Evaluating alternative harvest policies for yellow perch in southern Lake Michigan

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ABSTRACT

In the southern basin of Lake Michigan, yellow perch (*Perca flavescens*) are ecologically and economically important. However, there is no explicit harvest policy for the management of this resource, the authority for which is shared among four U.S. states. We used decision analysis and projections from a stochastic simulation model to aid managers in formulating a harvest policy. In workshops that included management agency personnel and other experts, critical uncertainties relevant to the population (e.g., alternatives for future stock–recruitment relationships and mixing of recruits among management areas) were identified as well as potential harvest policies (using constant fishing mortality or state-dependent control rules) and associated performance statistics. Our simulation model acknowledged uncertainty in the stock–recruitment relationship, parameter uncertainty given such a relationship, stochastic process variation, and uncertainty associated with assessment and implementation errors. We used the model to project age-, sex-, size-, and spatial-dynamics of the yellow perch population, and thus predicted likely distributions of performance statistics for different harvest policies. Performance statistics included time averages of recreational harvest, remaining spawning stock biomass (SSB), and length of harvested fish as well as the frequency of how often such measures were below desirable thresholds. Results indicate that state-dependent policies produce higher average harvests and lower frequency of years with low SSB, but sometimes more frequent years with low harvest, than constant-*F* policies that lead to similar depletion of average SSB.

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1. Introduction

### 1.1. Background on the yellow perch fishery in the southern basin of Lake Michigan

Yellow perch (*Perca flavescens*) are ecologically important given their intermediate role in the aquatic food web and economically important given their contribution to Lake Michigan fisheries since the late 1800s (Wells and McLain, 1972; Wells, 1977). They are a shared resource in Lake Michigan, spanning the boundaries of four U.S. states (Wisconsin, Illinois, Indiana, and Michigan), each of which has management jurisdiction over its own waters (Fig. 1). Commercial fisheries for yellow perch have operated continuously throughout the last century (Baldwin et al., 2002), although commercial fishing has been restricted to Green Bay since 1998. In addition, yellow perch have dominated the harvests of recreational anglers in recent decades (Bence and Smith, 1999). The recreational

fishery in the southern basin of Lake Michigan targets what is thought to be a distinct population from that in Green Bay (Miller, 2003). This paper evaluates harvest policies only for the yellow perch population in the southern basin of Lake Michigan (Fig. 1).

The yellow perch population in southern Lake Michigan declined substantially during the early 1990s (Marsden and Robillard, 2004; Wilberg et al., 2005). The causative factors behind the reduced abundance of the Lake Michigan yellow perch population are still not entirely clear, and multiple factors may have acted in concert to produce the observed decline (Clapp and Dettmers, 2004). Candidate factors include: unfavorable changes in zooplankton density and species composition (Bremigan et al., 2003; Clapp and Dettmers, 2004); competition, predation, and spawning interference by alewife (*Alosa pseudoharengus*; e.g., Shroyer and McComish, 2000); ecosystem alteration from zebra mussels (*Dreissena polymorpha*; Marsden and Robillard, 2004); and overfishing at levels that limited subsequent spawning potential (Wilberg et al., 2005).

To better understand and respond to the declining yellow perch population and coordinate management in Lake Michigan, the Lake Michigan Committee, the body charged with coordinating fishery management efforts on Lake Michigan, formed the Yellow Perch
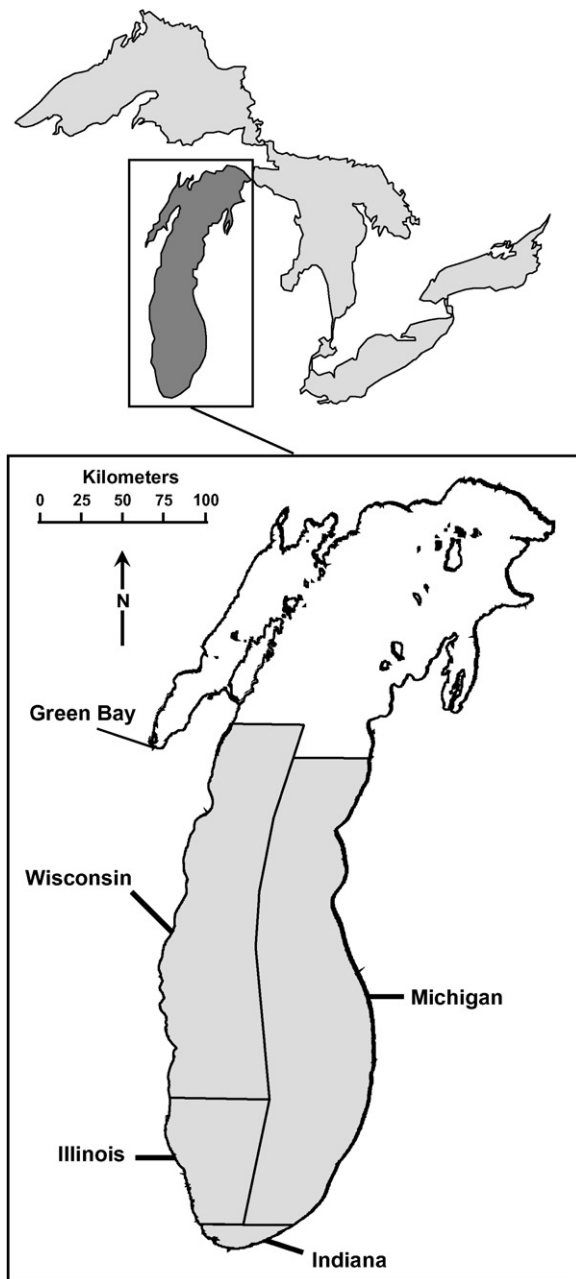
Fig. 1. Map of Lake Michigan with modeled management areas of the southern basin identified by U.S. state name. Green Bay lies outside of the modeled region and is also identified on the map. The inset shows the location of Lake Michigan in a regional map of the Laurentian Great Lakes.

Task Group (YPTG) in 1994 (Clapp and Dettmers, 2004). The YPTG includes representatives from U.S. state, U.S. federal, and tribal agencies, as well as members of academic institutions (Clapp and Dettmers, 2004). In an emergency response to reduced yellow perch abundance, more restrictive harvest limits were implemented for recreational fisheries and southern-basin commercial fisheries were closed (and continue to remain closed; Francis et al., 1996; Marsden and Robillard, 2004). The emergency restrictions of yellow perch harvest across management jurisdictions signified increased interagency cooperation (Francis et al., 1996; Clapp and Dettmers, 2004) and almost certainly helped to curtail the severity of overfishing in the short term. However, these regulations were not viewed as providing for optimal future performance for the yellow perch fishery.

For this population, critical uncertainties exist in relation to its future recruitment potential, as well as the degree of spatial independence among spawning stocks in the four management areas. Horns (2001) suggested geographic segregation of the yellow perch population based on regional differences in measurements of sagittal otoliths related to first-year growth. Conversely, Miller (2003) found little genetic differentiation among spawning groups of yellow perch within southern Lake Michigan, suggesting a single genetic stock. Adults are thought to generally remain within areas much smaller than those managed by each state, and thus most mixing of the population across management-area boundaries likely occurs during early life stages because larvae are pelagic and disperse via passive drift (Dettmers et al., 2005; Beletsky et al., 2007). As a result, mature yellow perch may be contributing to recruitment in areas other than where they reside (also see Wilberg et al., 2008). Indeed, there is substantial correlation in yellow perch recruitment among management areas (Wilberg, unpublished data), although this may also be influenced by regional-level drivers.

1.2. Decision analysis and scope of this paper

Decision analysis provides a comparative framework useful for explicitly including known uncertainties and selecting among multiple management options (Powers et al., 1975; Peterman and Anderson, 1999). The basic approach is to identify performance statistics related to broad fishery objectives, alternative management policies, and critical uncertainties, and then develop a model that predicts distributions of performance statistics that can be expected from a given policy choice. There are a number of fishery applications, including several aimed at evaluating alternative harvest polices (Robb and Peterman, 1998; Peterson and Evans, 2003; Vasconcellos, 2003; Haeseker et al., 2007). This approach is similar to management strategy evaluation (Smith et al., 1999; Sainsbury et al., 2000; Rademeyer et al., 2007). Previous fishery policy evaluations that can be described as decision analysis have integrated uncertainty about model hypotheses or parameter values into the resulting distributions of performance statistics but have generally not explicitly accounted for assessment or implementation uncertainty (but see Vasconcellos, 2003) as is more commonly done with management strategy evaluation.

In this paper, we describe the use of decision analysis to evaluate alternative harvest policies for yellow perch in the southern basin of Lake Michigan. First, we summarize a series of interactive project workshops, then describe a stochastic simulation model, and finally present and discuss comparative results across multiple performance statistics. Overall, our work was designed to provide information to the Lake Michigan Committee and its constituent agencies to allow them to select among different harvest policies to better meet their objectives for the fishery. Despite the focus on a specific application, we believe this work provides information of general interest with regard to the performance of harvest policies based on alternative control rules, as well as highlighting some of the benefits of working closely with managers during the process of model development.

2. Workshops and process of obtaining input from managers and stakeholders

2.1. Overview of the workshops

An important part of our process was to work with managers and other experts in a series of three project workshops and less formally in-between and after these workshops. The purpose of the

workshop series was to ensure involvement of managers and thus develop and use a simulation model that would better meet their needs. Workshop attendees primarily included academic scientists, and state, federal, and tribal fishery biologists and managers. Most of these individuals had previously participated as part of the YPTG, but several Lake Michigan Committee members and individuals suggested by that committee also participated.

