MODELS TO AID IN THE SELECTION OF PROCEDURES USED TO MANAGE LAKE ERIE WALLEYE (SANDER VITREUS)

By

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ABSTRACT

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Management procedures define the set of actions that will be used to guide effective fisheries management. Common procedures include collecting data, conducting a population assessment, and defining a set of harvest control rules to formulate a harvest policy. The objectives of my dissertation research were structured to address some of the key questions associated with each of these procedures in the management of Lake Erie walleye (Sander *vitreus*); thereby providing science-based support to some of the more critical decisions concerning rational walleye management. Walleye are intensely managed in Lake Erie because of the economic, social, and cultural value of the fishery to the North American Great Lakes region and because it is an ecologically important species (apex predator) in Lake Erie. I begin by introducing the walleye fishery, providing the essential context from within which it is currently managed (chapter 1), before explicitly evaluating each research objective. The first research objective (chapter 2) was to investigate if accommodation for spatial structure at scales relevant to walleye movement patterns, at the expense of model complexity, improved the annual population assessment procedure. There was strong statistical evidence that incorporating spatially referenced vulnerability and catchability parameters improved model fit, and the change altered estimates of stock size and fishing mortality. The second research objective (chapter 3) was to improve a data collection procedure – research survey indices of walleye abundance – by statistically accounting for factors inherent in survey data that confound the ability to detect true

trends in population abundance. Models recognized several factors (e.g., net set type, secchi depth, sampling week, and the presence of hypoxia) affecting the direction and magnitude of predicted abundance trends, though a different combination of factors were identified for Canadian and United States surveys. The third objective (chapter 4) was to directly aid decisionmakers by quantitatively comparing the performance of alterative walleye harvest policies under three different data collection and population assessment schemes while explicitly incorporating uncertainty in the management process (i.e., to conduct a management strategy evaluation). Because uncertainty leads to risk, quantitatively accounting for uncertainty gives managers a measure of how risky a particular management decision may be and provides a risk assessment framework in which to compare tradeoffs among alternative management procedures. Results indicate that harvest policy performance and the ensuing tradeoffs between conflicting objectives were conditional on the choice of a data collection and assessment scheme. For the explicit policies evaluated, annual age-structured procedures outperformed other procedural schemes (i.e., triennial age-structured and annual survey index) and provided the overall best balance between harvest and risk-related tradeoffs. However, the extra effort associated with implementing annual SCA management procedures only provided a modest improvement in policy performance over triennial SCA management procedures.

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The material presented in Chapters 2-4 was prepared in manuscript form with a specific scientific journal in mind. Therefore, I would like to acknowledge the intended coauthors of these manuscripts: Dr. Michael L. Jones, Dr. James R. Bence, and Dr. Yingming Zhao. Despite being in manuscript form, there will inevitable be differences between what is presented here and what is eventually published.

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CHAPTER 1

INTRODUCTION

Lake Erie is the smallest by volume of the five Laurentian Great Lakes, but it produces the highest fishery yields (Munawar and Munawar 1982). The nutrient-rich, eutrophic to mesotrophic going from west to east, waters of the lake provide the basis for a lucrative coolwater fishery. The Lake Erie percid fishery (represented historically by walleye, yellow perch, sauger, and the now extinct blue pike) has been both a socially and economically important resource throughout the twentieth century, representing about a quarter of the total commercial harvest and recreational effort in all of the Great Lakes combined (Koonce et al. 1999; Brown et al. 1999; Bence and Smith 1999). In recent years, the fishery has been dominated by catches of walleye and yellow perch with a conservative regional economic impact estimate of over \$1 billion (U.S.) per year (ASA 2006; Roseman et al. in press). Oversight and management are critical to ensure that this multi-use fishery remains sustainable. Maintaining a healthy walleye population has been recognized as a necessary condition to achieve broader fish community goals (Ryan et al. 2003), because walleye, the dominant terminal predator in much of the lake, act to stabilize the food web with top down predatory control (Knight and Vondracek 1992; Makarewicz and Bertram 1993).

The walleye fishery is managed by the Lake Erie Committee (LEC) under the auspices of the Joint Strategic Plan for Management of Great Lakes Fisheries (GLFC 1981). The LEC consists of a representative from each member authority (four U.S. states and one Canadian province) and is charged with setting annual harvest levels within the walleye quota management zone (the west and central basins). Management of walleye harvest is currently guided by an exploitation policy with a set of governing control rules, such that the allowable rate of fishing is lower when abundances are low and higher when abundances are high (Wright et al. 2005; Locke et al. 2005; Jones and Bence 2009). The annual fishing rate is then translated into a total allowable catch (TAC) quota and allocated among authorities and fisheries (recreational and commercial) by the LEC. The commercial walleye fishery is exclusive to Canadian waters and has limited fishing capacity with a finite number of licenses available; the recreational fishery is largely in U.S. waters (97% and 95% of total recreational harvest and effort, respectively; WTG 2009). Implementation of the exploitation policy requires knowledge of walleye population abundance. This is currently estimated on an annual basis using a statistical catch-at-age (SCA) stock assessment model that is informed by both fishery-dependent and fishery-independent sources of data (WTG 2009).

The research undertaken in this dissertation was designed to address questions associated with establishing suitable management procedures for the Lake Erie walleye fishery. "Management procedures" refer to the set of procedures commonly applied in pursuit of rational fisheries management including the collection of representative data, an assessment of population status, and the application of a harvest policy (Butterworth et al. 1997; Butterworth 2007). Improving the population assessment (chapter 2) and the interpretation of survey data (chapter 3) may help to reduce uncertainty associated with walleye population status and thus improve the efficacy of the harvest policy. Quantitatively evaluating trade-offs between alternative walleye management strategies (chapter 4) given uncertainty in the management process should provide valuable insight into the development of robust fishing policies and,

through the explicit involvement of stakeholders, credence in the resultant policy. The scope and relevance of this work extends beyond management of Lake Erie walleye because improving the way in which ecological knowledge, statistical methods, and decision science interact and ultimately result in science-based management decisions is of general importance to the conservation and management of freshwater and marine fisheries, and is an active area of research in fisheries science (Lane and Stephenson 1998; Peterman 2004).

A central component in the management process is the yearly assessment of population status. Because a vast majority of walleye in Lake Erie occur in the west and central basins, the population in this area is assessed independently of the smaller eastern basin population and is managed by allocating a total allowable catch (TAC) quota to each authority. The general structure of the current assessment model has been used as the standard evaluation tool to describe the walleye population since 2001 (Walleye Task Group 2002). As information on walleye population dynamics improves, alternative model structures (i.e., assumptions about the factors influencing walleye dynamics) should be explored periodically. For example, recent evidence suggests spatial differences in the age composition of walleye going from west (younger individuals near major spawning grounds) to east (older individuals utilizing more favorable habitat, further from spawning areas; Wang et al. 2007), which could imply a need for spatially incongruent assumptions about how vulnerable walleye of a given age (or size) are to fishing or survey sampling. Uncertainty surrounding catchability – the theoretical proportion of fish caught with one unit of effort - is a common source of process error in stock assessment models. Because not accounting for major changes or trends in catchability has been show to bias estimates (Wilberg and Bence 2006; Chen et al. 2008), it is important to also periodically

test assumptions regarding catchability in stock assessment models. Improving the stock assessment model is one way to increase knowledge about the population and improve management performance.

Chapter 2 investigates whether incorporating spatial structure at scales relevant to walleye movement patterns improves the annual population assessment procedure. Several alternative model formulations were developed and evaluated across assumptions relating to walleye vulnerability, catchability, and spatial structure. Results indicate a clear preference for incorporating spatial structure into the stock assessment by applying regional vulnerability and catchability parameters. Estimates of stock size and fishing mortality changed using the improved best spatial model over the best non-spatial or aggregate model. Accounting for key life history differences among individuals in the population (such as movement rates) can have a consequential impact on assessment results, and thus management advice that follows.

Improving the quality of data used in population assessments is another way to enhance management performance. Standardization of data that originate from either the fishery itself or from independent surveys can lead to marked improvements in data quality (Hilborn and Walters 1992; Maunder and Punt 2004). Standardization is the process of fitting statistical models to catch and effort data to account for confounding factors before extracting the effect of interest (e.g., annual abundance index; Quinn and Deriso 1999; Maunder and Punt 2004; Ye et al. 2005). For example, fishery-independent catch-per-effort (CPE) data are collected from annual research surveys and implemented as auxiliary time series indices of relative abundance to help improve SCA assessment model accuracy and precision (Deriso et al. 1989; Quinn and Deriso 1999;

Chen et al. 2003). However, there are many factors other than abundance that can influence survey catch rates and potentially render the nominal (or unadjusted) survey index misleading.

Chapter 3 investigates whether statistically accounting for factors inherent in survey data (i.e., catch rate standardization) has an influence on resulting abundance trends. General and generalized linear mixed models were used to standardize Canadian and United States fishery-independent surveys at the basin-level. Spatial, temporal, and environmental factors were recognized as affecting the direction and magnitude of predicted abundance trends, resulting in considerable annual variation in the difference between indices. Yet, overall abundance trends across the time series were generally similar between the standardized and nominal (non-standardized) indices. Alternatively, trends in abundance differed markedly between basins due to discrepancies in availability (population structure) and selectivity (gear efficiency) to fishing gear. Standardized indices for walleye population assessments are recommended because these account for factors other than abundance clearly demonstrated to influence catch rates.

Uncertainty is pervasive in fisheries management; thus it is prudent to account for this uncertainty when providing management advice. Consequently, it is beneficial to consider uncertainty associated with the entire management process (e.g., management strategy evaluation; MSE) when attempting to decide what management strategy will best meet objectives. Because population assessment and harvest strategy procedures are often linked in a closed system loop (i.e. the population assessment procedure influences the harvest strategy and in turn the harvest strategy influences the population assessment), it is especially critical that these procedures be evaluated concurrently (National Research Council 1998). By explicitly incorporating uncertainty into the management process, a more realistic range of plausible

outcomes from a given management strategy can be evaluated through simulation and then compared among alternative strategies so that information regarding the expected performance of each strategy is available to managing authorities. This method allows managers to quantitatively compare and contrast alternative harvest policy scenarios for a given data collection and population assessment method.

Similar to decision analysis (Peterman and Anderson 1999), management strategy evaluation utilizes the general themes of adaptive management and risk assessment (Walters 1986; Butterworth and Geromont 1997; Smith et al. 1999; Sainsbury et al. 2000). The five general steps in a management strategy evaluation (de la Mare 1996; Cox and Kronlund 2008) are to:

- 1. define clear management objectives
- 2. develop performance measures for each objective
- identify candidate management procedures (data collection, stock assessment, harvest strategy)
- 4. conduct a prospective evaluation of procedures against objectives
- 5. communicate results to decision-makers

This approach provides an objective basis for acquiring information on which to base management decisions, which can be particularly beneficial when there are multiple, conflicting objectives.

The current Lake Erie walleye harvest strategy applies a feedback (or state-dependent) policy that sets the fishing mortality rate according to the projected abundance in the upcoming

year (Locke et al. 2005). This policy specifies a constant rate of fishing at low and high abundances and proportional rates (according to population abundance) at intermediate abundances. The Lake Erie Committee broadly defines the state of the fishery into four categories: crisis (<15 million fish), rehabilitation (15-20 million fish), maintenance (20-40 million fish), and high quality (>40 million fish). This particular policy has been in use since the completion of the 2005 Lake Erie walleye management plan. Harvest policy performance should be revisited periodically to ensure that the current management strategy is operating as expected, and that there are no alternative management procedures that would be preferred.

Chapter 4 investigates whether the choice of management procedures (i.e., a data collection and population assessment scheme) influences the selection and performance of alterative walleye harvest policies. Candidate management procedures included (1) using annual fishery and survey data to inform a statistical catch-at-age (SCA) assessment model; (2) the same as in one except where survey data are collected triennially; and (3) using annual survey data as an indicator of population status. Results from simulations indicate that harvest policy performance and the ensuing tradeoffs between conflicting objectives were conditional on the choice of a data collection and assessment scheme. In general, annual age-structured procedures outperformed the two other procedural schemes examined and provided the overall best balance between harvest and risk-related tradeoffs. However, the extra effort associated with implementing annual SCA management procedures only provided a modest improvement in policy performance over triennial SCA management procedures. For the analysis presented in chapter 4, I focused on steps 3 and 4 of a management strategy evaluation. Management objectives (step 1) and performance measures (2) were assumed through discussions with

members of the LEC and the communication of results to decision-makers (step 5) left to other forums. Results from chapter 4 are currently being used by LEPMAG (Lake Erie Percid Management Advisory Group) in the application of a full management strategy evaluation. REFERENCES

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CHAPTER 2

Accounting for spatial population structure at scales relevant to life history improves stock assessment: the case for Lake Erie walleye *Sander vitreus*

Abstract

Stock assessments commonly allow parameters to vary across fishery or jurisdictional boundaries, often by treating each region as a unit stock. However, animals generally disperse in response to spatial habitat features to satisfy particular life history requirements, and these features are often not congruent with fishery or jurisdictional boundaries. Thus, populations are often spatially structured at scales distinct from those acknowledged in assessments. Furthermore, when the spatial-structure arises from dispersal of a common pool of recruits, redefining unit stock boundaries may not adequately capture these dynamics. Here we test the utility of spatially referencing parameters (vulnerability and catchability) in a statistical catch-atage stock assessment model as a simple approach to account for life history variation of walleve (Sander vitreus) when information on explicit movement rates is unavailable. We apply several alternative assessment models to Lake Erie walleye – a population identified as displaying agespecific differences in the extent of dispersal from spawning grounds – to investigate the importance of accounting for spatial heterogeneity at ecologically important scales in stock assessments. Comparisons of the most parsimonious assessment models (based on a deviance information criterion) with and without spatially referenced parameters (by basin) highlighted the importance of estimating regional vulnerability and catchability. There was strong statistical evidence that incorporating spatially referenced parameters at a scale relevant to walleye dispersal patterns improved model fit, and the change altered estimates of stock size and fishing mortality. For example, estimates of total age-2 and older walleye abundance in the most recent year decreased by 16% (34% for ages 7 and older) and fully selected fishing mortality increased by 70% after incorporating walleye spatial population structure. These results emphasize the

importance of considering spatial aspects in stock assessments at scales relevant to the life history of the species or group of species under consideration.

