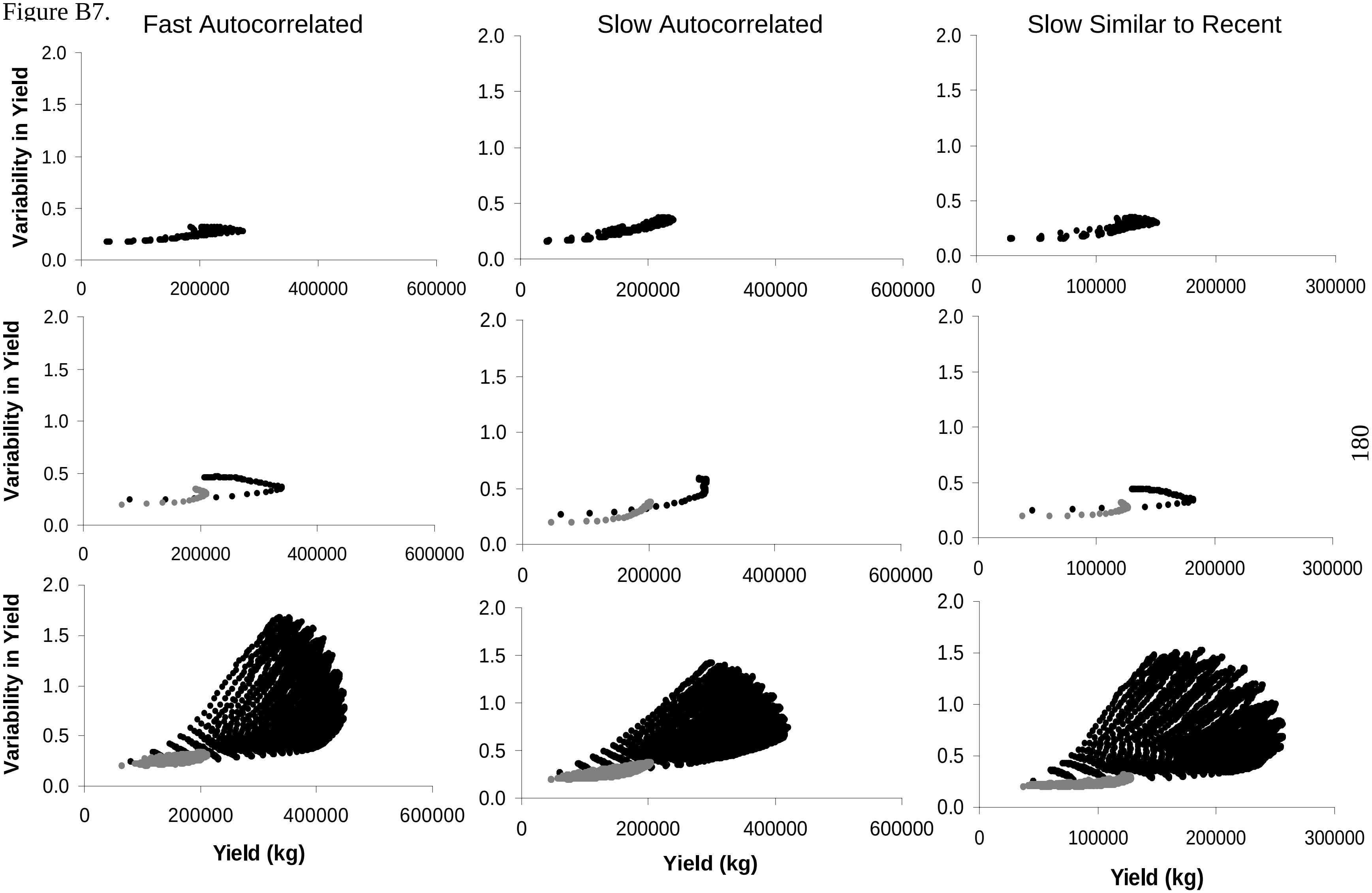
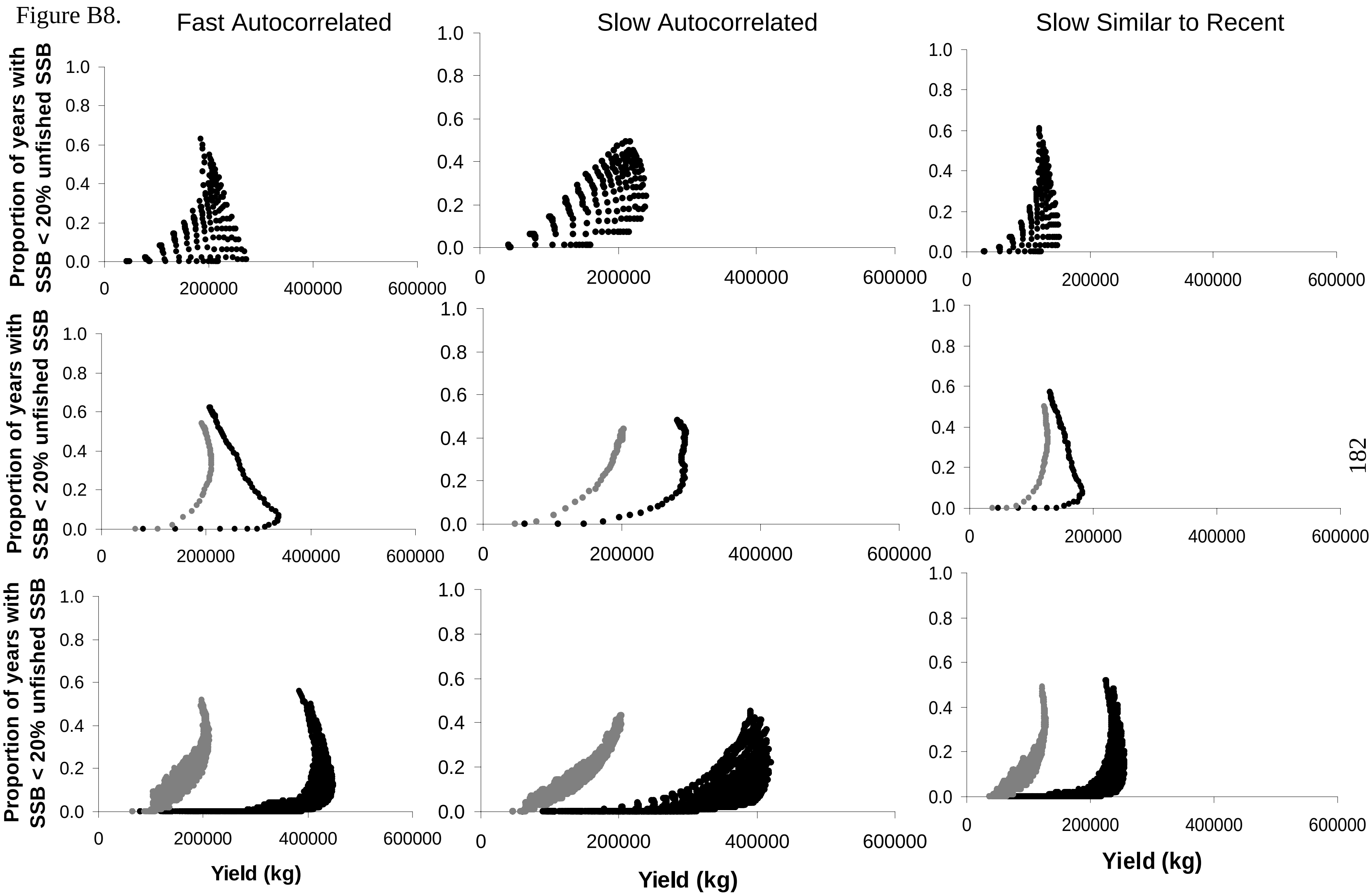

Fast Autocorrelated
Slow Autocorrelated
Slow Similar to Recent
Variability in Yield
Yield (kg)
0.0
0.5
1.0
1.5
2.0
0
200000
400000
600000
100000
300000

Figure B8.—As in Figure B5, except for yield versus the proportion of years with spawning stock biomass less than 20% of the unfished level.

Figure B8.



Fast Autocorrelated
Slow Autocorrelated
Slow Similar to Recent
Proportion of years with SSB < 20% unfished SSB
0.0
0.2
0.4
0.6
0.8
1.0
0
200000
400000
600000
Yield (kg)

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