The first workshop (23–24 March 2005) was intended to introduce and review the decision analysis approach, identify the most critical uncertainties in population processes, discuss general management objectives, identify associated performance statistics, identify the types of harvest policies to consider, and to discuss basic model structure. Based on this input, the modeling and analysis group began to develop an initial simulation model and presented preliminary results at the second workshop. The purpose of the second workshop (28–29 March 2006) was to obtain input on modeling details and parameterization, including how the critical uncertainties should be incorporated, implementation of harvest policies, and to fine-tune performance statistics. The third workshop (24–25 January 2007) was intended as a forum to present a near-final model and results, leading to a discussion of future policy options. In practice, the process was more fluid. For example, some substantial changes in performance statistics and incorporation of new uncertainties occurred even after the third workshop, and a fourth workshop is now planned to further communicate project results and allow managers to further use the simulation model to explore policy performance.

Consensus on the basic structure of the model was achieved during the first workshop. Managers strongly supported development of a spatially structured model, treating each of the four state jurisdictions as areas in which populations of yellow perch are found and to which state-specific management regulations may apply, but indicated that harvest policies should be considered at the basin level. The selected spatial structure was chosen because each bordering state has independent jurisdiction over the management of yellow perch in its waters and characteristics of fishable populations of yellow perch were recognized to differ at that scale (e.g., recruitment and growth; Horns, 2001; Wilberg et al., 2005). However, managers wanted to employ the same harvest strategy across management areas because use of different policies would be politically unpalatable and previous state-specific attempts to limit harvests were not successful (Francis et al., 1996). To be consistent with existing assessment models, it was agreed that an age-, size-, and sex-structured model operating with spatial structure and an annual time step would be appropriate.

2.2. Identifying objectives and performance statistics

During the first workshop, participants developed a list of potential general management objectives and associated specific measures of performance during a facilitated brainstorming exercise. Management objectives fell into six generalized categories: harvest, recruitment, stock composition, abundance, allocation, and user effort. It was evident that there would be some trade-offs among objectives such as maintaining consistent harvests, maximizing harvest opportunities, maintaining high catch per unit effort, and preserving biomass of females. In this paper, we focus on policies including only recreational fishing because commercial fishing is not currently allowed in southern Lake Michigan.

Measurements of performance (e.g., total annual harvest, the frequency of years in which harvest is low, the size of harvested fish, and the sex ratio of the population) were associated with the general management objectives identified for southern Lake Michigan by workshop participants, with some debate regarding specific target values. Some additional measures of fishery performance, such

as the number of expected recreational fishing licenses sold, were discussed but deemed outside the realm of realistic representation for this analysis. Some potential measures of performance were later dropped from consideration (e.g., catch per effort of larger fish) because of recognized redundancy with other measures.

A preliminary model was developed prior to the second workshop, and examples of simulation results were then presented at that workshop. These results emphasized numbers of fish harvested and spawning biomass because these variables were of particular interest to managers at the first workshop. Participants indicated that they would like to include other measures of performance that directly related to the average size as well as the number of fish harvested. There was general agreement that performance should be evaluated based on averages or sums over the entire southern Lake Michigan area. The participants reached consensus that a 50-year time horizon for evaluating performance was appropriate because it captured both multiple generations of yellow perch and a period of concern to managers.

Performance statistics were presented as time averages and associated standard deviations (e.g., for total harvest, remaining spawning biomass, and average size of harvested fish) during the third workshop. These performances statistics were also combined by first ranking each statistic among policies and then summing weighted ranks for a policy, using alternative weightings representing the possible importance of each statistic. As expected, no single policy was best able to achieve all of the general management objectives. In the end, workshop participants reached consensus that management concerns centered on avoiding too frequent low harvest, low stock size, or small harvested fish size, rather than on variation *per se*. Appropriate reference threshold values for these undesirable conditions were discussed based on manager perceptions of when they and stakeholders had previously been dissatisfied with fishery status. For example, managers indicated that angler dissatisfaction was evident when recreational harvest was below 1.5 million fish annually. Likewise, anglers have expressed interest in catching large yellow perch; managers suggested they received complaints when the average size in the recreational harvest was less than 21.5 cm (8.5 in.). Therefore, the proportion of years in which the value for the performance variable was below each of these thresholds was added as a performance statistic. The suite of performance statistics identified to be most useful for evaluating policies, based on discussions over the course of the workshops, are provided in Table 1.

2.3. Identifying critical uncertainties

Following a structured approach similar to that used to develop objectives and performance statistics, workshop participants quickly identified the recruitment process as the most critical uncertainty. Participants were uncertain if future recruitment would continue to be low, as has been observed since 1993 (i.e., a regime shift occurred, sensu Carpenter, 2003—which we refer to as "recent" recruitment) or whether there was some potential for occasional high recruitment events (i.e., long-term fluctuations exist, alternating between "high" and "low" recruitment—which we refer to as "variable"). Additionally, workshop participants were uncertain about recruitment sources and whether recruits in a management area were produced by adults residing in other areas. The workshop participants agreed that a reasonable approach to capturing these uncertainties about the recruitment process was by specifying alternate hypotheses ("uncertain states of nature"; e.g., Hilborn, 1987) and associated probabilities, *P*, for each (Table 1; Fig. 2). These associated probability values were subsequently set during the second workshop using an ad hoc expert elicitation method and averaging these expert-judgment probabilities. We

Table 1

Description of recruitment hypotheses, harvest policies (control rules and levels of maximum target instantaneous fishing mortality rate, F^*), and performance statistics

|	Description
Recruitment hypotheses	
Recent-area	Recruitment using recent productivity by SSB within each area
Recent-mixed	Recruitment using recent productivity by total SSB
Variable-area	Recruitment using variable productivity by SSB within each area
Variable-mixed	Recruitment using variable productivity by total SSB
Harvest policies	
Control rules	
Constant-F	$\tilde{F}$ is constant at F^* for all SSB
0–40	$\tilde{F}$ is reduced below F^* when SSB falls below 40% of B_0
0–70	$\tilde{F}$ is reduced below F^* when SSB falls below 70% of B_0
Levels of F^* (yr^{-1})	0.1, 0.3, 0.5, 0.7, 1.0, 1.5, 2.0
Performance statistics (averages are over the 50-year time horizon)	
% B_0	Average percentage of B_0 remaining in the system
Harvest (#)	Average recreational harvest
TL (cm)	Average length of yellow perch harvested in recreational fishery
% Years SSB < 20% B_0	Percentage of years with SSB below 20% B_0
% Years Harvest < 1.5 M	Percentage of years with harvest below 1.5 million fish
% Years TL < 21.59 cm	Percentage of years with TL below 21.59 cm

Following convention, the state-dependent control rules are denoted using percentages of unfished spawning stock biomass (B_0). SSB = spawning stock biomass (female yellow perch), TL = total length.

recognize that this process is subjective and agree with Punt and Hilborn (1997), who described assigning weights to alternative hypotheses as "the most difficult element in decision analysis".

A second major area of uncertainty identified during the first workshop was the importance of density-dependent individual growth. The models used during the second and third workshops represented this uncertainty in the form of two growth hypotheses (and associated probabilities) that either included or
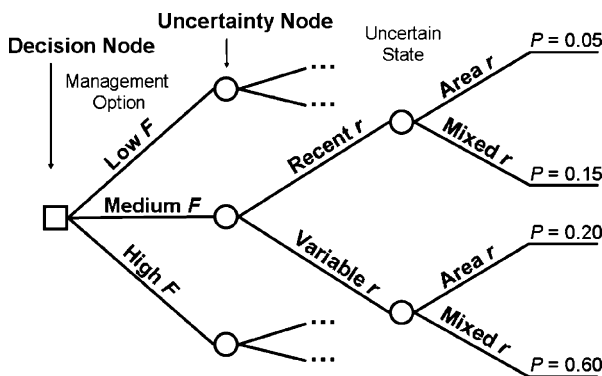
Fig. 2. A simplified decision tree illustrating alternative management options and uncertain states of nature for yellow perch in Lake Michigan. Management options are different levels of fishing mortality (F), and the subset of uncertainties shown are related to alternative hypotheses for stock–recruitment processes (r) including a potential regime shift (recent vs. variable) and independent versus mixed stocks (area vs. mixed). See Methods for additional details on uncertainties. Assumed probabilities (P) that an individual recruitment hypothesis is the true state of nature are shown at the end of each path.
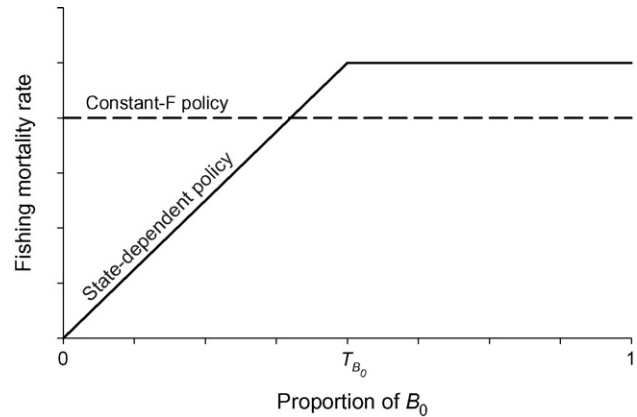
Fig. 3. Graphical representation of potential control rules. The dashed line represents a constant-fishing-mortality control rule, for which target fishing mortality is independent of stock size. The solid line represents a state-dependent control rule where target fishing mortality is constant above a threshold of spawning stock biomass (T_{B_0}) and declines in proportion to spawning stock biomass if below the threshold.

did not include density-dependent growth. By the time of the third workshop, consensus shifted to representing temporal variation in growth as a consequence of both density-dependent and density-independent factors rather than alternative possibilities. Thus, subsequent to the third workshop the two growth hypotheses were replaced by a single growth sub-model, where uncertainty in the relative importance of density-dependent and density-independent factors was captured by drawing model parameters from a distribution.