Introduction

Fishery stock assessments are often conducted using statistical models to infer critical demographic information (e.g., spawning stock biomass, age composition) from catch and survey observations (NRC 1998). A stock assessment model links how we think fishery, biological, and environmental processes that affect a population operate in time and space (i.e., system dynamics) with observations from one or more data sources to better understand current status and historical changes in the population. Empirical data provide the basis for informing assessment models, so these data should represent the temporal and spatial scales within which population dynamics are hypothesized to operate (Levin 1992). Stock assessment models are regularly fitted to time series data; however, many assessments implicitly assume that the stock is spatially homogenous, effectively ignoring spatial structure (Goethel et al. 2011). Regarding the population as a single 'dynamic pool' is a common assumption in modern stock assessments despite clear recognition of the importance of spatial fisheries management (Walters and Martell 2004; Ciannelli et al. 2008; Cadrin and Secor 2009; Goethel et al. 2011).

Population assessments that have accounted for spatial structure typically have done so at scales defined by fishery or jurisdictional boundaries (e.g., Hampton and Fournier 2001; Montenegro et al. 2009; Stewart et al. 2011). However, animals often disperse in response to spatial habitat features to satisfy particular life history requirements (e.g., foraging, reproduction), which results in non-homogenous patterns of abundance across the landscape at scales usually distinct from conventional management boundaries. When responses differ among groups of individuals within a population (contingent theory; Clark 1968; Secor 1999), as is often the case, the population will tend to exhibit some degree of spatial organization. For example, differential dispersal ability (i.e., diffusive instability; Levin 1976) of individuals can lead to non-uniform spatial organization. Accounting for spatial structure in stock assessments at scales relevant to life history may lead to more precise population estimates and derived management parameters. For example, it is possible that estimates will be sensitive to patterns of spatial variation in age-specific fishing mortality that result from dispersal or migratory behavior (Yakubu and Fogarty 2006), and thus models which account for these patterns could provide better estimates of stock status and exploitation history.

There are two general classes of techniques to incorporate spatial differences into assessment models which differ in whether explicit movement information is utilized. First, explicit movement information can be incorporated into models that follow individuals (Lagrangian approach) or fluxes in the population at points in space (Eulerian approach) to quantify changes to geographically apportioned subpopulations through time (Turchin 1998; Quinn and Deriso 1999; Goethel et al. 2011). These approaches demand substantial model complexity and require movement information that is costly and often unavailable. Second, spatially referenced parameters can be applied within an assessment model to account for the net effects of movement on observations of population structure at local sites (Quinn and Deriso 1999; Walters and Martell 2004). The benefits of this simpler, implicit spatial approach include making the stock assessment process more transparent (simplifying the modeling process), practical (eliminating the necessity for cost prohibitive movement information), and applicable to many fisheries. For example, vulnerability (defined here as the product of gear selectivity and species availability to the fishery or survey) could be allowed to vary among regions to reflect spatial differences in population structure that result from age-specific differences in the extent, duration, or timing of fish movements.

Parameters in stock assessments are often allowed to vary spatially among fisheries, jurisdictions, or other divisions convenient for management (Goethel et al. 2011) to account for differences in catch (e.g., Montenegro et al. 2009), fishing mortality (e.g., Ralston and O'Farrell 2008), or population structure (e.g., Punt et al. 2000; Stewart et al. 2011). However, there has been comparatively less effort to match model scale to ecologically-driven boundaries, owning to gaps in knowledge and data limitations (Cope and Punt 2011). Defining the appropriate spatial resolution remains a challenge, yet more attention should be devoted to incorporating scales relevant to the life history of the species or group of species under consideration and identifying the affect it has on key management parameters. For example, Saunders et al. (2009) found that blacklip abalone (*haliotis rubra*) management units off the southern coast of Australia that were redefined according to life history metrics rarely overlapped existing management units. Cope and Punt (2009) applied a set of clustering algorithms to standardized catch rate data to delineate management units at spatial scales relevant to Pacific cod (*Gadus macrocephalus*) life history.

Walleye (*Sander vitreus*) is a highly vagile species in both riverine and lacustrine environments with dispersal distances exceeding 160 km (Todd and Hass 1993; Wang et al. 2007). In Lake Erie, longitudinal dispersal of walleye from their primary spawning locations in the western basin appear to be related to size or age (Kershner et al. 1998; Jones et al. 2003; Wang et al. 2007), which could result in differential age composition, and hence age-specific vulnerability patterns, across the lake. Lake Erie walleye may disperse away from spawning grounds (Wang et al. 2007) to maximize growth (Kershner et al. 1999) by responding to longitudinal changes in forage availability and temperature (Kershner et al. 1999), water clarity (Ludsin et al. 2001), and dissolved oxygen gradients. Population status is of particular management concern because of the socio-economic importance of walleye to the region and because of its ecological role as the dominant terminal predator in the lake. The fishery consists of two main sectors: a commercial fishery exclusive to Canadian waters with limited fishing capacity (finite number of licenses available) and a recreational fishery largely in U.S. waters (97% and 95% of total recreational harvest and effort, respectively; WTG 2009).

Implementation of rational management often demands precise estimates of population abundance. Lake Erie walleye population parameters are estimated on an annual basis using a statistical catch-at-age (SCA) stock assessment model that is informed by both fishery and fishery-independent sources of data (WTG 2009). The current SCA assessment model assumes that the walleye population acts as one homogenous unit, applying spatially referenced selectivity and catchability parameters at fishery/jurisdictional boundaries to allow for differences between north (commercial/Canadian) and south (recreational/U.S.) regions. The goal of this research was to assess whether spatially referencing vulnerability and catchability parameters in a statistical catch-at-age stock assessment model at scales relevant to walleye life history improves assessment model fit and the precision of estimates used in management. Herein, we 1) assess evidence for spatial structuring of the walleye population in Lake Erie by comparing models that assume homogeneity (aggregate models) to those that allow for basinlevel population structure (implicit spatial models), and 2) contrast resulting inferences to investigate the importance of incorporating stock structure at scales relevant to species movement patterns in assessments, even when information on explicit movement rates is unavailable.

Methods

Lake Erie and the Walleye Population

Lake Erie is the 11^{th} largest freshwater lake by volume (483 km³) in the world. The lake is divided into three distinct basins (Figure 2.1), which contribute to considerable longitudinal variation in limnological attributes across the lake. The western basin is the shallowest (mean depth = 7.4 m) and most biologically productive of the three basins; the central basin (18.5 m) is intermediate in productivity; and the eastern basin (24.4 m) is the least productive (Ryan et al. 2003). Other general patterns in the physical environment along a west-east gradient are also prominent such as water temperature (decreasing) and water clarity (increasing). These features combine to provide a gradient of habitats suitable for warm-water (west basin), cool-water (west and central basin), and cold-water species (east basin).

Walleye, a cool-water species, predominantly occur in the west and central basins of Lake Erie. Since 1978, this area has consistently produced more than 95% of the total annual walleye harvest in Lake Erie (WTG 2009). Moreover, a vast majority of walleye spawn in areas associated with the western basin (the Maumee and Sandusky Rivers and a mid-lake reef complex; Regier et al. 1969; Busch et al. 1975; Figure 2.1). Despite common observations of spawning site fidelity in walleye (Crowe 1962; Spangler et al. 1977), gene flow does occur at moderate rates in these basins, indicating a single intermixing stock (Strange and Stepien 2007). The fishery is managed via the Great Lakes Fishery Commission (GLFC) under the auspices of the Joint Strategic Plan for Management of Great Lakes Fisheries (GLFC 1981) with representatives from each member authority (four U.S. states and one Canadian province). Managing authorities (guided by the GLFC) recognize the west and central basin walleye population as the primary population of interest and the area within which quotas are allocated and implemented (hereafter referred to as the walleye population; Locke et al. 2005; Figure 2.1). Accordingly, we adopt these boundaries to define the walleye population under consideration for all analyses presented in this paper (i.e., eastern basin population was excluded).

Prior to conducting stock assessments, age composition data (proportion of the total catch by age) collected during 1990-2008 from northern (Canadian) and southern (U.S.) fishery independent surveys was used to assess the scale at which population structure was most distinguishable. Observed age compositions changed markedly with longitude as relatively older (larger) walleye tend to move further east (central basin) while younger (smaller) walleye tend to remain near spring spawning grounds (western basin), indicating that the population is not strictly spatially homogenous (Figure 2.2). However, the proportion of individual age classes in each basin was relatively stable over time. Previous analyses indicated that the most parsimonious explanation of spatial differences in age composition was longitudinal at the basinscale (A. Berger unpublished data). Based on this, the ecological relevance of *in situ* habitat gradients between basins and previously described life history behavior for Lake Erie walleye (Kershner et al. 1999; Wang et al. 2007), exploration of SCA models with spatially referenced parameters were conducted at the basin-scale.

Data Sources
Time series of fishery-dependent and fishery-independent data were acquired for the period 1978–2008 when available from GLFC member agencies (Table 2.1). Commercial catch totals (biomass) and fishing effort (km of gillnet set) were reported monthly by 10-minute spatial grid. Numbers caught by age for the commercial fishery were determined from the catch biomass for each market classification and statistical district (strata) based on aged and weighed catch subsamples. Recreational catch-at-length and fishing effort (angler hours) estimates were available by month and 10-minute grid based on creel surveys and from charter boat reports. Catch-at-length was subsequently converted into catch-at-age using annual age-length keys. Fishery-independent surveys were conducted annually from August - November and utilized as auxiliary indices of abundance (catch-per-effort (CPE)). In Canadian waters, a stratified (depth) random gill-net survey (number of sites ranged from 75-94 annually) was conducted jointly by the Ontario Ministry of Natural Resources (OMNR) and the Ontario Commercial Fishers' Association. In U.S. waters, a stratified (depth) fixed-site gill-net survey (number of sites ranged from 4-53 annually) was conducted jointly by the Ohio Department of Natural Resources (ODNR) and the Michigan Department of Natural Resources (MDNR). Walleye captured during surveys were weighed and measured for length. All walleye captured in the Canadian survey were aged. On the U.S. side, subsamples were aged and age compositions of survey CPE were calculated using age-length keys. Walleye catch-at-age and CPE-at-age data were binned into six age classes beginning with age-2 (when walleye become vulnerable to fishing) and extending to an age-7 and older combined group (age-7 is the point where scale-otolith aging agreement begins to substantially decline). Hard structures (otoliths and anal fin spines) replaced soft structures (scales) in 2004-2005 as the basis for aging walleye.

Base Assessment Model

We implemented a Bayesian SCA assessment model using Automatic Differentiation Model Builder (ADMB; Fournier et al. 2011) software. SCA models are age-structured with assumed errors in the observations of catch-at-age that are used to fit cohorts of fish forward through time (Megrey 1989). We followed the general approach outlined in Fournier and Archibald (1982) and Deriso et al. (1985) for parameterizing catch-at-age models with auxiliary information, including separating fishing mortality into year and age components. In addition to catch-at-age data, auxiliary data sources are necessary to ensure model parameters are identifiable (Doubleday 1976; Pope 1977, Deriso et al. 1985). Fishing effort data and information on relative abundances from fishery-independent surveys (CPE) provided the necessary information to separate estimates of fishing mortality and abundance. Highest posterior density parameter estimates were obtained by minimizing the posterior negative log density (details below). We employed Monte Carlo Markov Chain (MCMC) simulations with a Metropolis-Hastings algorithm to acquire posterior density distributions for parameters and quantities of interest (e.g., total abundance, abundance-at-age, and exploitation rates). We used 15 000 MCMC samples to estimate posterior distributions – resulting from saving every 100^{th} sample of a 2.5 million sample chain and then ignoring the first 10 000 samples (chain burn-in to reduce the influence of starting values) (Gelman et al. 2004). Using the CODA package in program R (Plummer et al. 2006), we assured that chains converged to stationarity (Gelman and Rubin's diagnostic test; Gelman and Rubin 1992) and that there was adequate information available to predict posterior distributions for each parameter (the sample size after being adjusted for autocorrelation was well below 15 000 for all parameters).