During the first workshop, there was general discussion that parameter uncertainty would be included in the model. Thus, the participants agreed that when estimable (e.g., as part of stock assessment or data analysis), parameters with substantial uncertainty would be drawn from estimated distributions. Neither uncertainty in estimates of stock abundance nor implementation errors in controlling fishing mortality were discussed as major sources of uncertainty during any of the workshops. However, review of the peer-reviewed literature indicates that these uncertainties can substantially influence the relative performance of harvest policies (Deroba and Bence, 2008). Consequently, both assessment and implementation errors were incorporated into the simulation model after the third workshop.

2.4. Identifying realizable harvest policies

Initial discussion at the first workshop centered on whether alternative harvest policies should be implemented through choices among fishing-mortality control rules and their parameters or by choices among suites of specific harvest regulations (e.g., closed seasons or bag limits). Workshop participants recognized that changing the level of fishing mortality did not fully simulate all possible management actions but accepted this as a pragmatic approach to approximate the effects of imposing regulatory actions intended to influence fishing mortality. By the time of the second workshop, constant-F control rules and state-dependent control rules (Fig. 3) were selected for evaluation. Constant-F polices were considered because of their widespread use, low management cost (e.g., regulations might only be changed occasionally for a recreational fishery in response to changes in fishing power and angling effort), and good performance in achieving some management objectives in other situations (e.g., Walters and Parma, 1996; Deroba and Bence, this issue). Workshop participants were also interested in state-dependent rules because of their increasing use

and promise for achieving objectives beyond those only considering fishery yield (National Research Council, 1998; Quinn and Deriso, 1999; Deroba and Bence, this issue; Punt et al., this issue). Further, the process of implementing increasingly stringent fishery regulations as the Lake Michigan yellow perch stock size declined during the 1990s approximated such a policy. Lastly, concerns were expressed during the third workshop about using state-dependent policies that completely closed the recreational fishery. Managers strongly preferred policies that allowed some fishing even at low stock sizes and indicated that complete closures of the recreational fishery would be difficult to enforce. Therefore, the current analyses did not include control rules that closed the recreational fishery, although preliminary work where fishery closures were possible at low levels of spawning stock biomass (SSB) led to similar results to those presented here.

3. Modeling and simulation details

3.1. Overview of simulations and the yellow perch population model

We developed a stochastic simulation model to project the age-, sex-, size-, and spatial-dynamics of the yellow perch population in the southern basin of Lake Michigan and forecasted selected performance statistics for harvest policies representing combinations of fishing levels for a constant-F and two state-dependent control rules (Fig. 3, Table 1). For each harvest policy, 1000 simulations were run, consisting of 250 simulations for each of four recruitment hypotheses. Each simulation was a 50-year projection. The model tracked populations of yellow perch in four management areas of the southern basin of Lake Michigan (Fig. 1).

The model represented abundance of yellow perch in eight age groups ranging from age 2 through an age-9 "plus" group that was an aggregate group including ages 9 and older. All simulations began with area-specific initial abundance- and length-at-age values that were derived from stock assessment models for each management area. Assessment models included updated versions of the Wisconsin and Illinois models used in Wilberg et al. (2005) as well as similar assessment models applied to data for Indiana and Michigan stocks. Likewise, other associated parameters were also largely based on these fitted stock assessment models. Parameter definitions and equations used in the various population sub-models are provided in Tables 2 and 3. Initial parameter values and corresponding standard errors and correlation coefficients are provided in detail elsewhere (Irwin et al., 2008).

Our model included uncertainties that can be roughly grouped as (a) model uncertainty—uncertainty about the nature of the stock–recruitment relationship, (b) parameter uncertainty—given a stock–recruitment relationship, uncertainty about parameter values for that relationship, (c) process uncertainty—given the model parameters, uncertainty about what specific process errors will occur during a given simulation, and (d) assessment and implementation uncertainty—uncertainty arising during a given simulation because of errors in population assessment and policy implementation. Aside from recruitment model parameters, the sequence of randomly selected parameters and stochastic errors were shared across the four recruitment hypotheses. For parameters shared among hypotheses, simulations for each harvest policy started with the same random number seed, and thus results for each recruitment hypothesis reflect the same 250 sets of random numbers. For each simulation, recruitment, growth, and other parameters were drawn from specified distributions for each management area. Below, we describe how the population model incorporated Ricker stock–recruitment models for the four recruitment hypotheses, allowed for density-dependent growth and process errors in

Table 2

Symbols and descriptions of variables used in the stochastic forecasting model (Table 3)

Symbol	Description
Index variables	
y	Year
m	Management area (WI, IL, IN, MI)
g	Sex (male = 1, female = 2)
a	Age (2–9+)
l	Length bin (≤ 9, 9–10, ..., 37–38, ≥ 38 cm)
r	Recruitment hypothesis indicator
State and control variables	
N	Actual abundance
$\hat{N}$	Assessed abundance
R	Recruits
SSB	Actual spawning stock biomass (kg, females)
$S\hat{S}B$	Assessed spawning stock biomass (kg, females)
B_0	Unfished spawning stock biomass (kg, females)
$\dot{T}$	Transition matrix for post-recruitment movement
b_0	Intercept for density-dependent growth increment
b_1	Slope for density-dependent growth increment
L	Mean length (cm)
W	Mass-at-length (kg)
Mat	Maturity-at-length
T_{B_0}	Biomass threshold for state-dependent harvest policy
F^*	Asymptotic maximum target F
F	Actual instantaneous fishing mortality rate
$\tilde{F}$	Target F given estimated SSB
$\hat{F}$	F applied to N that would produce same catch as $\tilde{F}$ applied to $\hat{N}$
Z	Instantaneous total mortality rate
C	Catch in numbers (harvest)
$\tilde{C}$	Target catch that would result from applying $\tilde{F}$ to $\hat{N}$
$\dot{p}$	Proportions at length for each age
s	Fishery selectivity
Structural parameters	
α	Ricker stock–recruitment parameter (sim)
β	Ricker stock–recruitment parameter (sim)
c	Ricker stock–recruitment parameter (sim)
p	Proportion of recruits allocated to an area (year)
$\bar{b}_1$	Mean slope for density-dependent growth increment (sim)
τ_0	Intercept for density-dependent length at age 2 (constant)
τ_1	Slope for density-dependent length at age 2 (constant)
γ_0	Intercept for growth model intercept (sim)
γ_1	Slope for growth model intercept (sim)
CV_a	Coefficient of variation of length-at-age (constant)
$\dot{a}$	Mass-at-length parameter (constant)
b	Mass-at-length parameter (constant)
m_1	Maturity-at-length parameter, slope (constant)
m_2	Maturity-at-length parameter, half-saturation (constant)
M	Instantaneous natural mortality rate (constant)
Distributional parameters and associated stochastic errors	
ρ_φ	Autocorrelation coefficient for error in b_1 (constant)
ρ_ϕ	Autocorrelation coefficient of assessment error (constant)
ε	Recruitment deviation (year)
ζ	Error for mean length at age 2 (year)
δ	Error in b_1 (year)
φ	Error for δ (year)
ψ	Assessment error (year)
ϕ	Error for ψ (year)
ν	Implementation error (year)
Σ_ε	Variance–covariance matrix for correlated ε among m (sim)
σ_ε	Standard deviation for ε (sim)
σ_ζ	Standard deviation for mean length at age 2 errors (constant)
σ_φ	Standard deviation for b_1 errors (constant)
σ_ϕ	Standard deviation for assessment errors (constant)
σ_ζ	Standard deviation for implementation errors (constant)

Structural parameters and parameters associated with stochastic errors are identified as constant over simulations and time ("constant"), randomly drawn for a given simulation ("sim") or randomly drawn for each year ("year"). See text and Table 3 for additional details on distributions.

Table 3
Equations used in stochastic simulation model

Population model equations

$$N_{y,m,g,a} = \begin{cases} \dfrac{R_{y,m}}{2} & \text{if } a = 2 \\[2mm] \displaystyle\sum_i \dot{T}_{m,i} N_{y-1,i,g,a-1}\, e^{-Z_{y-1,i,g,a-1}} & \text{if } 2 < a \le 8 \\[3mm] \displaystyle\sum_i \dot{T}_{m,i}\left((N_{y-1,i,g,a-1}\, e^{-Z_{y-1,i,g,a-1}}) + (N_{y-1,i,g,a}\, e^{-Z_{y-1,i,g,a}})\right) & \text{if } a = 9+ \\[2mm] \text{sums over}\{i = \text{WI, IL, IN, MI}\} \end{cases}$$ (T.3.1)

"Area" recruitment

$R_{y,m} = \alpha_{r,m} \text{SSB}_{y-2,m}\, e^{(-\beta_{r,m}\text{SSB}_{y-2,m})}\, e^{\varepsilon_{y-2,m}}; \ \underline{\varepsilon}_y \sim MVN(0, \Sigma_\varepsilon)$

where

$$\alpha_{r,m} = \begin{cases} \alpha_{\text{"recent"},m} \\ \alpha_{\text{"variable–high"},m} \\ c_m \alpha_{\text{"variable–low"},m} \end{cases}$$ (T.3.2)

"Mixed" recruitment

$R_{y,m} = p_m \alpha_r \text{SSB}_{y-2}\, e^{(-\beta_r \text{SSB}_{y-2})}\, e^{\varepsilon_{y-2}}; \ \varepsilon_y \sim N(0, \sigma_\varepsilon^2)$

where

$$\alpha_r = \begin{cases} \alpha_{\text{"recent"}} \\ \alpha_{\text{"variable–high"}} \\ c\alpha_{\text{"variable–low"}} \end{cases}$$ (T.3.3)

$Z_{y,m,g,a} = M + F_{y,m,g,a}$ (T.3.4)

$F_{y,m,g,a} = F_{y,m} s_{y,m,g,a}$ (T.3.5)

$s_{y,m,g,a} = \displaystyle\sum_l \dot{p}_{y,m,g,a,l} s_l$ (T.3.6)

$C_y = \displaystyle\sum_m \sum_g \sum_a \dfrac{F_{y,m,g,a}}{Z_{y,m,g,a}}(1 - e^{-Z_{y,m,g,a}})N_{y,m,g,a}$ (T.3.7)

$$L_{y,m,g,a} = \begin{cases} \tau_{0m} + \tau_{1m}\left(\displaystyle\sum_g \sum_a N_{y-1,m,g,a}\right) + \zeta_{y,m}; \quad \zeta_{y,m} \sim N(0, \sigma_\zeta^2) & \text{if } a = 2 \\[3mm] L_{y-1,m,g,a-1} + \Delta L_{y,m,g,a} & \text{if } a > 2 \end{cases}$$ (T.3.8)

$\Delta L_{y,m,g,a} = b_{0y,m,g} + b_{1y,m,g} L_{y-1,m,g,a-1}$

where

$$b_{0y,m,g} = \gamma_{0m,g} + \gamma_{1m,g}\left(\sum_g \sum_a N_{y-1,m,g,a}\right)$$ (T.3.9)

$b_{1y,m,g} = \bar{b}_{1m,g}\, e^{\delta_{y,m}}; \ \delta_{y,m} = \rho_\varphi \delta_{y-1,m} + \varphi_{y,m}; \ \varphi_{y,m} \sim N(0, \sigma_\varphi^2)$

$\dot{p}_{y,m,g,a,l} = \Phi\left(\dfrac{l+1 - L_{y,m,g,a}}{\text{CV}_a L_{y,m,g,a}}\right) - \Phi\left(\dfrac{l - L_{y,m,g,a}}{\text{CV}_a L_{y,m,g,a}}\right)$ (T.3.10)

where Φ is the normal cumulative distribution function

$\text{SSB}_{y,m} = \displaystyle\sum_l W_{y,m,2,l} \text{Mat}_{y,m,2,l} N_{y,m,2,l}$ (T.3.11)

$W_l = \dot{a}(l + 0.5)^b$ (T.3.12)

$\text{Mat}_l = \dfrac{1}{(1 + e^{(-m_1(l - m_2))})}$ (T.3.13)

Observation and policy implementation

$$\tilde{F}_{y,m} = \begin{cases} (F^*)\dfrac{(\hat{\text{SSB}}_{y,m}/B_{0m})}{T_{B_0}} & \text{if } \hat{\text{SSB}}_{y,m}/B_{0m} < T_{B_0} \\[3mm] F^* & \text{for constant-}F \text{ or if } \hat{\text{SSB}}_{y,m}/B_{0m} \ge T_{B_0} \end{cases}$$ (T.3.14)

$\hat{N}_{y,m,g,a} = N_{y,m,g,a}\, e^{\psi_{y,m}}; \ \hat{\text{SSB}}_{y,m} = \text{SSB}_{y,m}\, e^{\psi_{y,m}}$
$\psi_{y,m} = \rho_\phi \psi_{y-1,m} + \phi_{y,m}; \ \phi_{y,m} \sim N(0, \sigma_\phi^2)$ (T.3.15)

$\tilde{C}_{y,m} = \displaystyle\sum_g \sum_a \dfrac{\tilde{F}_{y,m,g,a}}{\tilde{Z}_{y,m,g,a}}(1 - e^{-\tilde{Z}_{y,m,g,a}})\hat{N}_{y,m,g,a}$ (T.3.16)

where $\tilde{Z}_{y,m,g,a} = M + \tilde{F}_{y,m,g,a}$

$\tilde{C}_{y,m} = \displaystyle\sum_g \sum_a \dfrac{\hat{F}_{y,m,g,a}}{\hat{Z}_{y,m,g,a}}(1 - e^{-\hat{Z}_{y,m,g,a}})N_{y,m,g,a}$ (T.3.17)

where $\hat{Z}_{y,m,g,a} = M + \hat{F}_{y,m,g,a}$

$F_{y,m} = \hat{F}_{y,m}\, e^{\nu_{y,m}}; \ \nu_{y,m} \sim N(0, \sigma_\zeta^2)$ (T.3.18)

growth, and incorporated assessment and implementation error to influence the actual fishing mortality rate that was applied.

3.2. Recruitment models

Recruitment was defined as the number of age-2 yellow perch entering the population annually and was generated for each management area, with an equal sex ratio at recruitment (Eq. (T.3.1)). Yellow perch recruitment is often described by a Ricker stock–recruitment function (e.g., Bronte et al., 1993). We included a separate recruitment model for the area-specific (Eq. (T.3.2)) and mixed-stock (Eq. (T.3.3)) recruitment hypotheses, within which two additional alternative hypotheses for future recruitment potential were represented (recent and variable). As such, these alternatives yielded four stock recruitment hypotheses (Table 1). Depending on the recruitment hypothesis, log-scale Ricker model parameters were drawn from different multivariate normal distributions (i.e., these parameters varied across simulations) with variances and covariances equal to the asymptotic variance–covariance matrix derived from fitting Ricker models to stock-assessment model estimates of SSB and recruitment time series (Wilberg, unpublished data). A multiplicative lognormal error was applied to median recruitment each year (i.e., recruitment was stochastic over time). The log of the standard deviation of the recruitment errors was drawn from a normal distribution; the standard deviation of this distribution was estimated as part of fitting the Ricker models. In connection with the implemented recruitment uncertainty, area-specific maximum-recruitment levels were imposed at four times the maximum estimated recruitment because simulations without this limit produced a few cases of unbelievably high recruitment that strongly influenced the performance statistics.

For the case of recent productivity, Ricker parameters were based on spawner-recruit patterns from stock assessment models for the 1993–2002 year classes (Wilberg, unpublished data). For the case of variable productivity, parameters for two recruitment regimes were identified by classifying year classes as either "high" or "low", regardless of the year, and fitting Ricker models to these subsets of data assuming a common density-dependent term (β; Eqs. (T.3.2) and (T.3.3); Fig. 4). For a given simulation of the variable recruitment hypothesis in the model, the selected Ricker α parameter was scaled downward (c in Eqs. (T.3.2) and (T.3.3)) for years designated to have "low" recruitment. The designation of either a "high" or "low" recruitment regime for a given year was determined by a random Bernoulli variable. The parameter of the Bernoulli distribution (probability of "high" recruitment) was drawn for each simulation from a uniform distribution, $U[0.1, 0.25]$. This uniform distribution was based on an analysis of z-transformed relative year-class strength of age-2 abundance across several decades (cohorts from 1961 to 2000) where the proportion of "above average" recruitment was about 0.2 (Wells, 1977; Wells and Jorgensen, 1983; Wilberg et al., 2005). For hypotheses in which the SSB in each management area produced the recruits for that area ("area"; Eq. (T.3.2)), recruitment errors were correlated among areas for a given year to replicate the high correlation in observed recruitment across areas (Wilberg, unpublished data). Alternatively, the mixed-recruitment scenarios were modeled using total SSB for the entire modeled region to determine the annual number of recruits, and recruitment errors were applied to this total recruitment ("mixed"; Eq. (T.3.3)). Then, total recruits were allocated among the four management areas, with expected proportions of total recruits in an area derived from stock assessment models from 1996 to 2004. Process error was included by considering the proportions of returning recruits to be a random draw from a multinomial distribution with a sample size of 100 so that the expected proportions mimicked the variation in proportional recruitment seen in the stock assessments.

3.3. Post-recruitment abundance dynamics

Over time, the abundance of individual cohorts decreased as they aged and were exposed to sources of mortality that depended upon management area, year, age, and sex (Eqs. (T.3.1) and (T.3.4)). In all simulations, we assumed an instantaneous natural mortality rate of 0.37 yr^{-1} that was held constant across age, sex, area, and time as was the case for the assessment models (Wilberg et al., 2005). Fishing mortality was scaled by age- and sex-specific selectivity that varied over time and among areas (Eq. (T.3.5)), although length-based selectivity was constant over sex, area, and time (Wilberg et al., 2005; Fig. 4). The length-based selectivity pattern was the average selectivity for the recreational fishery in Wisconsin and Illinois (Wilberg et al., 2005). Age-based selectivity was the weighted average of the length-based selectivities with weights equal to the numbers at length for a given age (Eq. (T.3.6)). Thus, variation in growth across sex, area, and time led to the variation in age-based selectivity. Fishery harvest was calculated within each management area, and total annual harvest was used as one of the performance statistics (Eq. (T.3.7)). Modest movement of yellow perch among management areas occurred at the end of the year and was based on a migration matrix that was parameterized using mark-recapture data (Glover, 2005; Eq. (T.3.1)), with the annual amount of emigration for any one area not exceeding 20%.