The general structure of our base assessment model consisted of population and observation submodels (Table 2.5), and was an extension of the model currently used to aid regulation of walleye harvest since 2001. Walleye population dynamics were based on annual time intervals beginning in 1978 and six age classes (2, 3, 4, 5, 6, and 7^+) for a single aggregated population. Based on previous tagging studies (as noted in Locke et al. 2005), we assumed the natural mortality rate to be constant and known without error (M = 0.32 yr⁻¹). Biomass was calculated as the product of estimated abundance-at-age and observed mean weight-at-age, where mean weights were obtained from OMNR and ODNR surveys (Eq. 2.5.8).

To facilitate comparisons with spatially implicit models that allowed for basin-level vulnerability and catchability parameters, we disaggregated fishery catch-at-age and survey CPE-at-age into annual values by basin so that our base model used the same fishery and survey data set as the spatial models. We chose to pursue spatially implicit models that recognize basins to account for spatial heterogeneity at an ecologically important scale.

Age-specific vulnerability (i.e. product of gear selectivity and species availability to capture), relative to a fully vulnerable age, was estimated as a free parameter (no assumed functional form). For each fishery and survey, vulnerability was assumed to be time and space-invariant, with the exception of Ohio and Michigan recreational fisheries, which allowed for a temporal change in age-2 vulnerability in 2005 to reflect a regulatory increase in the minimum harvestable length. Catchability was assumed constant (time and space invariant) for each fishery/survey, implying a direct proportionality between expected fishing mortality on a given age of fish and observed fishing effort, with actual fishing mortality varying from direct

proportionality based on multiplicative year, basin, and fishery specific errors (Eq. 2.5.4 and 2.5.5).

We fit the model to observed harvest, effort, survey, and age composition data for each basin (Table 2.6). The basin-specific recreational and commercial harvest at-age and survey CPE data were recast in the form of annual totals and proportions at age. This was done so that basin-specific totals for a fishery or survey could be modeled as lognormal with proportions at age treated as arising from sampling a multinomial distribution, as suggested by Fournier and Archibald (1982). The objective function was the posterior negative log density, with some constants dropped, which included additive components associated with the log-likelihood for each data source and for a prior for effort deviations (errors in the effort-fishing mortality relationship; Fournier et al. 1998). The prior for effort deviations assumed a normal distribution (Eq. 2.6.3), whereas non-informative uniform priors (Gelman et al. 2004) on the log-scale were placed on the remaining parameters (number of recruits each year, abundance-at-age in the first year, vulnerability, catchability, and the error variance associated with a single data source, the OMNR survey). The uniform priors were implemented by constraining the allowable range for these parameters, and were not explicitly included in the objective function (Maunder and Starr 2001).

The use of auxiliary information such as fishing effort (combined with an assumed relationship to fishing mortality) or survey abundance indices can greatly enhance the quality of stock assessments (Fournier and Archibald 1982; Deriso et al. 1985). However, the relative quality of different data sets often vary and appropriate weighting terms need to be assigned to control how strongly each data set influences the fit of the assessment model. Weights were

assumed to be inversely proportional to the variance associated with each data source (Quinn and Deriso 1999). In effect, relative weights were used to scale the error variance of each data source to that estimated for the OMNR survey. Relative weights for assumed lognormal distributed catch, effort, and CPE time series were established for all data sources (Table 2.1) by using a survey to solicit expert opinions from Lake Erie managers and assessment biologist about the relative quality (magnitude of observation and process error variance) of each data set (WTG 2010). Proportions assumed to arise due to multinomially-distributed aged samples were weighted according to the effective sample size (i.e. an adjusted number of walleye aged each year), which was found by iteratively adjusting effective sample sizes of the objective function components to match the residual variance (McAllister and Ianelli 1997). Effective sample sizes were set for each data source, directly applied to years when aging was performed with hard structures (otolith or spine), and down weighted 10% when aging was performed with scales to account for the higher mean error rate among age groups when assigning ages with scales (scale error was evaluated by comparing scale estimates of age with otolith estimates of age).

Alternative Models and Model Selection

We evaluated 11 alternative assessment models to assess key structural assumptions associated with the parameterization of vulnerability and catchability (Table 2.2). The main goal here was to evaluate how basin-level vulnerability parameters may help to account for differential dispersal movements of walleye by age, but in doing so we felt it necessary to investigate additional alternative hypotheses about both vulnerability and catchability as the two are inextricably related (both are scaling factors on age-specific fishing mortality). Alternative models differed from the base assessment in the following ways: i) vulnerability was assumed to follow a gamma function of age, ii) vulnerability was allowed to vary spatially (by basin), iii) catchability was allowed to vary temporally (by blocks of time), and iv) catchability was allowed to vary spatially (by basin). The gamma function was used to specify a smooth, reduced parameter, vulnerability curve because it is sufficiently flexible to fit dome-shaped curves such as those often associated with gill-net catches or monotonically increasing curves such as those often associated with trophy sport fishery catches. Using the gamma vulnerability function, fishery and survey vulnerability-at-age was defined as

$$v_{a,k} = \frac{a^{\alpha_k} exp^{-\beta_k a}}{j_k^{\alpha_k} exp^{-\beta_k j_k}}$$

where *a* is age, *k* is timeblock, *j* is the age that maximizes vulnerability, and α (shape) and β (scale) are parameters. Specification of the temporal blocks between which catchability was allowed to change arose from discussions with GLFC member agency biologists who were directly involved in data collection and had practical knowledge of major ecosystem (e.g., introduction of *Dreissenid* spp.) or fishing (e.g., harvest regulation) changes during the study period. The number of blocks varied by data source (4 time blocks: Ohio recreational fishery; 3 time blocks: commercial fishery, Michigan recreational fishery, ODNR/MDNR survey; 2 time blocks: OMNR survey).

We reduced the total number of candidate models *a priori* by restricting hypothesized changes in vulnerability or catchability to be similar across all data sources (except for the use of catchability time blocks where changes were data source specific) and by constraining

catchability to be spatially homogenous except in cases where vulnerability was allowed to vary by basin. Such restrictions ensured that results would be interpretable within the context of our proposed hypotheses and helped to keep the number of models to a manageable level. Regardless of the inclusion or omission of basin-specific parameters, we used the assessment models to estimate quantities (e.g., abundance and mortality) for the population as a whole because that is the level at which the harvest control rule is implemented. As noted above, to facilitate model comparisons, observed data were disaggregated by basin for all model versions, whether catchability or vulnerability were basin-specific or not.

Deviance information criterion (DIC; Spiegelhalter et al. 2002) was used to evaluate the relative performance of each model. DIC is an information theoretic index sharing some similarities with AIC, which is often used when models are fit by maximum likelihood (Spiegelhalter et al. 2002). Like AIC, the index trades off model fit (deviance) with model complexity (effective number of parameters). Deviance is defined as twice the negative log-likelihood (Gelman et al. 2004). The effective number of parameters is the difference between the mean deviance and the deviance associated with the best fit parameters. For this purpose we used highest posterior density estimates. We calculated DIC as the mean deviance from the 15 000 saved MCMC runs plus the effective number of parameters based on the same MCMC sample. When the goal is to select among alternative models to provide management advice, DIC seems to perform well at choosing the best structural model for predicting unobserved quantities (Wilberg and Bence 2008). Following Spiegelhalter et al. (2002), we considered models with a difference in DIC (ADIC) of less than 7 units from the best model (lowest DIC) to be plausible and thus used to make inferences.

Sensitivity Analysis

Sensitivity to the selection of the overall best spatial and aggregate models resulting from alternative data source weighting and natural mortality assumptions were explored. We evaluated the data weighting assumptions by increasing and decreasing weights by 200% and 50%, respectively, from the nominal assumption. Natural mortality (*M*) was adjusted by 25% above or below the nominal value of 0.32 yr^{-1} . Catchability and vulnerability assumptions were tested explicitly within our analytical framework (DIC model selection), and as such, we did not further evaluate them. Differences in DIC (Δ DIC) between the best spatial and aggregate models were then calculated for each perturbation and compared to the nominal Δ DIC value.

Results

Best Assessment Model

The most complex model we considered, which had age-specific selectivities and allowed for spatial differences in vulnerability and spatial differences as well as time-blocks for catchability, far outperformed all alternative models (best spatial model, BSM; Table 2.2). No other model was plausible and the DIC model weight for this model was 1.0. It is instructive to make pairwise comparisons between models that are identical except for including one of the effects. In such comparisons simplification invariably led to a poorer fit (larger DIC). The largest degradation occurred by changing vulnerability from being freely-estimated age-specific parameters to following a gamma distribution, followed by not allowing for spatial vulnerability, not allowing for spatial catchability, and then not allowing for time blocks in catchability.

Influence of the Spatial Structure Assumption on Assessment Results

Comparisons were made between BSM and the best non-spatial or aggregate model (BAM; Table 2.2) to evaluate the importance of accounting for spatial population heterogeneity. The two models were different solely by the inclusion (BSM) and exclusion (BAM) of basinlevel estimates of vulnerability and catchability. Hence, BAM allowed for differences in vulnerability and catchability at a jurisdictional or fishery defined scale (latitudinal), whereas BSM extended that to include an ecologically relevant scale (basin; longitudinal) defined by dispersal patterns. BSM produced much more reasonable fits to all data sources than BAM given a substantial amount of contrast in the observed data (Appendix C; Figure 2.6-2.9). Mean deviations between observed values and predicted values were substantially larger for BAM (compared to BSM) with values ranging from 18-61% (11-19%) for fishery catch and 23-144% (22-59%) for survey CPE data sources. Deviations between observed and predicted proportions at age ranged from 4-10% (4-7%) of the predicted value for both fishery and survey data sources.

Estimates of key management parameters were dependent upon the assumptions regarding spatial structure. Despite having similar overall trends, absolute estimates of total and age-specific population quantities were substantially different between best models (Figure 2.3). Compared to BAM, results using BSM suggest an 11% lower mean population size (16% lower in the last year), a 61% increase in mean instantaneous [fully selected] fishing mortality (70% increase in the last year), and a 26% decrease in the proportion of older individuals (age-7 and older) in the population (21% decrease in the last year). The most recent estimates of age-2 walleye recruitment decreased by 6% and estimates of spawning stock biomass (kilograms of

age-5 and older walleye) decreased by 19%. The magnitude of the difference between BSM and BAM estimates increased with age for abundance (negative direction) and fishing mortality (positive direction; Figure 2.3c-d). Although there was overlap in the posterior distributions for total walleye abundance between best models, uncertainty associated with these estimates was substantially reduced using BSM in most years (Figure 2.4). For example, CVs (coefficient of variation: standard deviation of posterior distribution divided by the highest posterior density estimate) increased considerably for estimates of abundance (40%) and recruitment (28%) in the last year when using BAM.

The overall BSM suggested that fishery and survey vulnerability estimates differed by basin, reflecting longitudinal differences in walleye availability and gear efficiency (Figure 2.5). In general, vulnerability for younger (smaller) walleye was higher in the western basin, whereas vulnerability for older (larger) walleye was higher in the central basin. This basin-level contrast in vulnerability patterns was evident in both the northern (Canadian) and southern (U.S.) surveys, suggesting that longitudinal differences in vulnerability may be mostly due to differences in population structure rather than gear efficiency, because gear and survey techniques differ between Canada and the U.S. BAM estimates were mainly intermediate of those from BSM, but more closely followed west basin patterns.

The overall BSM suggested that fishery and survey catchability estimates differed by basin and time blocks (Table 2.3), reflecting temporal and longitudinal differences in how fishing mortality relates to fishing effort and how catch rates relate to total abundance. Catchability estimates were larger in the west basin for all data source and time block combinations, with the exception of larger central basin estimates associated with the Ohio recreational fishery post-1985. The time blocks that were selected to represent major temporal shifts in catchability seemed appropriate (differences generally greater than 1 standard deviation) for most data sources. Estimates from BAM were consistent with the smaller of the two basin-specific estimates from BSM. In almost all cases (10 of 12), uncertainty (CVs) associated with catchability estimates increased when using BAM.

Model Sensitivity

The underlying model structure of the BSM and BAM remained consistent across all sensitivity trials and was the same as that described in Table 2.2. Model selection results and the subsequent directional effect on abundance in the last year (2008) were insensitive to data source weighting schemes and assumptions of natural mortality (Appendix D; Table 2.7). For most trials, the difference in DIC was similar to the nominal value ($\Delta DIC = 619$). The exception to this was the assumption related to the effective sample size for age composition data (N_{eff}). Adjusting the relative importance of age composition data considerably altered ΔDIC values, but not to the extent required to alter inferences ($\Delta DIC < 7$).