3.4. Growth, size composition, maturity, and biomass calculations

Growth was represented using a form of the incremental von Bertalanffy growth model that included density-dependent and independent components (Eqs. (T.3.8) and (T.3.9)). Increments in mean length from one age to the next in the following year were projected by management area and sex (Eqs. (T.3.8) and (T.3.9)) so that female yellow perch grew faster and achieved a larger maximum total length than males (e.g., Wilberg et al., 2005; Fig. 4). Growth rates of yellow perch often appear density dependent (Mayer et al., 2000; Headley and Lauer, 2008), with reduced growth rates during periods of high density. However, density-independent processes also have been important for yellow perch growth in Lake Michigan (Horns, 2001). Density dependence was represented by modeling the intercept of the increment in mean length versus initial mean length relationship for each sex and area as a linear function of total abundance in that management area (Eq. (T.3.9)). Density-independent variation in growth was incorporated by modeling the slope of the same relationship by a first-order autoregressive process (AR(1); Eq. (T.3.9); $\rho_\varphi = 0.118$ and $\sigma_\varphi = 0.144$). For all autoregressive processes, the first value of the autocorrelated time series was drawn from a distribution, defined as $N(0,(\sigma^2/1 - \rho^2))$, where σ and ρ are the parameters of the AR(1) process (e.g., σ_φ and ρ_φ for Eq. (T.3.9)). Parameters of the growth models were estimated from mean-length-at-age data for each management area (Wells, 1977; Wells and Jorgensen, 1983; Wilberg et al., 2005). However, these parameters estimates produced unreasonably large or small length-at-age values in the simulation model for population sizes that were outside those used in the estimation. Therefore, we adjusted the parameter values of the density-dependent component so that growth would be reasonable for population sizes outside those used to estimate model parameters while still being consistent with available data. A multivariate normal distribution was then used to generate parameter values (γ_0, γ_1, and $\bar{b}_1$) for the growth sub-model for each simulation. Next, annual size distributions for a given management area and sex were generated by allocating fish from each age class into thirty-one
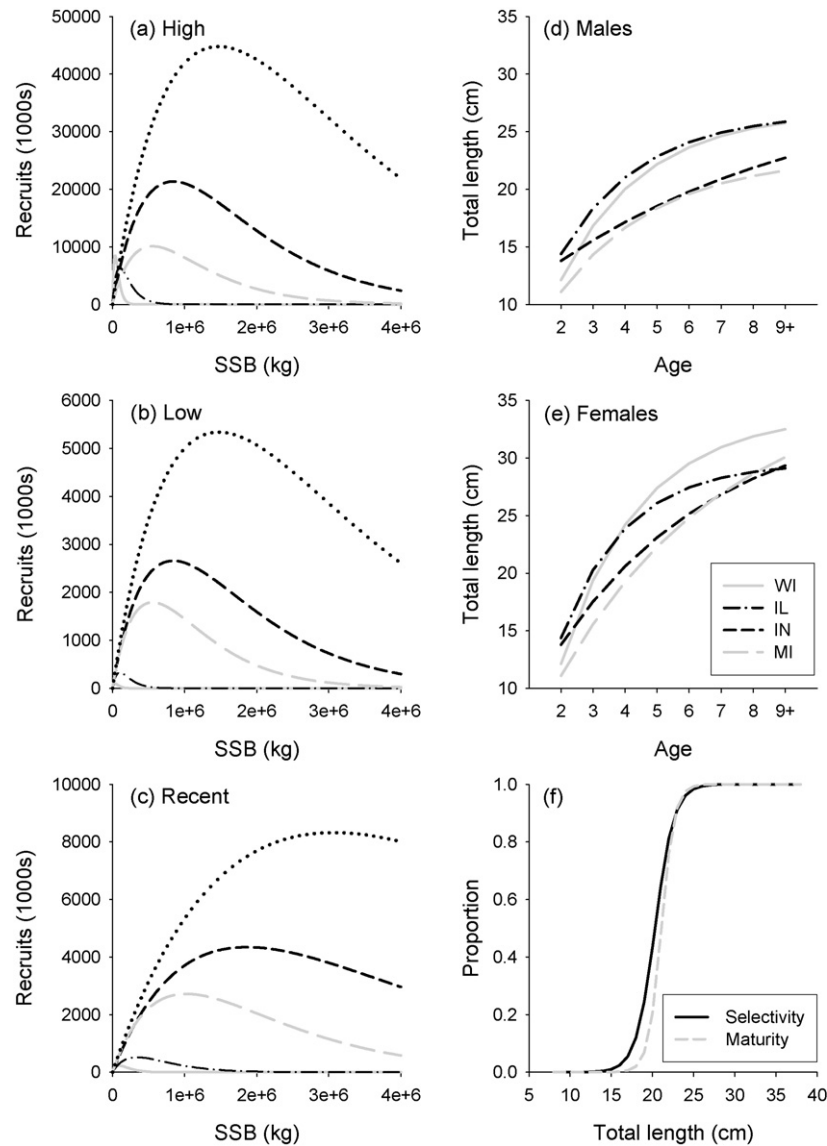
Fig. 4. Relationships for stock–recruitment, growth, maturity, and recreational fishery selectivity. Area-specific and mixed-stock Ricker recruitment models for (a) a "high", (b) a "low", and (c) a recent (1993–2002) recruitment regime. Mixed-stock recruitment relations are indicated with a dotted line in panels a–c, while area-specific curves are identified in the figure legend. Area-specific density-dependent growth curves of (d) male and (e) female yellow perch, based on initial densities. (f) Length-based maturity of female yellow perch and selectivity of the recreational fishery for yellow perch in Lake Michigan. Stochastic variation was not included for these general presentations of recruitment and growth. See text for more details on these population representations.

length bins ranging from <9 to ≥38 cm, in 1 cm increments. Allocation among length bins was done assuming normally distributed length-at-age for each sex, with mean lengths-at-age from the von Bertalanffy model and corresponding CVs (Wilberg et al., 2005; Eq. (T.3.10)).

Rapid growth sometimes allows female yellow perch to become sexually mature at age two (Herman et al., 1964; Brazo et al., 1975; Headley and Lauer, 2008). SSB was calculated based on abundance by length categories of females at the start of the year (reproduction is in spring before growth or substantial mortality), mass-at-length, and the proportion mature at length (Eq. (T.3.11)). Mass-at-length was calculated for the mid-point of each total-length bin, and the relationship between length and mass was constant over time (Wisconsin Department of Natural Resources, unpublished data; Eq. (T.3.12)). Female maturity-at-length followed a constant logistic function (Eq. (T.3.13); Fig. 4) based on a relationship determined for yellow perch collected in Indiana waters of Lake Michigan

(Ball State University, unpublished data; also see Wilberg et al., 2005).

3.5. Harvest policies and control rules

We considered both constant-F and state-dependent control rules. For each control rule, we included simulations for seven levels of the maximum target instantaneous fishing mortality rate (F^*; Table 1), for a total of 21 harvest policies. This range for F^* nearly encompassed the range of fishing mortality rates that have been observed for yellow perch in Lake Michigan since 1986 (Wilberg et al., 2005). For the constant-F control rule, target fishing mortality ($\tilde{F}$) was always equal to F^* (Table 1). For the state-dependent control rules, the maximum $\tilde{F}$ was F^*, and $\tilde{F}$ decreased in proportion to SSB as SSB declined below a threshold, T_{B_0}, of either 0.4 or 0.7 of unfished SSB (B_0; Eq. (T.3.14); Table 1; Fig. 3). Because the recreational fishery was never closed, we refer to the state-dependent

control rules as either 0–40 or 0–70. $\tilde{F}$ was defined in terms of an average fishing mortality rate over ages four and older for females (this relative definition was selected to facilitate future implementation of a commercial fishery with a different selectivity pattern). $\tilde{F}$ was specified separately for each management area, but each harvest policy was implemented as a common basin-wide management strategy in response to preferences expressed by managers for moving towards use of a common strategy across areas. The values of B_0, required for the state-dependent policies, were obtained by repeatedly simulating the population without fishing mortality and calculating the weighted (across recruitment hypotheses) average of SSB for each area in year 50 of the simulations.

3.6. Assessment and implementation error in determining fishing mortality

The model included assessment and implementation errors, so control rules were applied with imperfect knowledge. When state-dependent control rules were used, $\tilde{F}$ depended on estimated, rather than true, SSB. Using an approach similar to Punt et al. (2008), assessment error was modeled by applying a common within-year lognormal error, derived from a first-order autoregressive process ($\rho_\varphi = 0.7$ and $\sigma_\varphi = 0.223$), to actual abundance at each age at the end of each year (Eq. (T.3.15)). Thus, we assumed that assessments have a lognormal error with a CV of about 0.3, which is slightly higher than the CV of posterior estimates of SSB in Wisconsin, about twice as high as the CV of posterior estimates of SSB in Illinois (Wilberg et al., 2005), and is consistent with error levels from similar statistical catch-at-age methods (Wilberg and Bence, 2006). We assumed that stock assessments would be median-unbiased so that an equal amount of the stock assessments were overestimates as were underestimates (Wilberg and Bence, 2006; Eq. (T.3.15)). As part of a sensitivity analysis, we considered an alternative, larger value of assessment error with a CV of 0.75 ($\rho_\varphi = 0.7$ and $\sigma_\varphi = 0.536$). Implementation of the harvest policy assumed that assessments would take place each year at the end of the year, and that SSB within a management area would be calculated by projecting the estimated abundances at age forward using the target fishing mortality rate to determine the estimated SSB for the next year.

Assessment error also influenced the recreational fishing mortality rates applied to the simulated population in another way. Although we do not explicitly model the regulatory process by which managers attempt to influence recreational fishing mortality, we presume this process is designed to target a desired numerical harvest, which the simulated analyst believes will achieve $\tilde{F}$. This desired harvest, however, corresponds to $\tilde{F}$ applied to the assessed, rather than actual, abundance (Eq. (T.3.16)). We therefore calculated this desired harvest for each management area based on the assessed abundance for that area, then numerically solved using Newton–Raphson iterations for the area-specific fishing mortality rate, $\hat{F}$, that would produce this same harvest when applied to the actual population (Eq. (T.3.17)). We set a maximum on $\hat{F}$ of 2.7 yr^{-1}, because in some cases assessment error led to a desired harvest that could not be achieved. This value was arbitrary but reasonable in that fully selected individuals would experience about 95% annual mortality if this cap on fishing mortality was reached.

Once determined, $\hat{F}$ would only be achievable if managers had perfect control of the harvesting process (i.e., if there were no implementation error). Implementation error can be substantial in recreational fisheries because the effective amount of fishing pressure can differ from what was expected. In our simulations, an independent lognormal implementation error ($\sigma_\zeta = 0.08$) was added to $\hat{F}$ to produce the actual fishing mortality rate, F, applied to the population (Eq. (T.3.18)). This level of implementation error corresponds to about one third of the annual variability in recre-

ational fishing effort during a baseline period when the recreational fishery for yellow perch was largely unregulated (Wilberg, unpublished data). We assumed that managers would be able to achieve a lower amount of variability than an unregulated fishery.