Discussion

The Lake Erie walleye population has been identified as displaying consistent spatial structuring (Wang et al. 2007; A. Berger unpublished data), likely due to the location of spawning sites and age-specific dispersal distances from spawning grounds, which suggests that a homogenous population model may not be the most appropriate. Because explicit movement information between walleye sub-populations was unavailable, we incorporated spatially referenced vulnerability parameters into a single, spatially implicit population assessment model to account for the net spatial effects of such differential dispersal behavior. Differences in vulnerability can ultimately result from disparity in the proportions of walleye at age that are available for capture (population structure) and from spatial differences in how effective fishing gear is at retaining walleye (gear efficiency). Data were unable to differentiate which mechanism was responsible for improved fit when parameters were spatially referenced. However, we suggest that population structure was the main factor contributing to basin-level differences in vulnerability. Northern (Canadian) and southern (U.S.) fishery independent surveys used the same sampling gear within their respective jurisdiction irrespective of sampling location, yet vulnerability patterns remained different between basins in both cases. Further, consistent patterns in observed age/size composition that appeared across the lake seemed to be associated with physical habitat characteristics (Kershner et al. 1999; Wang et al. 2007), linking what we know about walleye ecology to observed differences in spatial population structure. For example, larger (older) walleye have been noted to disperse further from warming summer water temperatures in the western basin to the east than smaller (younger) individuals in search of food resources in cooler water temperatures to optimize growth (Kershner et al. 1999).

Inferences about the Lake Erie walleye population were affected by spatially referencing the population dynamics model to account for life history patterns at an ecologically relevant scale. In particular, assessment results that are used to inform walleye management were influenced by the choice of best model which included (BSM) or excluded (BAM) basin-level vulnerability and catchability parameters. Vulnerability estimates from the BAM (homogeneity assumption) were more similar to those attributed to the west basin in the overall BSM (Figure 2.5), which was a result of the aggregate model attempting to optimize fit by following walleye trends in the more heavily populated (and generally more intensely fished) western basin. Estimates of catchability from the overall best model also differed by basin suggesting that the relationship between fishing effort and fishing mortality (and similarly survey CPE and population abundance) varied by the area where fishing (and the surveys) occurred. Spatial differences in catchability seem plausible and were somewhat expected given the considerable contrast in fishable habitat between the west (shallow, low visibility) and central (deep, high visibility) basins.

There was strong statistical evidence that incorporating spatially referenced parameters at a scale relevant to walleye dispersal patterns improved model fit, and the change altered estimates of stock size and fishing mortality. This finding was insensitive to the assumed natural mortality rate and to alternative data weighting schemes, providing a robust indication of the importance of accounting for life history variation in stock assessment models. Although the differences we illustrate are not drastic compared to changes in assessment estimates that are sometimes seen when assessment models are changed, they are large enough to be of practical management concern. Divergent population estimates that resulted from the choice of best model (based on assumptions of spatial population structure) were mainly a consequence of the interplay between basin-level differences in walleye availability and catchability due to walleye dispersal patterns. Similar to results for Pacific albacore (Fournier et al. 1998), ignoring walleye spatial structure significantly reduced the predictive power (precision) of the population dynamic model.

Fisheries management is often guided by harvest policies that utilize state-dependent control rules to translate current population estimates, such as abundance or biomass, into the following year's fishing rate (e.g., total allowable catch). Increasingly often, the selection of a harvest policy is aided by conducting simulation experiments where performance metrics used to evaluate alternative policies depend on the chosen assessment model. For example, Cox and Kronlund (2008) demonstrated important differences (and similarities) in policy performance between data-based and model-based assessments. Williams (2002) showed that ignoring the size-structure of discarding rates in the assessment model altered the selected harvest policy, resulting in harvests above the maximum sustainable yield. More research is needed to evaluate how robust exploitation policies are to alternative assessment models and assumptions of spatial population structure (e.g., Punt and Hobday 2009). For example, does accounting for structure using spatially referenced parameters affect policy performance in a meaningful way over models that do not spatially reference parameters? Herein, we show that alternative assumptions regarding population structure can considerably affect quantities necessary for rational management (e.g., estimates of population size, fishing mortality, and population age structure), which could ultimately influence harvest policy decisions.

Appropriately accounting for spatial structure in assessments appears to be important. Previous simulation studies have shown that allowing for spatial structure, when present, can both reduce bias and improve precision of estimates. For example, Punt (2003) found that less biased and more precise estimates resulted from separate stock assessments carried out at small spatial scales as opposed to pooling data across spatial regions. Sub-dividing the stock assessment into smaller spatial levels can also be convenient for satisfying assumptions (Quinn

and Deriso 1999). In contrast, Butterworth and Geromont (2000) showed that biased estimates of fundamental management parameters can also result when a single homogenous population is unnecessarily sub-divided. In many cases, the decision to spatially disaggregate observed information will be dependent upon the level of spatial heterogeneity present in the population and sample sizes. Hobday and Punt (2009) used an information-theoretic approach to decide on appropriate assessment spatial scale. Spatially referencing some parameters is one possible approach when entirely separate stock assessments at a finer scale does not seem appropriate and explicit modeling of dispersal is not possible. We illustrated this approach for Lake Erie walleye and justified estimating additional parameters on information-theoretic grounds. Survey data suggest that walleye age compositions change continually along a longitudinal gradient (Figure 2.2). Future work could investigate whether finer-scale spatial referencing of parameters is justified for Lake Erie walleye, perhaps by modeling parameters as a function of longitude.

Integrating tagging data into stock assessment models can help facilitate the estimation of key parameters such as natural mortality or movement rates (Punt et al. 2000; McGarvey et al. 2010) and can reduce uncertainty in spatial assessments (Punt et al. 2000). Yet explicitly modeling spatial dynamics requires more extensive information (e.g., spatial population structure, movement, and site-specific demographics) and may propagate uncertainty (Conroy et al. 1995). In the case of Lake Erie walleye, information about age-specific movement rates (e.g., timing and duration) between the west and central basins of Lake Erie would be especially critical for developing a spatially explicit model, although there could be advantages to incorporating movements at a finer spatial scale. Future work should investigate the advantages

and tradeoffs of incorporating tagging data into a spatially explicit assessment model as data become available, in contrast with the approach of spatially referencing parameters.

In application, spatially referencing vulnerability parameters to account for regional differences in distribution (e.g., "fleets" model; Cope and Punt 2011) is appropriate when age- or size-classes are not uniformly distributed over space and the proportion of each age- or size-class in each spatial stratum does not change over time (this was generally the case for Lake Erie walleye). Density-dependent distributions, for example, would be problematic for this approach. The approach presented here can be a practical way to incorporate spatial population structure into stock assessments, particularly when the spatial-structure arises from dispersal of a common pool of recruits such that simply redefining unit stock boundaries inadequately captures important dynamics.

The assessment models evaluated herein were based on the current walleye assessment model used as an input to the management process on Lake Erie. Important differences were from choices we made in how to model vulnerability and data distributions, and were necessitated by the need to use disaggregated data and basin specific error terms for the relationships between fishing mortality and effort, in order to make statistical comparisons between aggregate and spatial models. Consequently, results presented here should be viewed as providing evidence on the importance of incorporating spatial population dynamics in assessment models, rather than suggesting specific alternative stock size estimates for management of Lake Erie walleye.

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APPENDIX 2A

Main Tables and Figures

Table 2.1.—Commercial fishery, recreational fishery, and survey data series relating to both the western and central basins of Lake Erie that were used to inform analyses. Error structure and weights refer to that assumed in statistical catch-at-age assessment models. Catch, CPE, and effort weights are proportional to the inverse of the assumed variance associated with each data series and normalized to a single estimated variance associated with a standard data series (Ontario survey). Age composition (proportion) weights correspond to the annual effective sample size of aged fish (west basin/central basin).

Series	Туре	Source	Years	Error Structure	Weight
Total Catch	Commercial	Ontario	1978 - 2008	lognormal	0.91
Total Catch	Recreational	Ohio	1978 - 2008	lognormal	0.85
Total Catch ^a	Recreational	Michigan	1978 - 2008	lognormal	0.76
Effort Effort Effort ^a	Commercial Recreational Recreational	Ontario Ohio Michigan	1978 - 2008 1978 - 2008 1978 - 2008 1978 - 2008	lognormal lognormal lognormal	0.89 0.86 0.80
Total CPE	Survey	Ontario	1990 - 2008	lognormal	1.00
Total CPE	Survey	Ohio/Michigan	1983 - 2008	lognormal	0.86
Age Composition	Commercial	Ontario	1990 - 2008	multinomial	106/56
Age Composition	Recreational	Ohio	1978 - 2008	multinomial	156/146
Age Composition ^a	Recreational	Michigan	1986 - 2008	multinomial	124/-
Age Composition	Survey	Ontario	1990 - 2008	multinomial	110/76
Age Composition	Survey	Ohio/Michigan	1983 - 2008	multinomial	100/395

Ontario = Ontario Ministry of Natural Resources; Ohio = Ohio Department of Natural Resources; Michigan = Michigan Department of Natural Resources.^a Data available for the west basin only. Table 2.2.—Relative comparison of walleye SCA assessment models describing alternative hypotheses about the applicability of spatially referencing basins combined with a particular estimation method to describe assumptions for vulnerability and catchability (see text for further details). Vulnerability parameters were either estimated freely (unconstrained) or constrained to follow a gamma function. Catchability (*q* in Table 2.5) was either assumed constant or allowed to vary according to discrete blocks of time. Models are ranked according to differences in DIC (Δ DIC) from the model with the least DIC value. K is the estimated effective number of parameters.

SCA Assessment Models					
Vulnerability		Cate	chability		
Spatial	Estimation	Spatial	Estimation	<u>ADIC</u>	<u>K</u>
yes ^a	free	yes	time blocks	0.0	180.4
yes	free	yes	constant	62.0	177.8
yes	free	no	time blocks	119.5	161.8
yes	free	no	constant	165.0	169.3
no ^b	free	no	time blocks	619.4	133.9
no	free	no	constant	645.1	136.0
yes	gamma	yes	time blocks	2712.2	154.8
yes	gamma	yes	constant	2749.3	144.1
yes	gamma	no	time blocks	2869.1	129.1
yes	gamma	no	constant	2874.5	124.2
no	gamma	no	time blocks	3272.4	121.7
no	gamma	no	constant	3289.8	119.1

^{*a*} Best spatial model (BSM; with basin-level referenced parameters) and ^{*b*} best aggregate model (BAM; no basin-level referencing).

		<u>Spat</u>	ial (west)	Spatia	l (central)	Agg	regate
Data Source	Time Block	q (10 ⁻⁵)	$SDq(10^{-6})$	q (10 ⁻⁵)	$SDq(10^{-6})$	q (10 ⁻⁵)	SD q (10 ⁻⁶)
Fishery							
Commercial	1978 - 1986	0.88	1.74	0.50	0.97	0.56	1.10
	1987 - 2000	0.67	0.96	0.39	0.57	0.38	0.58
	2001 - 2008	0.72	1.37	0.39	0.78	0.38	0.89
Recreational (OH)	1978 - 1985	8.02	13.33	5.76	11.69	5.95	11.02
	1986 - 1993	1.58	2.76	2.74	5.24	1.68	3.36
	1994 - 2003	2.83	4.46	4.14	6.67	2.48	4.38
	2004 - 2008	2.13	4.98	3.57	8.40	2.09	5.75
Recreational (MI)	1978 - 1985	2.81	6.05	-	-	3.00	8.61
	1986 - 2003	1.50	1.96	-	-	1.32	2.25
	2004 - 2008	0.98	2.45	-	-	0.87	3.55
Survey							
Ontario	1990 - 1998	0.06	0.07	0.02	0.02	0.03	0.05
	1999 - 2008	0.05	0.07	0.01	< 0.01	0.02	0.03
Ohio/Michigan	1983 - 1986	0.29	0.57	0.20	0.40	0.21	0.41
	1987 - 2003	0.41	0.48	0.26	0.30	0.29	0.38
	2004 - 2008	0.14	0.29	0.11	0.23	0.11	0.31

Table 2.3.—Spatially-referenced and time-varying values of catchability (q) for each model component as estimated by the overall best walleye spatial (BSM) and aggregate (BAM) models. Note that posterior standard deviations (SD) are presented on a different scale than highest posterior density estimates.



Figure 2.1.—The west basin (WB), central basin (CB), and east basin/Pennsylvania ridge (EB/PR) geomorphologic regions of Lake Erie have distinct bathymetric and water quality attributes. The main walleye population occurs in the west and central basins.



Figure 2.2.—Mean age composition (%) of recruited walleye smoothed over 20 minute longitudinal bins (defined by bin midpoint). Age composition changed markedly with longitude as relatively older (larger) walleye tend to move further east (central basin) while younger (smaller) walleye tend to remain near spring spawning grounds (western basin). Data are from gillnet surveys (September – October) for years when both Ontario and Ohio/Michigan surveys were conducted concurrently (1990 – 2008).



Figure 2.3.—Highest posterior density estimates of age-2 and older walleye abundance (millions of fish; panel A) and fully selected instantaneous fishing mortality (panel B) from the overall best model with basin-level parameters (BSM; solid line) and the best model without basin-level parameters (BAM; dashed line). The median (bar) percent difference (calculated across years, 1978-2008; circles) between estimates from BSM and BAM decrease with age for walleye abundance (panel C) and increase with age for fishing mortality (panel D).



Figure 2.4.—Posterior distributions for estimates of annual total walleye abundance (age-2 and older) from the best spatial (BSM; solid line) and aggregate (BAM; dashed line) models. The peak of each curve represents the highest posterior density estimate while the spread represents estimated precision.



Figure 2.5.—Comparison of vulnerability estimates (\log_e ; ± 1 posterior SD) between the overall best model (BSM) which includes basin-level spatially referenced vulnerability parameters from the west (solid) and central (dash) basins and the best aggregate model (BAM) which does not spatially reference basins (dotted; see Table 2.2 for description). Estimates were relative to age-

4, the reference level, which was set to one (zero on the log_e scale) and thus had no uncertainty associated with it. In both models, recreational fishery age-2 vulnerability was allowed to change in 2004 (not shown but declined in all cases) because of a regulatory amendment increasing the minimum harvestable length.

APPENDIX 2B

Description of Symbols and Equations

Table 2.4.—Descriptions of symbols in Table 2.5 and 2.6 describing the base assessment model.

Symbol	Description
a	Subscript Indicators (range/level) age (2-7+)
y y	year (1978-2008)
f	fishery (commercial = 1; recreational (OH) = 2; recreational (MI) = 3)
S	survey (Ontario = 1; Ohio/Michigan = 2)
r	region (west basin = 1; central basin = 2)
ĸ	recreational vulnerability time block (1978-2003; 2004-2008)
	Assumed Values
M	instantaneous rate of natural mortality (0.32 yr ⁻¹)
${}^{\lambda}f$	weight for fishery catches (relative to standard data source; 1able 1)
λ_{S}	weight for fishery effort deviations (relative to standard data source: Table 1)
λ _ε	
$C_{y,r,f}$	total numbers of walleye caught by fishery and region
I _{y,r,s}	survey abundance index
P _{y,a,r,f}	proportions of catch at age by fishery and region
P _{y,a,r,s}	proportions at age from survey abundance index
n Fc	sample size (number of years data)
^L y,r,f W u a	mean weight
y,u	Estimated Parameters
R_{ν}	Recruitment for each year
G_{a}^{y}	Initial abundances at age (>2) in the first year
q_f	catchability coefficient for each fishery
q_s	catchability coefficient for each survey
v _{a,f,k}	vulnerability at age for each fishery and time block
v _{a,s}	vulnerability at age for each survey
σ_{std}	offert deviations
^e y,r,f	
F c	Calculated Parameters
r y,a,r,f Z z	instantaneous total mortality rate
$\frac{2}{N}$	abundance at age in year y
$N_{v}^{y,u}$	total abundance in year y
B_y	total biomass in year y

Table 2.4.—(cont'd).

$\hat{C}_{y,a,r,f}$	model predicted catch at age
$C_{y,r,f}$	model predicted total catch
$\hat{I}_{y,a,r,s}$	model predicted survey abundance index at age (catch per unit effort)
Î _{y,r,s}	model predicted survey abundance index
$\hat{P}_{y,a,r,f}$	model predicted proportions of catch at age
$\hat{P}_{y,a,r,s}$	model predicted proportions at age from survey abundance index
N eff	effective sample size
σ_f	coefficient of variation for fishery catches $(\sigma_{std} / \lambda_f)$
σ_s	coefficient of variation for survey index catch rates (σ_{std} / λ_s)
σ_{ϵ}	standard deviation for effort deviations (σ_{std} / λ_{ϵ})

Equation	Reference			
Population Submodel				
Recruitment and initial numbers at age				
$N_{y,a=2} = R_y$	(2.5.1)			
$N_{y=1978,a>2} = I_a$	(2.5.2)			
Mortality rates				
$Z_{y,a} = M + \sum_{r} \sum_{f} F_{y,a,r,f}$	(2.5.3)			
$F_{y,a,r,f=1} = q_f s_{a,f} E_{y,r,f} e^{\varepsilon_{y,r,f}}$	(2.5.4)			
$F_{y,a,r,f>1} = q_f s_{a,f,k} E_{y,r,f} e^{\varepsilon_{y,r,f}}$	(2.5.5)			
Population dynamics				
$N_{y+1,a+1 a<7} = N_{y,a}e^{-Z_{y,a}}$	(2.5.6)			
$N_{y+1,a=7} = N_{y,a=6}e^{-Z_{y,a=6}} + N_{y,a=7}e^{-Z_{y,a=7}}$	(2.5.7)			
$B_{y} = \sum_{a} N_{y,a} w_{y,a}$	(2.5.8)			
Observation Submodel				
$\hat{C}_{y,a,r,f} = \frac{F_{y,a,r,f}}{Z_{y,a}} (1 - e^{-Z_{y,a}}) N_{y,a}$	(2.5.9)			
$\widehat{P}_{y,a,r,f} = \frac{\widehat{c}_{y,a,r,f}}{\widehat{c}_{y,r,f}}$	(2.5.10)			
$\hat{I}_{y,a,r,s} = q_s s_{a,s} N_{y,a} e^{-(0.75 \cdot Z_{y,a})}$	(2.5.11)			
$\widehat{P}_{y,a,r,s} = \frac{\widehat{I}_{y,a,r,s}}{\widehat{I}_{y,r,s}}$	(2.5.12)			

Table 2.5.—Equations for population and observation submodels used in the base walleye assessment model.

Components	Source	Reference
$n_{r,f} ln \frac{\sigma_{std}}{\sigma_f} + \frac{\sigma_f}{2\sigma_{std}^2} \sum_{y} \left[ln \left(\frac{C_{y,r,f}}{\hat{C}_{y,r,f}} \right) \right]^2$	$r_{1,2}; f_{1,2,3}$	(2.6.1)
$n_{r,s} ln \frac{\sigma_{std}}{\sigma_s} + \frac{\sigma_s}{2\sigma_{std}^2} \sum_{\mathcal{Y}} \left[ln \left(\frac{l_{\mathcal{Y},r,s}}{\hat{l}_{\mathcal{Y},r,s}} \right) \right]^2$	<i>r</i> _{1,2} ; <i>s</i> _{1,2,3}	(2.6.2)
$n_{r,f} ln \frac{\sigma_{std}}{\sigma_{\varepsilon}} + \frac{\sigma_{\varepsilon}}{2\sigma_{std}^2} \sum_{y} \left[\varepsilon_{y,r,f} \right]^2$	$r_{1,2}; f_{1,2,3}$	(2.6.3)
$-\sum_{y} N_{r,f}^{eff} \sum_{a} \left[P_{y,a,r,f} \ln \left(\hat{P}_{y,a,r,f} \right) \right]$	$r_{1,2}; f_{1,2,3}$	(2.6.4)
$-\sum_{y} N_{r,s}^{eff} \sum_{a} \left[P_{y,a,r,s} \ln \left(\hat{P}_{y,a,r,s} \right) \right]$	$r_{1,2}; s_{1,2,3}$	(2.6.5)

Table 2.6.—The objective function was the posterior negative log density calculated by summing weighted individual normal and log-normal likelihood and prior components for all source combinations. Highest posterior density estimates minimized this function.

APPENDIX 2C

Comparisons of Observed and Predicted Values



Figure 2.6.—Time series of observed (filled circle) and predicted (BSM: solid line; BAM: dashed line) fishery harvest (thousands of fish) for commercial (Ontario waters) and recreational (Ohio and Michigan waters) fisheries in the west and central basins, Lake Erie.



Figure 2.7.—Time series of observed (filled circle) and predicted (BSM: solid line; BAM: dashed line) fishery mean age for commercial (Ontario waters) and recreational (Ohio and Michigan waters) fisheries in the west and central basins, Lake Erie.


Figure 2.8.—Time series of observed (filled circle) and predicted (BSM: solid line; BAM: dashed line) CPE (catch-per-effort) from annual Ontario gill net surveys and combined Ohio/Michigan gill net surveys in the west and central basins, Lake Erie.



Figure 2.9.—Time series of observed (filled circle) and predicted (BSM: solid line; BAM: dashed line) survey mean age from annual Ontario gill net surveys and combined Ohio/Michigan gill net surveys in the west and central basins, Lake Erie.

APPENDIX 2D

Sensitivity Analysis

Table 2.7.—Sensitivity to the selection of the overall best spatial (BSM) and aggregate (BAM) models resulting from data source weighting and natural mortality (M) assumptions. For all cases, the best spatial and aggregate model was structurally the same as the best models shown in Table 2.2. Upward and downward adjustments (%) to the nominal assumption were made for each identified model component. Data source weights were implemented in the objective function to control how strongly each data set influenced model fit. These included commercial and recreational effort and total catch, survey total catch-per-effort (CPE), and the effective sample sizes (N_{eff}) for commercial, recreational, and survey age composition data. Estimated total abundances (N) are shown for the last year (2008). Differences in DIC (Δ DIC) show the relative improvement in model fit (lower DIC values) when basin-level spatially referenced parameters were applied.

		BSM		BAM		
Model Component	Adjustment	DIC	N	DIC	N	∆DIC
Data Source Weights						
effort	200	70320	43.05	70930	51.17	610
	50	70341	46.94	70979	52.95	638
catch	200	70301	46.74	70948	51.87	647
	50	70355	43.43	70967	51.83	612
Index survey CPE	200	70390	44.23	70997	52.80	607
	50	70310	46.46	70933	51.10	623
Age comp. (N _{eff})	200	133202	45.52	134291	47.32	1089
	50	35675	46.52	36057	52.99	383
Mortality						
М	125	70355	57.69	70963	64.70	608
	75	70349	38.42	70945	41.97	596

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CHAPTER 3

Improving Fishery-Independent Indices of Abundance for a Migratory Walleye Population

Abstract

The primary goal of many fishery surveys is to provide an unbiased representation of population trends. Even when surveys are designed to be representative of the population being assessed, there are often biotic and abiotic factors other than abundance that can vary over time and influence catch rates and thus inferences about abundance trends. This is particularly true for highly mobile species such as walleye (Sander vitreus) because of interannual variation in the timing, extent, and duration of movements. We developed general and generalized linear mixed models to standardize Canadian and United States fishery-independent surveys used to provide an index of basin-level walleye population trends in Lake Erie (1983-2008). In Canadian waters, the probability of a non-zero catch was associated with the type of gill net set ("canned" had a positive effect over "bottom"; +), the presence of hypoxia (-), and secchi depth (-). Positive catch rates were associated with the set type (+), water depth (+), and the presence of hypoxia (-). In United States waters, survey catch rates were associated with secchi depth (-) and surface water temperature (+). For each case, the best model included random effects (interactions between year, week, basin, and sub-basin) which accounted for a modest amount of the total variation. General abundance trends were similar between the standardized and nominal indices, but we observed substantial annual variation in the direction and magnitude of the difference between indices. Overall trends in abundance differed markedly between basins due to discrepancies in availability (population structure) and selectivity (gear efficiency) to fishing gear. We recommend the use of standardized indices for walleye population assessments because these account for factors influencing catch rates other than changes in abundance.

Introduction

The Lake Erie percid fishery is a socially and economically valuable resource, representing nearly a quarter of the total commercial harvest (metric tons) and recreational effort (angler-hours) in all the Laurentian Great Lakes combined (Bence and Smith 1999; Brown et al. 1999; Koonce et al. 1999). Prior to the 1960s, the fishery included major contributions from sauger (*Sander Canadensis*), walleye (*Sander vitreus*), yellow perch (*Perca flavescens*), and blue pike (*Sander vitreus gl.*); more recently the fishery has become solely dependent upon catches of walleye and yellow perch (Ryan et al. 2003). Maintaining a healthy walleye population has been recognized as a necessary condition to achieve broader fish community goals (Ryan et al. 2003), because walleye, the dominant terminal predator in much of the lake, act to stabilize the food web with top down predatory control (Knight and Vondracek 1992; Makarewicz and Bertram 1993). As the sport and commercial fisheries are highly valued, ensuring long-term sustainability of the walleye population remains a paramount management objective (Locke et al. 2005). Over the past decade, annual landings of Lake Erie walleye have exceeded 2 800 mt on average, 61% from commercial harvest and 39% from recreational harvest (WTG 2009).

Stock assessments are conducted to provide decision makers with pertinent regulatory information such as population trends, demographic rates, and occurrences of overfishing in order to implement effective harvest management. A statistical catch-at-age (SCA) stock assessment model, informed by both fishery-dependent and fishery-independent data, is used to estimate Lake Erie walleye population parameters of interest to decision makers (WTG 2009). Fishery-independent catch-per-effort (CPE) data are collected from annual research surveys and implemented as auxiliary time series indices of relative abundance to help improve SCA assessment model accuracy and precision (Deriso et al. 1989; Quinn and Deriso 1999; Chen et al. 2003). A basic assumption in many stock assessments is that CPE is directly proportional to average abundance with the coefficient of proportionality called catchability – the proportion of the population caught with one unit of survey effort (Hilborn and Walters 1992). There are many reasons why this direct proportionality might not be the case (e.g., hyperstability, *cf* Hilborn and Walters 1992), but the assumption remains very common in fishery assessments. In addition, there are many factors other than abundance that can influence survey catch rates and potentially render the nominal survey index misleading. For example, spatial and temporal variation in environmental conditions, such as water temperature and clarity, are likely to influence the encounter rates of fish with survey gear. Although methods exist to allow for spatial and temporal variations in catchability within stock assessment models (e.g., state space methods; Schnute 1994; Wilberg et al. 2010), large changes at unknown times or locations still pose substantial difficulties. Consequently, correcting for known factors affecting abundance indices remains a priority (NRC 1998; Wilberg et al. 2010).