3.7. Performance statistics

Performance statistics were either time averages of performance variables or the percentage of years when performance variables were below designated thresholds during a 50-year simulation (Table 1). The performance variables highlighted here are based on SSB, numbers of fish harvested, and mean length of harvested fish. Values for each performance variable were first generated by combining across ages, sexes (when necessary), and management areas for each year of each simulation. For threshold-based performance statistics, indicator variables were defined and set to 1.0 for years when performance variables were below desirable thresholds and otherwise to zero. First, we present summaries of the distributions of performance statistics for each policy as box plots (1000 simulations per policy), where the performance statistics for each simulation were weighted by the probability assigned to that simulation (Fig. 2). We also considered alternative weighting schemes, when summarizing the results, including equal probabilities for each recruitment hypotheses as well as assigning a probability of 1.0 to each recruitment hypothesis in turn as part of a sensitivity analysis. We present only the means of these distributions for graphical presentation of tradeoffs among performance statistics.

4. Results and discussion

4.1. Temporal patterns in average abundance and harvest

After initial transient dynamics, average annual abundance and recreational harvest appeared to approach or fluctuate about a long-term mean by the end of the 50-year time horizon for constant-F and state-dependent control rules for both a low ($F^* = 0.3$ yr^{-1}) and a high ($F^* = 1.5$ yr^{-1}) level of fishing intensity (Fig. 5). Initial transients appeared to stem from the age distribution used at the start of each simulation, which was dominated by a single older cohort. Qualitative differences in yellow perch abundance among the control rules at a given F^* ranked as 0–70 > 0–40 > constant-F (Fig. 5a). Differences in abundance among control rules were larger when F^* was higher because under these lower abundance conditions the state-dependent rules often had reduced fishing mortality rates.

Average harvest underwent a decline and subsequent increase during the first 10 years for all policies, with this being more marked when target fishing mortality was higher ($F^* = 1.5$ yr^{-1}; Fig. 5b). At this higher level of fishing, average harvest then remained relatively high for the state-dependent control rules for the duration of the 50-year simulation period. In contrast, harvest declined markedly during years 10 through 30 for a constant-F rule ($F^* = 1.5$ yr^{-1}), approaching the level seen for all control rules when fishing intensity was lower ($F^* = 0.3$ yr^{-1}). In part, this result reflects an expected dome-shaped relationship between harvest and fishing mortality rate. However, the state-dependent rules produced higher harvests than the peak from the constant-F rule.

4.2. Performance statistics versus F^*

Performance statistics showed different patterns across the seven levels of fishing mortality and among control rules. SSB decreased as F^* increased, with this effect being largest for the constant-F rule and smallest for the 0–70 rule (Fig. 6a). For all control rules, an F^* as low as 0.3 yr^{-1} led to average SSB on the order
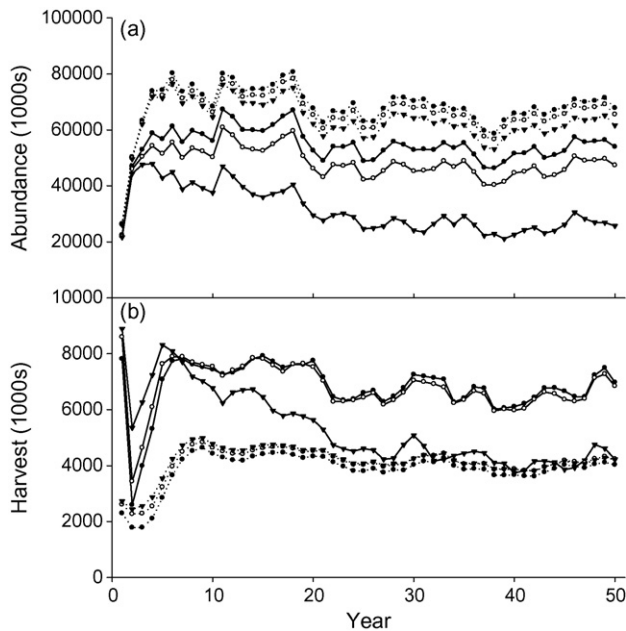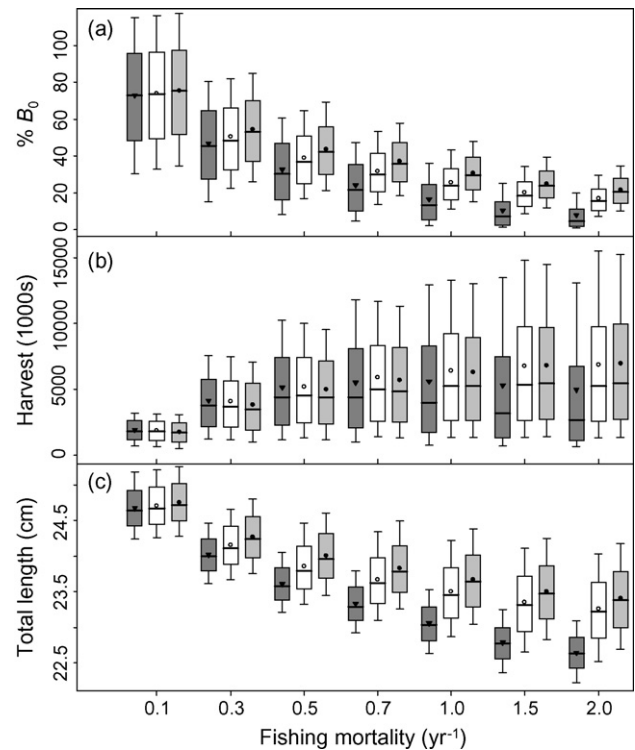
Fig. 5. Time series of (a) average yellow perch abundance and (b) average recreational harvest for constant-F (▼), 0–40 (○), and 0–70 (●) control rules. The group of dotted lines refer to $F^* = 0.3\,\mathrm{yr}^{-1}$, and the group of solid lines to $F^* = 1.5\,\mathrm{yr}^{-1}$.

Fig. 6. Distributions of performance statistics calculated on the basis of the 50-year simulation time horizon for constant-F (▼), 0–40 (○), and 0–70 (●) control rules across seven fishing mortality rates as measured in terms of (a) average percentage of unfished spawning stock biomass (B_0) remaining in the system, (b) average recreational harvest, and (c) average size of yellow perch in the recreational fishery. Symbols on box plots are averages; box plots are defined as the containing the 25th and 75th percentiles with the median value identified with a heavy horizontal line, and whisker bars are the 10th and 90th percentiles. These distributions are calculated over the recruitment hypotheses by weighting results from each of the 1000 stochastic simulations by the probability for the associated hypothesis.

of 50% or less of unfished levels. While this is not completely unexpected, it is important for managers of this fishery to recognize that even fishing rates that are low by historical standards are likely to have appreciable effects on population size.

For a constant-F control rule, average harvest peaked at an intermediate F^*, although the similar results for $F^* = 0.5$, 0.7, and $1.0\,\mathrm{yr}^{-1}$ show that there is a broad range of fishing rates that can produce average harvest near the peak amount (Fig. 6b). Average harvest appears to approach an asymptote as F^* increased for the state-dependent rules in contrast to the constant-F control rule, and this apparent asymptote substantially exceeded the peak for the constant-F rule (Fig. 6b). Given the recreational selectivity and maturity patterns of yellow perch and our use of state-dependent control rules where the fishery is not closed at low stock sizes, average harvest must also eventually decline when fishing mortality is sufficiently high for those rules. Thus, the apparent asymptote actually reflects a broad peak in the harvest versus F^* curve, with declines in harvest occurring outside the range of F^* explored by these simulations.

Qualitative patterns for average total length of harvested yellow perch were similar to those for average SSB; it decreased with increasing F^*, even though growth was modeled as density dependent. At any given F^*, the control rules ranked as 0–70 > 0–40 > constant-F for the average length performance statistic (Fig. 6c). The relationship between the average size of fish harvested and level of fishing mortality is to be expected (Russell, 1942; Allen and Miranda, 1995).

Performance statistics that considered the amount of time spent in an undesirable state also revealed differences among the constant-F and state-dependent polices (Fig. 7). For these performance statistics, low percentages (fewer years) were preferable. As might be expected, the average percentage of years when SSB was less than 20% of B_0 increased with increasing F^*, and the control rules ranked the same as for average SSB (Fig. 7a). Harvest was more frequently below the desired annual amount of 1.5 million fish for all control rules at the lowest levels of fishing intensity, with a substantial decrease in the percentage of years below this amount when F^* increased to $0.3\,\mathrm{yr}^{-1}$ (Fig. 7b). The percentage of years

below the threshold was generally less sensitive to further increases in fishing mortality for the state-dependent rules; whereas, the percentage increased substantially as F^* increased beyond $0.7\,\mathrm{yr}^{-1}$ for the constant-F rule. The percentage of years with harvest below the threshold was markedly more variable for the constant-F rule than for state-dependent rules. For all policies, the average percentage of years with harvest below the threshold exceeded 25% (Fig. 7b). The average percentage of years with average total length less than the desirable threshold was less than 6% across all policies (Fig. 7c), and the qualitative patterns in average percentage were the same as reported for average total length of harvested fish and for SSB. At the higher levels of F^* in particular, the percentage of years below the threshold became markedly greater for the constant-F rule.