One way to account for confounding factors (and thus decrease the extent to which catchability varies) is to develop a standardized index by fitting statistical models to catch and effort data and then extracting the temporal effect of interest (Quinn and Deriso 1999; Maunder and Punt 2004; Ye et al. 2005). This process usually involves selecting data points and explanatory variables to be used in the analysis and an appropriate statistical model (e.g., general or generalized linear models) and error distribution (e.g., Poisson, lognormal, or gamma). On Lake Erie, two fishery-independent gill net surveys are used to collect walleye CPE data to index the population: a Canadian survey administered jointly by the Ontario Ministry of Natural

Resources and the Ontario Commercial Fisheries' Association to the north, and a United States survey administered jointly by the Ohio Department of Natural Resources and the Michigan Department of Natural Resources to the south (Figure 3.1). The two surveys are treated as independent indicators of relative abundance because they are assumed to have differing abilities to capture fish of a given size or age (i.e., selectivity patterns).

The Lake Erie walleye population does not appear to be distributed randomly. Instead there is consistent longitudinal spatial patterning of individuals by size (or age) such that a greater proportion of larger, older individuals tend to migrate further from spring spawning grounds in the west basin than smaller, younger individuals, apparently to optimize growth by taking advantage of seasonal water quality and foraging conditions favorable to these older fish (Kershner et al. 1999; Wang et al. 2007; Berger et al. *in press*). Surveys occur in autumn during a time when migratory walleye are actively returning to the west basin (Wang et al. 2007; pers. comm., C. Vandergoot, Ohio Department of Natural Resources, 1 June 2011), and interannual variation in the timing and extent of migration could present inconsistencies in survey data, altering survey catchability and obscuring abundance trends. Given that the portion of the target population that is available can vary spatially and seasonally, these factors are important to consider when interpreting what survey CPE indicates about abundance.

A wide range of factors have been included in statistical models developed to standardize catch rates: location (Punt et al. 2000; Tian et al. 2009), time (Rodriguez-Marin et al. 2003; Deroba and Bence 2009), vessel (Battaile and Quinn 2004; Helser et al. 2004; Tyson et al. 2006), catch rates of other species (Punt et al. 2001), and environmental factors (Buijse et al. 1992; Smith and Page 1996; Hart et al. 2011). For example, Smith and Page (1996) identified water

temperature and salinity as factors influencing trawl survey catch rates of Atlantic cod. The use of environmental variables has been recognized as an important contribution when standardizing data or accounting for varying catchability (NRC 1998). In this paper, we examine how sitelevel environmental variation in low dissolved oxygen (hypoxia), surface water temperature, water clarity and depth, and set type of survey gear influence walleye catch rates.

The stock assessment model used to assess the status of Lake Erie walleye considers observed population trends from fishery-independent surveys as highly informative (i.e., surveys have comparatively more influence on how the model is fit than fishery-dependent data; Berger et al. *in press*; WTG 2010), and thus have considerable influence on resulting population estimates used for management. Therefore, it is critical to have a fishery-independent index that as best as possible accounts for factors that might confound real abundance trends. We sought to 1) develop a standardized index of relative abundance from annual survey data for Lake Erie walleye; 2) identify a set of factors that significantly contribute to the standardized index; and 3) compare trends between standardized and nominal (non-standardized) CPE data.

Methods

Study Area

Lake Erie is the smallest of the Laurentian Great Lakes in terms of volume yet is the most productive (Beeton et. al. 1999). The lake consists of three main basins. The west basin (mean depth = 7.4 m) and central basin (18.5 m) support warm and cool-water fisheries, while the east basin (24.4 m) is dominated by cool and cold-water species. Walleye are most abundant in the west and central basins of Lake Erie; although smaller populations do reside in the eastern basin;

it is this west/central basin population for which stock assessment and harvest policy management procedures have been used to set annual harvest levels. The analyses presented in this paper focuses on this population.

Survey Design

Catch rates (or CPE) were computed from annual gill net survey data as the total catch (numbers of age-2 and older walleye) divided by the total effort (days standard net fished) at each site. Nets were set and retrieved generally during daylight hours, allowing them to fish over a single night. Survey sites were rarely sampled more than once in the same year (<2% of sites). In such cases, catch rates were averaged across repeated samples after removing foul sets. A subset of selected sites were omitted (15% CAN; 7% US) from our analyses because of missing effort, location, or environmental covariate data. A different standard gill net configuration was used in Canadian and U.S. waters, although configurations remained consistent through time within each jurisdiction. The number of survey sites sampled differed by year, basin, and jurisdiction (Table 3.1). The annual index of abundance was calculated as the average catch rate across sites for each year and jurisdiction (non-standardized version; hereafter referred to as the nominal index).

The Canadian gill net survey was initiated in 1989 as a fish community index (OMNR 2009) and expanded to include sites in both the west and central basins in 1990. Sampling locations were selected at random each year among bottom depth strata (west basin: 0-10 and >10 m; central basin: 0-15, 15-20, and >20 m) with the number of locations in each stratum being proportional to area (Figure 3.1). At each location, gill nets were set on the bottom and

suspended in the water column ("canned") at a depth determined by bottom depth and random selection (west basin: 1.8m; central basin: 5m, 11m, 17m). Individual sites were thus uniquely identified by latitude, longitude, and depth. In general, west basin sites were sampled in September and central basin sites in October to mid-November. The standard Canadian survey gill net set consisted of 25 monofilament mesh panels (each $15.25 \times 1.8 \text{ m}$) graded at 1.25, 1.5, 1.75, 2.0, 2.25, 2.5, 2.75, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, and 6.0 inch increments (32 to 152 mm) for a total net length of 0.38 km. Two panels of each mesh size were fished, except for the smallest sized (<2.0 in) meshes where a single panel was fished.

The U.S. gill net survey was initiated in 1978 to primarily index walleye and white bass and expanded to include sites in both the west and central basins in 1983 (ODW 2009; Thomas and Hass 2009). Sampling occurred at fixed locations throughout the west basin and largely along the western half of the central basin during the month of October. In the central basin, sites were selected along transects perpendicular to shore and stratified by depth (<5, 5-10, 10-15, 15-20, and >20 m). Standard U.S. survey gill nets were fished suspended in the water column (1.8 m below the surface) at each location. Each net set consisted of 13 randomly ordered nylon multifilament mesh panels (each 30.5 x 1.8 m) graded from 2.0 to 5.0 inches (51-127 mm) in 0.25 inch (6 mm) increments for a total net length of 0.40 km.

Confounding Variables

Temporal, spatial, and environmental variables were identified as prospective covariate factors based on prior knowledge of walleye movement and habitat selection behavior, and the availability of relevant data. Separate analyses were conducted for Canadian and U.S. surveys

because of the difficulty in separating spatial effects from differences in how the surveys were implemented. Factors associated with Canadian survey sites that were examined included year (1990-2008), week (ordered 1 to 8 by Julian days; week 1 and 8 represented 14 days to capture sites sampled unusually early and late), basin (West, Central), sub-basin (W1,W2,C1,C2,C3,C4; Figure 3.1), surface water temperature (°C), secchi depth (m), water depth (m), the presence of hypoxia (<4mg·L⁻¹ O₂), and the type of set for gill nets ("bottom", "canned"). In U.S. waters, factors examined included year (1983-2008), week (ordered 1 to 6 by Julian days), basin, surface water temperature, secchi depth, water depth, and hypoxia. Surface water temperature, secchi depth and water depth were treated as continuous variables; all others were treated as categorical variables. Correlations among the environmental covariates were low (max $r^2 = 0.15$), so analytical problems due to collinearity (Maunder and Punt 2004) were not considered serious. Preliminary analyses based on sample sizes and model selection results (see Model Selection Procedure) indicated the use of week over bi-week as an intra-annual temporal factor and the inclusion (Canadian) and exclusion (U.S.) of sub-basin as a spatial factor nested within basin to further account for the effect of sampling location on catch rates.

Models to Standardize Catch Rates

One difficulty with the Canadian survey CPE data was the high proportion of sites with zero catch (0.364; Figure 3.2). A large number of sites with zero catches can invalidate model assumptions, restrict analytical capabilities (e.g., log transformations), reduce estimator efficiency, and influence ensuing inferences if not properly handled (Pennington 1983; Maunder and Punt 2004). We therefore applied a delta approach ("Delta models") within a generalized

linear mixed model (GLMM) framework (Aitchison and Brown 1957; Lo et. al. 1992; Vignaux 1994), which has been shown to lead to more consistency between model assumptions and observed catch rates (Ortiz and Arocha 2004). The delta approach is a two-stage process whereby the proportion of survey sites with a non-zero CPE is modeled first (a Bernoulli process often evaluated using the binomial error distribution) followed by a model evaluating CPE given that it is not zero (often using the lognormal, gamma, or censored versions of the Poisson or negative binomial error distribution). The relative abundance index is then calculated as the probability of a non-zero catch multiplied by the expected CPE given that it is non-zero (Punt et. al. 2000). Here, we assumed the proportions of non-zero catches followed a binomial error distribution and positive CPE values followed a lognormal error distribution. The lognormal was chosen because of a good fit to the relationship between the variance and mean of observed walleye CPE (Figure 3.3). Other error distributions (gamma and censored Poisson and negative binomial) did not result in a better fit to these data. The logit link function ($\log_e (x) - (\log_e(1 - 1))$) x))) was used to map the nonlinear binomial response data (zero or non-zero catch) to the linear predictors.

General linear mixed models were fitted to standardize U.S. survey CPE data because assumptions of normality were reasonably met using a \log_e transformation ($\log(x+1)$), the proportion of sites with no catches was small (0.016), and because the lognormal error model fit observed data reasonable well (Figure 3.3). Subsequent analyses revealed that results were insensitive to the choice of dealing with zero catches (simply discarding sites with zero catches or adding a small constant (CPE+1) before log-transforming). Prospective factors were identified as either fixed or random effects based on properties of the data (e.g., explicit use of all possible levels of an effect would warrant a fixed effect), the theoretical scope of inference desired, and the anticipated presence of random variations in distribution among levels of a particular factor or from statistical interactions. Fixed effects included year (y), week (w), basin (b), sub-basin (l), surface water temperature (t), secchi depth (s), water depth (d), presence of hypoxia (h), type of gill net set (n), and the interaction between year and basin (part of the effect of interest; described further below). Random effects included all other 2, 3, and 4-way interactions with year, basin, sub-basin, and week. The distribution associated with each random effect was assumed to be normal (on the logit scale for binomial data and on the log scale for positive data) with a mean of zero and a variance estimated by the model.

For the Canadian survey, the fully parameterized mixed model for the binomial case where observations were whether CPE was positive or not was

$$g(E(X_{ywbtsdh})) = u + \alpha_y + \alpha_w + \alpha_b + \alpha_l + \alpha_t + \alpha_s + \alpha_d + \alpha_h + \alpha_n + \alpha_{yb} + \beta_{yw} + \beta_{yl} + \beta_{wb} + \beta_{wbl} + \beta_{bl} + \beta_{bl} + \beta_{ywbl} + \beta_{ywbl} + \beta_{ywbl};$$

and the mixed model for the lognormal case on CPE given that CPE was positive was

$$\log_{e}(\text{CPE}_{ywbtsdh}) = u + \alpha_{y} + \alpha_{w} + \alpha_{b} + \alpha_{l} + \alpha_{s} + \alpha_{d} + \alpha_{h} + \alpha_{n} + \alpha_{yb} + \beta_{yw} + \beta_{yl} + \beta_{wb} + \beta_{wbl} + \beta_{wbl} + \beta_{wbl} + \beta_{ywbl} + \beta_{$$

For the United States survey, the fully parameterized mixed model with lognormal error was

$$\log_{e} (CPE_{ywbtsdh}+1) = u + \alpha_{y} + \alpha_{w} + \alpha_{b} + \alpha_{t} + \alpha_{s} + \alpha_{d} + \alpha_{h} + \alpha_{yb} + \beta_{yw} + \beta_{wb} + \beta_{ywb} + \beta_{ywb} + \epsilon_{ywbtsdh}$$

The function $g(E(X_i))$ is the inverse of the logit link function and specifies the expected proportion of positive CPE values from individual binomial observations; *u* is the overall mean evaluated at the reference level for categorical effects and the mean value for continuous effects (Table 3.2); α_i is the parameter coefficient for fixed effect *i*; β_i is the parameter coefficient for random effect *i*; and ε_i is the residual error term. All analyses were conducted using the lme4 package (Bates et al. 2011) implemented in the R statistical computing environment (R Core Development Team 2011).