4.3. Tradeoffs between performance statistics

Evaluating tradeoffs becomes a critical step in decision making when managers are interested in multiple performance statistics. In general, managers face a tradeoff between maintaining a population near its pristine state and achieving high harvest (e.g., Rademeyer et al., 2007). The existence of such tradeoffs was evident when comparing performance statistics related to either SSB or average length of fish harvested with those related to harvest as F^* increased (Figs. 6 and 7). It was conceivable *a priori* that the different control rules would make similar tradeoffs so that constant-F and each of the state-dependent rules could achieve the same expected values of performance statistics, albeit at different F^* values (Katsukawa, 2004). This turned out not to be the case,
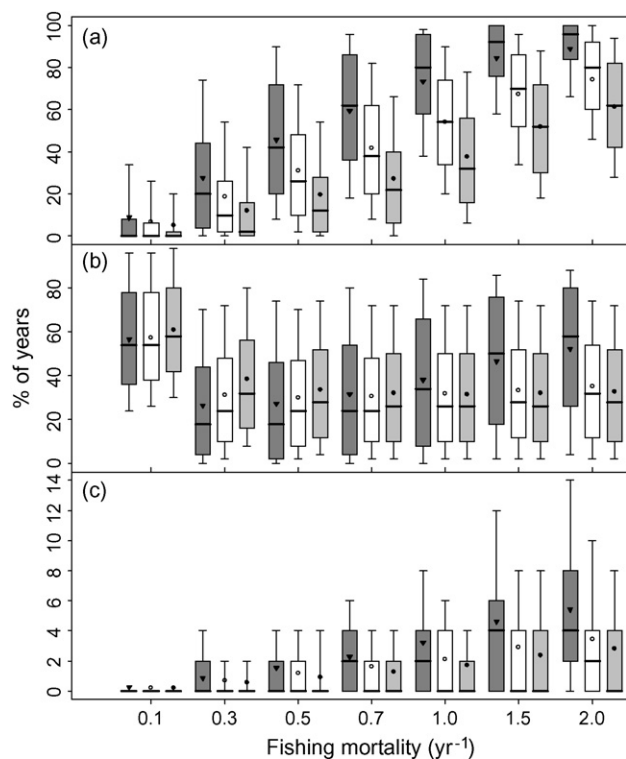
Fig. 7. Distributions for percentage of years spent below undesirable threshold conditions for constant-F (▼), 0–40 (○), and 0–70 (●) control rules across seven fishing mortality rates as measured in terms of (a) years with less than 20% of unfished spawning stock biomass, (b) years with recreational harvest less than 1.5 million fish, and (c) years with an average size of yellow perch in the recreational harvest less than 21.59 cm (8.5 in.). Symbols on box plots are average values. For definition of averages and box plots, see Fig. 6 caption. Note differences in y-axes.

as shown, for example, by the higher peaks of average harvest for state-dependent control rules than for the constant-F control rule (Fig. 6b).

We further explored tradeoffs among performance statistics through pairwise comparisons of their expected values. These comparisons emphasized that state-dependent rules produced higher expected recreational harvests and generally lower expected percentage of years with depleted stocks than the constant-F rule when a similar expected percentage of unfished SSB remained in the system (Fig. 8a and b). In contrast, the constant-F rule had lower expected frequencies of low harvest years (more desirable) than did the state-dependent rules, when expected SSB was in the range of about 30–60% of unfished levels (Fig. 8c). Similarly, the expected percentage of years with low harvests was lower for the constant-F control rule for intermediate values of the expected percentage of years with low SSB (Fig. 8d). State-dependent polices produced a lower frequency of years with low SSB levels across the range of expected harvests (Fig. 8e); whereas, the constant-F rule could more often avoid low harvests for some intermediate expected harvests (Fig. 8f). Tradeoffs between size of harvested fish and other performance statistics are not shown but displayed similar patterns.

### 4.4. Comparison of recruitment hypotheses and recruitment uncertainty

Stock productivity will affect the performance of implemented harvest policies (e.g., Ianelli and Heifetz, 1995; Deroba and Bence, this issue; Punt et al., this issue). Here, our primary goal was to integrate over the uncertainty in possible stock–recruitment rela-

tionships rather than to explore how policies responded to the particular relationships. Nevertheless, results of a sensitivity analysis illustrate the importance of the relationship (Fig. 9a–e) and strongly suggest that if one of the four recruitment hypotheses was known to be true, then this knowledge would likely influence preferred levels of fishing. The qualitative patterns in the distributions among control rules based on alternative weightings of the recruitment hypotheses were similar to those in Figs. 6 and 7 (results not shown). While the general patterns among harvest policy tradeoffs were quite robust to alternative weightings (Fig. 9a–e), the magnitude of several expected performance statistics were sensitive to adjusting the degrees of belief assigned to alternative states of nature (e.g., average harvests were relatively low in the "area" recruitment scenarios). Given the parameterizations used here, the "mixed" stock–recruitment representations typically produced higher average recruitment than did projections based upon independent spawning stocks (Fig. 4a–c). Yellow perch attained larger sizes when recruitment was lower, and the average size of yellow perch harvested was larger for the lower recruitment hypotheses because of density-dependent growth. However, this increased individual biomass did not fully compensate for reduced population abundance, and expected SSB was considerably lower for the lower recruitment hypotheses. Likewise, expected harvests were lower for these hypotheses (Fig. 9a–e).

Actual performance statistics that will result in the future will be strongly influenced by the level of recruitment in the Lake Michigan yellow perch population. Unknown factors will play a large role, and our simulations suggest that there is a substantial chance that low recruitment will lead to some years of low harvest, regardless of the implemented policy (Figs. 6b and 7b). Beyond the four recruitment hypotheses considered here, there is some evidence supporting an alternative hypothesis that areas on the western side of Lake Michigan potentially contribute an even larger proportion of recruits per unit spawning biomass than was considered in our analysis (Wilberg et al., 2008). This possibility was not incorporated into the current analysis. However, Wilberg et al. (2008) used the yellow perch simulation model described here to explore how sensitive our results are to such extreme cases of "source–sink" population dynamics. Data that better characterize the stock–recruitment relationship for yellow perch could be very informative (sensu Clemen and Reilly, 2001), especially if these data reduced the uncertainty attributed to mixing of recruits among management areas. The justifiable amount of investment in research to improve our understanding of this issue is a topic for further analysis, as the research costs could also be substantial.

4.5. Summary and general discussion

Deciding upon an appropriate harvest strategy should rely on cooperation among researchers and resource managers (Johnson and Martinez, 1995). An important part of this process for the yellow perch fishery of southern Lake Michigan was a series of workshops with fish biologists and fisheries managers, where their opinions were elicited. This input led us to restrict consideration to policies that allowed some fishing at all stock sizes and to consider performance statistics related to harvested fish size and those based on proportions of years below thresholds. Without these workshops and input, it is likely that we would have considered unacceptable harvest policies and not summarized results for some of the measures that are important to managers. In retrospect, one could argue that consideration of the length of harvested fish did not add much to our evaluation. Mean length did not change substantially over the full range of policies, was correlated with
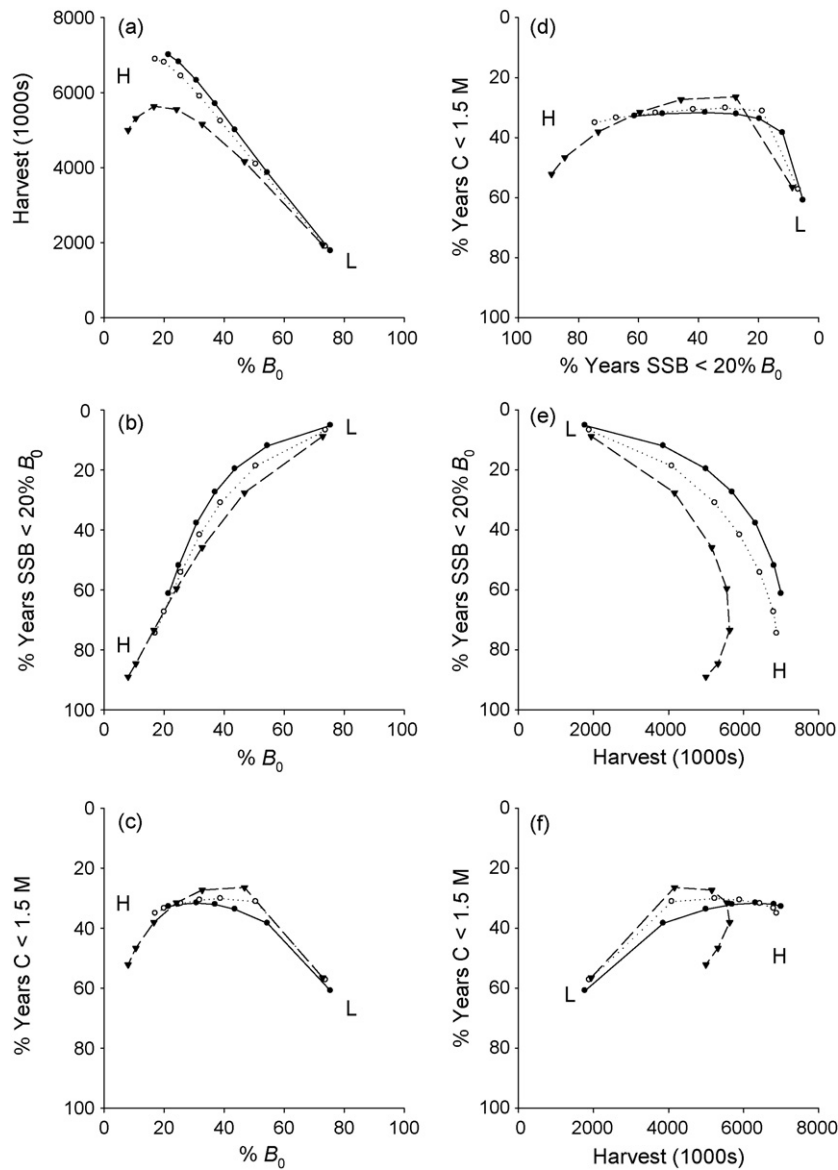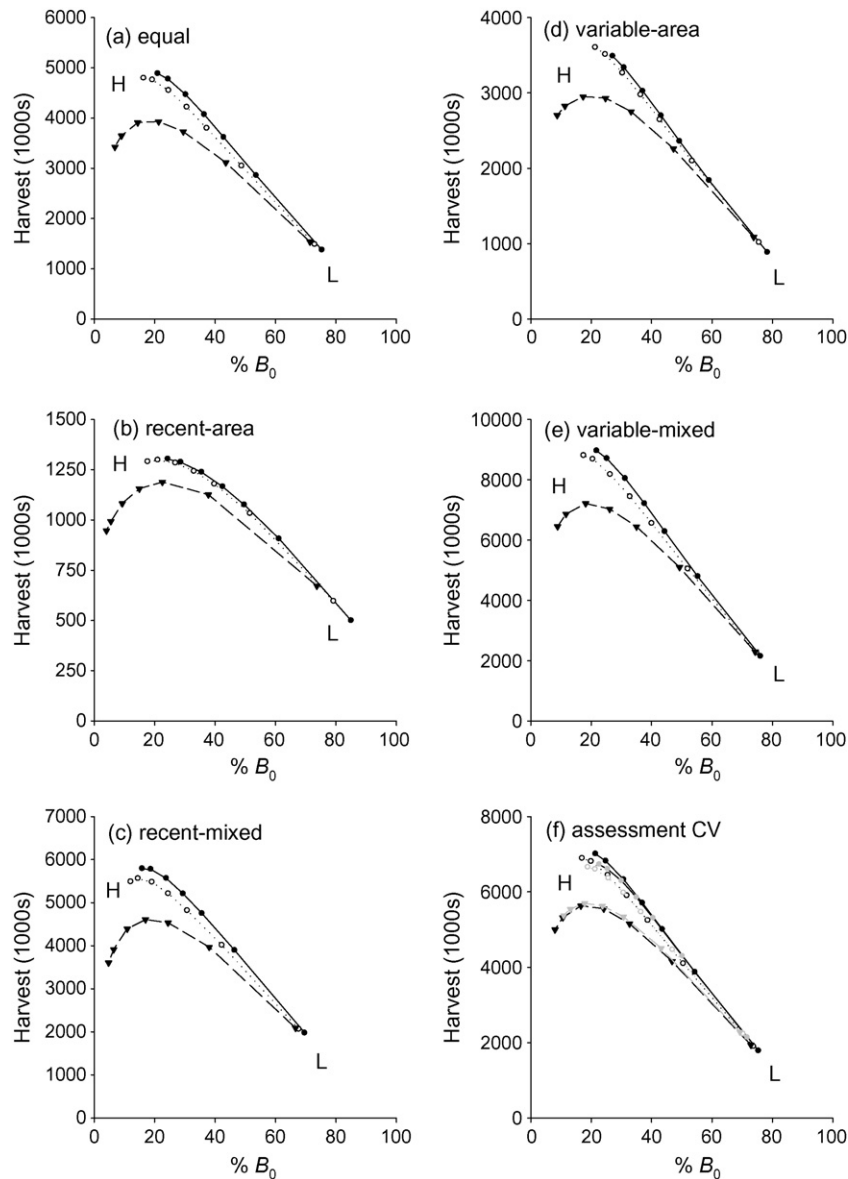
Fig. 8. Pairwise plots illustrating tradeoffs among performance statistics for constant-F (▼) 0–40 (○) and 0–70 (●) control rules for seven fishing mortality rates. Performance statistics are shown as averages over the 1000 realizations illustrated in Figs. 6 and 7 and include average recreational harvest (Harvest), the average percentage of unfished spawning stock biomass remaining in the system (% B_0), the average percentage of years that SSB was below 20% of B_0 (% Years SSB < 20% B_0), and the average percentage of years that recreational harvests were below 1.5 million fish (% Years C < 1.5 M). For each panel, axes are arranged so that the preferred range of the performance statistics is farthest from the origin, and low (L) and high (H) fishing mortality rates are indicated towards their respective ends of the plotted lines.