Model Selection Procedure

Reduced models (i.e., fewer parameters) were evaluated for improved goodness of fit by using Akaike's information criterion corrected for small sample sizes (AIC_c) to select the best model (Akaike 1973; Burnham and Anderson 2002). Following Deroba and Bence (2009), a modified backward selection approach was used to compare alternative mixed models for each survey dataset because of the large number of possible models (all subsets \geq 56 models). The

best set of random effects was identified first while holding all fixed effects constant by dropping those random effects from the final model that appreciably deteriorate model fit (a change in AIC_c (ΔAIC_c) of more than 2), beginning with the higher order interactions. All subsets of fixed effects were then evaluated using the best set of random effects. Lognormal error models were fit using restricted maximum likelihood (REML; McCulloch and Searle 2001) when selecting among random effect components and by maximum likelihood when selecting among fixed effect components. After a final model was chosen the model was fit using REML. The binomial model was fit by maximum likelihood using a Laplace approximation to integrate out random effects in all cases.

The relative importance of specific factors affecting walleye survey indices was assessed by calculating the difference in AIC_c from the best model and a model reduced by the factor of interest (Δ AIC_c = AIC_c reduced model - AIC_c best model). In this way, factors associated with larger Δ AIC_c values particularly influenced model fit, and thus were identified as a significant source of undesired variation in the abundance index. The fixed effects of year, basin and the interaction of year and basin were not assessed in this manner because these factors were kept in the final model to describe the annual abundance trend of interest regardless of assessed importance (as measured by Δ AIC_c).

Extraction of Standardized Indices

A basin-level annual index of abundance was extracted from the final model for each survey. To do so, all other factors included in the final model were set to their respective reference levels (categorical variables) or mean values (continuous variables) (Table 3.2). For the delta-lognormal approach to handling zero catches, the Canadian standardized index was calculated by multiplying the probability of a nonzero catch (estimated from best binomial error model) by the expected catch rate given that the catch was nonzero (estimated from lognormal error model) for each basin and year combination (Punt et. al. 2000). The United States standardized index was simply the extracted basin by year expected catch rates. Binomial estimates were back transformed to proportions using the inverse logit function. Log transformed estimates were back transformed to mean values by applying the standard bias adjustment:

$$\overline{\text{CPE}}_{y,b} = \exp\left(\tau + \frac{s_{\tau}^2}{2}\right) - 1,$$

where τ is the estimated effect for each basin and year combination (i.e., $\alpha_y + \alpha_b + \alpha_{yb}$), and *s* is the standard error of τ . Approximate confidence intervals were calculated by back transforming log_e intervals for log-normal models (Candy 2004) and by applying a normal approximation of the log_e catch rate for delta-lognormal models (Shono 2008). Confidence intervals represent error bounds related to a change in the year effect from the reference level (first year in this case).

Results

A single best model was specified according to AIC_c for each data set (Canada zero/nonzero; Canada positive CPE; US CPE). In each case, the overall best model included both random- and fixed-effect factors. Despite the fact that several alternative, yet plausible models were identified (Δ AIC_c < 2), we present results from the single best model because other plausible models differed solely by the addition of a single parameter that, in all cases, had an estimated 95% confidence bound overlapping zero and resulted in similar abundance trends (more than 0.99 correlation with the single best model).

There were differences in the selection of random effects (i.e., interaction terms between spatial and temporal factors used to account for variance in CPE) for each data set (Table 3.3). Positive random variations in non-zero Canadian survey CPE were apparent among years, weeks, basins and sub-basins, although the predominant source of variation (12% of the total) was attributed to spatial differences at the smallest resolution evaluated (i.e., the basin and sub-basin interaction term ($\beta_{b,l}$), Table 3.3). A moderate amount of the total variance (13%) associated with the probability of a non-zero catch in Canadian waters was attributed to the interaction among year, week, and sub-basin factors. In U.S. waters, a small amount of the total variance in log_e(CPE+1) was attributed to weekly differences in sampling time for each year and basin. In all three cases, the amount of the total variation explained was small relative to the residual variation.

The overall best fixed effects model for each data set included both categorical and continuous environmental variables (Table 3.4). For the Canadian survey, the probability of a non-zero catch was associated with, in order of importance, set type ("canned" had a positive

effect over "bottom"; +), the presence of hypoxia (-), and secchi depth (-). When catches were non-zero, the catch rate was associated with the set type ("canned"; +), water depth (+), and the presence of hypoxia (-). The salient factor influencing Canadian survey catch rates was the type of net set, the factor describing the general location in the water column where standard gill nets were set (either "canned" at depth or on the bottom), as drastic declines in model fit occurred when it was removed (Table 3.4). For the United States survey, catch rates log_e(CPE+1) were associated with secchi depth (-) and surface water temperature (+). However, secchi depth had a greater influence on model fit (Table 3.4). Factors that marginally influenced model fit but were not incorporated into the final model included surface water temperature (CAN models) and the presence of hypoxia (US model).

Standard general and generalized linear model diagnostics were used to evaluate the goodness of fit for models used to standardize fishery-independent surveys. For both Canadian (Figure 3.4) and United States (Figure 3.5) surveys, positive catch rates fit reasonably well to the log-linear model. Plots of observed versus expected values (panel A) indicated that these models did an adequate job reducing variance in the data, however some lack of fit was apparent at the lowest CPE values. Residuals seemed to behave adequately in accordance with model assumptions; no trend with the expected value (model specified correctly, panel B), homoscedastic (constant variance across expected values, panel C), and appeared to be normally distributed on the loge scale (panel D). Additionally, there was no evidence of overdispersion or extra binomial variation (variance inflation factor $(\hat{c}) \sim 1$) related to the full, fixed effects only model describing the proportion of non-zero catches in Canadian waters. The variance inflation factor $(\hat{c} = 0.98)$ was estimated by taking the ratio of the residual deviance to the residual degrees

of freedom. Quantile-quantile plots provided graphical evidence that the assumption of normality for random effects was reasonably met (not shown here).

After accounting for potential confounding factors, the coefficients describing annual differences by basin (α_y , α_b , and $\alpha_{y,b}$) from the overall best models were used to develop standardized indices of walleye abundance, and compared to nominal indices (lower panel of each quadrant, Figure 3.6). In general, years with the highest- and lowest-ranked indices were similar between model-based (standardized) and data-based (nominal) approaches. However, rankings differed considerably among basins and surveys in many cases. In Canadian waters, for example, the 2nd highest central basin standardized abundance index in the time series occurred in 2006, whereas the west basin 2006 index was the 10th highest. Similarly in U.S. waters, the 1996 central basin index was ranked 3rd highest, yet it ranked much lower (14th) in the west basin. Since 1990, when Canadian and U.S. surveys operated concurrently, the single highest standardized Canadian abundance index was distinctly in 2005 in both basins, due largely to a very strong 2003 year class showing up in the 2005 survey. The 2003 year class did not show up as strongly in U.S. western and central basin surveys (2005 ranked 7th and 4th, respectively). General abundance trends were mostly similar between standardized and nominal indices (nominal value within standardized 95% confidence interval; Figure 3.6) for each survey and basin combination. Because indices are relative, a constant difference in scale between standardized and nominal indices was not of importance. However, there was noticeable annual variation in the direction and magnitude of the difference, suggesting that standardized surveys indicate a different index of walleye abundance compared to the nominal survey. This can best

be seen by plotting the proportional difference (PD; upper panels, Figure 3.6) between the two indices and looking for departures from a constant PD. Hence, PD values are unit less and indicate how many times greater the nominal index is compared to the standardized index. Although annual variability in PD was present in all cases, there was some evidence that this variation was trending with a decreasing PD in the Canadian central basin index and an increasing PD in the United States western basin index. A trend in PD suggests that factors not accounted for in the nominal abundance index have a directional temporal effect on the standardized index, ultimately suggesting deviating abundance trends between the nominal and standardized indices or a differential trend in catchability that is not accounted for by factors used in the analysis.

Discussion

Fishery-independent surveys have been used to assess relative changes in Lake Erie walleye population abundance over time. Our model of standardized catch rates suggested a different temporal pattern of abundance compared to nominal catch rates for each survey and basin combination. In some cases, the standardized index suggested changes in year-to-year abundance in the opposite direction as the nominal index, and the difference between standard and nominal indices may be trending across the time series. The former implies a completely opposite indication of population status in a given year (i.e., from increasing to decreasing or vice versa). The latter is of particular concern because it implies that the nominal index could be incorrectly characterizing relative abundance at an increasing or decreasing rate through time, thereby misleading managers and potentially affecting management decisions. Although in many cases the nominal index was within the standardized estimated 95% confidence interval, we recommend the use of the standardized index because it accounts for inconsistencies in survey data not attributed to changes in abundance.

Discrepancies in abundance trends between surveys could be a result of spatial differences in availability (population structure) and selectivity (gear efficiency) to fishing gear or due to differences in survey design and sample sizes (Table 3.1). There are clear differences in walleye population structure longitudinally in Lake Erie as a result of spawning activity and other seasonal environmental conditions (Kershner et al. 1999; Wang et al. 2007; Berger et. al. in press), however latitudinal differences, as defined by the international border, are less clear. A broader range of individuals at size were vulnerable to survey gear in northern waters because Canadian standard nets spanned a broader range of mesh sizes than United States nets. Thus, recruitment variability could be one explanation of differences in the relative size of indices between surveys as the Canadian survey would be more effective at capturing newly recruited (smaller) walleye, particularly during high recruit years (e.g., the 2005 recruit class) when juveniles would be expected to grow at a collectively slower rate (i.e., density dependent growth; Venturelli et al. 2010). Further, stratified fixed-site survey designs (United States survey) cannot be expected to provide the same information as stratified random designs (Canadian survey) when the sampling unit displays inconsistent spatial patterning (Hilborn and Walters 1992; NRC 1998), at least not without some form of adjustment (e.g., spatial interpolation or "kriging"). This phenomenon is further exacerbated when sample sizes differ by several orders of magnitude between survey designs (Table 3.1). Thus, Canadian and United States fishery-independent surveys should remain separate indicators of population size. Experimentally fishing nets sideby-side to normalize catchability and combine surveys may be an insufficient adjustment in and of itself because of differences in survey design and the influence of localized environmental factors on catch rates.

Fishery-independent surveys are often used as an auxiliary source of information to supplement fishery dependent data when fitting stock assessment models (Deriso et al. 1989, NRC 1998). When survey indices of abundance considerably influence stock assessment model fit (i.e., highly weighted component in the model objective function; Quinn and Deriso 1999), as is the case for Lake Erie walleye, management parameters that result from the assessment will be sensitive to the quality of survey data. Further, because walleye abundance trends inferred from Canadian and United States standardized surveys (1990-2008) differed in terms of the relative change in magnitude and direction (28% of years) of indices, defining weights for each survey index (more weight given to higher quality data) are of critical importance and assessment results should always be evaluated for sensitivity to assigned weights. Empirical variances associated with standardized CPE indices could be used to set weights between surveys, although variances calculated from non-random, systematic or fixed location sites may not represent the population on whole (Hilborn and Walters 1992). Maunder and Starr (2003) suggest the use of within year CVs (coefficient of variation) instead of averaging over years to capture interannual differences in precision between individual index values, especially in the presence of strong outliers, when fitting fisheries assessment models to CPE abundance indices. For Lake Erie walleye, interannual variability in index value CVs was modest for the Canadian (range = 0.46-0.65) and United States (0.34-0.69) survey.

Lake Erie walleye move in response to seasonal conditions to optimize growth (Kershner et al. 1999), resulting in a general longitudinal migratory pattern where the extent of movement is positively related to walleye size or age (Kershner et al. 1999; Wang et al. 2007; Bowlby and Hoyle 2011; Berger et al. *in press*). To adjust for annual differences in the timing and extent of walleye movements as it relates to survey timing and location, random effect terms (σ^2_i ; Table 3.3) were implemented to account for random fluctuations in and correlations between catch rates among interacting spatial and temporal factors. For example, 13.2% of the variation in the proportion of non-zero catches resulted from differences among each combination of year, week, and sub-basin. For each best model, random effect terms were identified as important sources of variability in catch, and the inclusion of these could result in abundance indices with reduced and more appropriately characterized uncertainty (Helser et al. 2004) and improved stock assessment results (Chen et al. 2003).

Recognizing variability in catchability and availability as a result of environmental factors and accounting for this variation when interpreting survey data has received more attention recently (Maunder et al. 2006; Tian et al. 2009), particularly in light of directional environmental change (Hart et al. 2011). Site-level measurements of surface water temperature, lake depth, water clarity, and the presence of hypoxic conditions taken during autumn sampling events influenced Lake Erie walleye survey catch rates. Surface water temperature and water depth are perhaps the most commonly assessed environmental factors when standardizing fishery or survey indices of abundance because these data are either directly measured or easily interpolated from location information. For example, Schmalz and Staples (2011) found that walleye gill net catchability in a large Minnesota lake was influenced by both water temperature

and depth. In Canadian waters, gill nets set on the bottom of the lake captured far fewer walleye than gill nets set in the water column ("canned"). In United States waters, surface water temperature was a marginally important factor describing catch rates, though the largest discrepancy between nominal and standard indices was associated with unusually cold water temperatures during the sampling period (PD, west basin 2008; Figure 3.6). Secchi depth had a negative effect on positive catch rates (US) and the proportion of non-zero catches (CAN). For example, the largest differences (PDs; Figure 3.6) between nominal and standardized catch rates in the central basin were associated with high $(>75^{\text{th}} \text{ percentile})$ mean secchi depths. In addition to being sub-optimum habitat for walleye (i.e., decreased availability; Lester et al. 2002), areas of increased water clarity can also decrease gear efficiency by increasing net avoidance behavior (Buijse et al. 1992; Olin et al. 2004). In general, survey nets were set infrequently (e.g., ~3% of CAN central basin sites) in hypoxic conditions (dissolved oxygen $\leq 4 \text{ mg} \cdot \text{L}^{-1}$), although positive catch rates and the proportion of non-zero catches in Canadian waters decreased substantially (48% and 28%, respectively) at sites with low levels of dissolved oxygen. Other prospective environmental factors that might be expected to influence walleye catch rates but where comprehensive data was limiting for the current analysis include wind direction and speed (Roseman et al. 2005; Zhao et al. 2009; Hart et al. 2011), current direction and speed (Roseman et al. 2005; Zhao et al. 2009), and wave or seiche height (Trebitz 2006; Rydell et al. 2010).