other performance statistics, and exceeded the threshold in most years. This said, without producing these results it would have been difficult to convince managers that a given policy could produce harvests of acceptable sizes of fish. This could have undermined the entire process given that harvested fish size is important to Lake Michigan yellow perch anglers, as is often the case in recreational fisheries. Consideration of thresholds did help emphasize tradeoffs important to managers. For policy parameters producing similar amounts of average stock depletion and harvest, the state-dependent rules led to fewer years with low biomasses but sometimes more years with low catches.

Our approach was to parameterize a simulation model based on available data for yellow perch in southern Michigan, which we used to forecast policy performance. The model incorporated multiple recruitment hypotheses, other parameter uncertainty, process variation, and uncertainty associated with stock assessment and policy implementation. This can be considered a management

strategy evaluation (Smith et al., 1999; Sainsbury et al., 2000; Rademeyer et al., 2007), because multiple performance statistics and harvest control rules were considered, and errors in assessment and implementation were incorporated. In contrast with some management strategy evaluations, we modeled assessment error in a simplified fashion, drawing errors from an assumed distribution rather than incorporating the process of fitting assessment models into our simulations. We adopted this approach because it allowed for conducting many more simulations, given the computational costs of the actual assessment process. Although incorporating the full assessment process would have been more realistic, we suspect our results were robust to this simplification, given the general lack of sensitivity to changes in assessment error variance.

The relative performance of state-dependent and constant-F control rules reported here generally appears to be consistent with previous reports. When different control rules used policy param-

Fig. 9. Pairwise plots illustrating tradeoffs between average recreational harvest (Harvest) and the average percentage of unfished spawning stock biomass remaining in the system (% B_0; scaled to hypothesis-specific B_0) for constant-F (▼), 0–40 (○), and 0–70 (●) control rules for seven fishing mortality rates. Alternative weightings across the four recruitment hypotheses include (a) equal weighting as well as (b–e) assigning 100% probability to each recruitment hypothesis in turn. (f) The base-case weighting scheme (black) is also shown along with results for higher assessment error (gray). For each panel, axes are arranged so that the preferred range of the performance statistics is farthest from the origin, and low (L) and high (H) fishing mortality rates are indicated towards their respective ends of the plotted lines.

eters that produced similar amounts of average stock depletion, state-dependent rules led to better results in terms of other performance statistics, except that constant-F rules allowed for fewer years with low harvests at moderate levels of fishing mortality. Katsukawa (2004) reported similar results for the same state-dependent control rules for a much simpler operating model that did not incorporate parameter uncertainty. The higher percentages of years with low harvest for the state-dependent rules is consistent with the general observation that the benefits of state-dependent control rules come at the expense of higher variances in the amount of fish extracted (Lande et al., 1997; Deroba and Bence, this issue).

The lack of sensitivity to the magnitude of assessment error variance in this study (Fig. 9f) is one result that appears to diverge from previous reports. In the absence of assessment error, average yield is generally highest for a constant escapement rule relative to

any other control rule (Frederick and Peterman, 1995; Lande et al., 2001). However, average yield can become higher for a constant-F rule in the presence of assessment error (Frederick and Peterman, 1995; Deroba and Bence, this issue). The state-dependent control rules that we explored can be viewed as intermediate between constant escapement and constant-F rules, and generally such rules can produce higher yields than constant-F rules in the absence of substantial assessment error (Deroba and Bence, 2008). This advantage over a constant-F rule has been shown to diminish or disappear as assessment error variance increases (Katsukawa, 2004; Deroba and Bence, this issue). Although we explored a range of assessment error variances, where such effects were evident in other studies, we did not see them. We suspect that complexities in our simulation model, particularly the large demographic parameter uncertainty, and use of a single control rule across management areas with different stock–recruitment relationships, eclipsed most

effects of assessment error on the relative performance of control rules. This is a topic warranting further investigation.

The decision analysis approach used in this study integrated parameter uncertainty into evaluation of how distributions of performance statistics were influenced by control rules. Although not unique among harvest strategy evaluations (e.g., Vasconcellos, 2003), such explicit integration of parameter uncertainty is not standard. We believe that much is left to be learned about how parameter uncertainty interacts with process variation and uncertainty associated with stock assessment and policy implementation. Decision analysis often focuses on expected values of performance variables, integrated over the possible parameter values. We emphasize that actual performance may depart greatly from these expected values (Peterman and Anderson, 1999) and urge careful consideration of the estimated distribution of performance statistics because some possible, but relatively unlikely, outcomes may be considered disastrous should they occur (Punt and Hilborn, 1997).

The analyses reported here are currently being considered by managers of the Lake Michigan yellow perch fishery as they strive to develop a harvest policy. Some individuals, such as the authors of this paper, would prefer a state-dependent control rule with a modest fishing level. It is important to recognize that this preference reflects a value judgment. Others with less concern about low stock sizes relative to concern about low harvest might argue for a higher rate of fishing, or perhaps for the constant-F rule to more often avoid years with low harvests. These kind of issues need to be considered by the managers of this and other fisheries. Perhaps an ideal approach would be to construct an agreed upon utility function that appropriately and completely integrates over possible outcomes and multiple variables and thus completely captures the goals for management. However, this challenge is often unmet.

We emphasize that not all uncertainty can be captured by any model, and unexpected changes could occur in the Lake Michigan system in the future. For example, depensatory mortality may occur for early life stages of yellow perch when at low densities (Forney, 1971), but such a mechanism was not included in our model. Likewise, our analysis did not include annual, sex-, area-, or age-based variation in natural mortality, or uncertainty in the constant value that we assumed, in order to focus on uncertainties selected through a series of project workshops. While discussions and interactive workshops were critical to the development of this decision analysis, we recognize that they do not ensure that the most important uncertainties will be identified. Future exploration of how robust our results are to alternative assumptions about natural mortality would be valuable. Given our uncertainties about uncertainty and ongoing collection of new information, performance of any harvest policy that is implemented should be carefully evaluated, and the policy should be updated when important new information becomes available.

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