It is commonly accepted that the use of CPE as an index of abundance – one of the most fundamental relationships in fisheries stock assessment – can be problematic and misleading when applied to fishery dependent data (NRC 1998; Harley et al. 2001; Maunder et al. 2006) because CPE may not be directly proportional to abundance across the time series. This phenomenon can have major ecological, social, and economic implications as was the case with the collapse of the northwestern Atlantic cod fishery (Rose and Kulka 1999; Gien 2000; Frank et. al. 2005). In contrast, problems associated with using fishery-independent data as an abundance index have not received as much attention because the objective of these surveys is usually to representatively sample the target population. Yet, non-linearity in the proportionality between abundance and CPE can still arise in survey data (e.g., Swain et al. 1994; Hansen et al. 2004), despite accounting for as many confounding factors as possible given available data. Thus, the assumption of constant catchability may remain invalid and applying several methods to adjust for space or time-varying catchability when using survey abundance indices may be prudent (Wilberg and Bence 2006; Wilberg et al. 2010). In fact, the result that Canadian and U.S. surveys had different abundance trends suggests that catchability was drifting over time or that the surveys sampled different populations; either way, how these indices are used in the stock assessment should be evaluated further.

Inconsistencies in survey data that arise from behavioral processes can be very challenging to overcome. For highly mobile species, for example, survey indices of abundance may remain inaccurate because of seasonal or local changes in distribution within and among management units used in population assessments (Schwarz and Seber, 1999; Gerber et al., 2003). Although the knowledge base is growing (e.g., Wang et al. 2007; Zhao et al. *in press*), a comprehensive treatment of walleye movement and migratory patterns in Lake Erie and the ensuing impact it has on rational management remains a critical goal. Such information could provide insight into specific factors that affect the timing, extent, and duration of walleye migratory patterns and how these influence abundance indices used in stock assessment.

Surveys used to index the Lake Erie walleye population could be improved by gathering more information related to walleye movements (e.g., prey distribution), coordinating the collection of environmental data among jurisdictions, increasing the power to detect temporal trends (Wagner et al. 2009), and incorporating movement metrics inferred from tagging data directly into the stock assessment to improve interpretation of survey index data. The current work disaggregates survey data by basin (owing to population structure; Wang et al. 2007; Berger et al. *in press*) and jurisdiction (owing to differences in gear mesh sizes and survey design). Future work should explore the sensitivity of population trends at alternative disaggregation levels because the spatial scale at which catch rate and environmental data are aggregated can greatly influence the standardization of index data (Tian et al. 2009).

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APPENDIX 3A

Main Tables and Figures

Table 3.1.—Number of sites used in the analysis that were sampled during annual Canadian (CAN) and United States (US) fishery-independent gill net surveys in the west and central basins of Lake Erie. Canadian sites were selected following a stratified (depth) random design each year, and United States sites followed a stratified (depth) fixed design (not all sites sampled every year and new sites added opportunistically).

	CAN		U	U.S.		
Year	West	Central	West	Central		
1983			2	2		
1984			2	5		
1985			2	1		
1986			2	5		
1987			7	10		
1988			6	12		
1989			6	8		
1990	37	92	9	8		
1991	29	120	7	7		
1992	38	125	10	7		
1993	38	110	4	4		
1994	36	64	4	5		
1995	22	54	4	6		
1996	40	60	10	6		
1997	27	124	10	6		
1998	25	100	8	6		
1999	44	76	8	7		
2000	42	142	10	8		
2001	40	122	7	3		
2002	44	144	9	4		
2003	44	142	9	6		
2004	44	139	11	22		
2005	44	166	14	26		
2006	42	120	10	35		
2007	28	141	14	16		
2008	44	138	12	25		

Variable	CAN	U.S.
year	1990	1983
week	1	1
basin	west	west
sub-basin	W1	-
hypoxia	no	no
set type	bottom	-
surface water temp. (°C)	16.8	14.3
secchi depth (m)	2.5	1.4
water depth (m)	16.6	12.3

Table 3.2.—Reference levels for categorical variables and mean values for continuous variables used to standardized Canadian (CAN) and United States (U.S.) fishery-independent surveys.

Canadian Survey			United States Survey		
Best Model	Source	σ_{i}^{2}	Best Model	Source	σ_{i}^{2}
Log-normal	$\beta_{y,w,l}$	0.045	Log-normal	$\beta_{w,b}$	0.054
	$\beta_{y,b,l}$	0.012		$\beta_{y,w}$	0.031
	$\beta_{w,b,l}$	0.020		E _{ywbtsdh}	0.916
	$\beta_{y,w}$	0.039			
	$\beta_{y,l}$	0.003			
	$\beta_{W,b}$	0.029			
	$\beta_{W,l}$	0.000			
	$\beta_{b,l}$	0.118			
	Eywbltsdhn	0.742			
Binomial	$\beta_{y,w,l}$	0.132			
	$\beta_{y,w}$	0.000			
	$\beta_{y,l}$	0.000			
	$\beta_{W,l}$	0.000			

Table 3.3.—Source of variation from estimated random effects ($\beta_{i's}$) and residual variation ($\epsilon_{i's}$) associated with the best models used to standardize Canadian and United States fishery-independent surveys.

Notes: y is year; w is week; b is basin; and l is sub-basin (others refer to text).

Table 3.4.—Comparison of the relative importance of fixed effect factors $(\alpha_{i's})$ included in the best model used to standardize Canadian and United States fishery-independent surveys. Estimates (±1 SE) of fixed effects from the overall best model are shown for each survey and assumed error structure. Each factor was evaluated by removing it from the overall best model (random effects held constant) and assessing the resultant change in AIC_c (Δ AIC_c) such that larger values signify increased importance in model fit. The base model is shown as a reference point, describing differences in catch rates due solely to year and basin effects (i.e., trends of interest) prior to accounting for other factors. The factors week and sub-basin were included in the best model through random effect interaction terms (see Table 3) and thus were not further evaluated here. The combination of $\alpha_y + \alpha_b + \alpha_{yb}$ represents effects describing the annual trend of interest for each basin.

Model	Factor	ΔAIC_{c}	Estimate	SE
Canadian Survey				
Log-normal				
best: $a_y + a_b + a_{yb} + a_w + a_l + a_d + a_h + a_n$		0.00		
	α_d	12.48	0.025	0.007
	α_h	8.05	-0.565	0.181
	α_n	144.10	0.522	0.042
base: $\alpha_y + \alpha_b + \alpha_{yb}$		259.30		
Binomial				
best: $\alpha_v + \alpha_b + \alpha_{vb} + \alpha_w + \alpha_l + \alpha_d + \alpha_h + \alpha_n$		0.00		
, ,	α_s	1.20	-0.087	0.048
	α_h	4.88	-0.945	0.356
	α_n	143.54	1.144	0.097
base: $\alpha_y + \alpha_b + \alpha_{yb}$		238.38		
United States Survey				
Log-normal				
best: $\alpha_v + \alpha_b + \alpha_{vb} + \alpha_w + \alpha_t + \alpha_s$		0.00		
	α_t	0.44	0.030	0.017
	α_s	37.25	-0.438	0.074
base: $\alpha_y + \alpha_b + \alpha_{yb}$		34.75		

Notes: y is year; w is week; b is basin; l is sub-basin, t is surface water temperature, s is secchi depth, d is water depth, h is the presence of hypoxia, and n set type.



Figure 3.1.—Canadian (Ontario) and United States (Michigan and Ohio) fishery-independent gill net surveys were used to index the west (W) and central (C) basin Lake Erie walleye population. Dots indicate the locations of sampling sites for the most recent year (2008), which was a standard sampling year in Canadian waters and an intensive sampling year in US waters. Large sample sizes to the north enabled the analysis of sub-basin effects on catch rates (W1, W2, C1-C4). Overall site selection followed a stratified (depth) random sampling design (CAN) and a stratified (depth) fixed sampling design (US).



Figure 3.2.—Histogram of observed walleye (age-2 and older) catch rates in numbers of individuals from Canadian (1990-2008; panel A) and United States (1983-2008; panel B) fishery-independent surveys. The proportion of sites with zero catch was high (0.36) in the Canadian survey and low (<0.02) in the United States survey.



Figure 3.3.—Fits of alternative error distributions to observed mean and variance in walleye CPE for Canadian and United States fishery-independent surveys. Each observation corresponds to a year for years with 5 or more sites sampled (only excludes U.S. 1983).



Figure 3.4.—Standard diagnostic plots that evaluate the adequacy of the overall best log-linear model used to standardize positive catch rates for the Canadian fishery-independent survey. Plots assess model fit (A) and adequacy (B) qualitatively and evaluate assumptions of constant variance (i.e., no trend in C) and normality (i.e., straight line in D).



Figure 3.5.—Standard diagnostic plots that evaluate the adequacy of the overall best log-linear model used to standardize positive catch rates for the United States fishery-independent survey. Plots assess model fit (A) and adequacy (B) qualitatively and evaluate assumptions of constant variance (i.e., no trend in C) and normality (i.e., straight line in D).



Figure 3.6.—Trends in walleye relative abundance for Canadian (CAN) and United States (US) fishery-independent surveys in the west and central basins. The lower panel for each region compares trends in walleye relative abundance as inferred from a standardized index (mean (solid line), 95% confidence interval (dotted lines)) and a nominal index (normalized to the first year standardized index value; circles). The upper panel for each region shows the proportional difference (PD; solid line) between the raw nominal and standardized indices of walleye abundance and the mean PD across the time series (dotted line).

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CHAPTER 4

The effect of alternative walleye (*Sander vitreus*) management procedures on harvest policy choice and performance

Abstract

Rational management of fisheries requires consideration of multiple, and often conflicting, societal objectives. Management procedures (data collection, population assessment, and harvest policy) are the actions taken to ensure that fishery performance best meets objectives specified by stakeholders. Computer simulations have proven to be effective tools for facilitating the expected performance of alternative management procedures given system and management uncertainties, thus providing valuable insights to decision-makers. Simulation analyses were used here to evaluate how the choice of data collection and population assessment procedures influenced the selection and performance of alternative harvest policies. Candidate management procedures included using relatively complex (annual age-structured), complex but less frequent (triennial age-structured), and simple (survey index) data collection and population assessment approaches to inform three general types of harvest control rules (constant fishing mortality, feedback, and conditional constant catch). A suite of common policy performance metrics were computed for each case and compared among candidate procedures. Results indicate that harvest policy performance and the ensuing tradeoffs between conflicting objectives were affected by the choice of a data collection and assessment scheme. In general, annual SCA procedures outperformed the other procedural schemes evaluated here, providing the best overall balance between the harvest and risk-related tradeoffs that were explicitly considered in simulations. However, annual SCA procedures only afforded a modest improvement in policy performance over triennial SCA procedures in exchange for the extra effort associated with implementing annual management procedures. Ultimately, the choice of data and assessment

procedures are of non-trivial significance when it comes to the quality and quantity of information, costs, and effort associated with managing fisheries.

Introduction

Contemporary fisheries management often entails, in some cases under statutory obligation (MSA 2007; FMA 2011), the development and subsequent application of well-defined management plans to guide long-term "optimal" resource use and prevent overfishing. The decision-laden process of developing comprehensive management plans along with the general call for science-based decision-making has resulted in an increased use of model-based approaches (e.g., closed-loop simulations) as decision support tools. Management strategy evaluation (MSE) is one such tool that has been applied to many marine fisheries worldwide (e.g., Butterworth and Geromont 1997; Smith et al. 1999; Punt 2011) to compare and contrast the relative performance of alternative management procedures (data collection, stock assessment, and harvest control rules) against a set of operational objectives while accounting for uncertainties associated with each procedure in the management cycle (Walters and Hilborn 1976; De la Mare 1996; Sainsbury et al. 2000). The goal of such analyses is often to aid in the selection of an appropriate harvest policy, given a particular assessment method and data collection scheme. However, the choice of assessment and data procedures can also have important consequences for the performance of procedures used to manage fisheries. Incorporating alternative assessment methods and data collection schemes into an MSE-type of framework can provide information about the expected consequences for and tradeoffs among alternative management strategies with different economic realities (i.e., the need to reduce management costs) that by necessity play a role in management choice.

Three important questions that fishery managers must address when developing management plans are: (1) what data should be collected to monitor the population of interest;

(2) how should the information be used to evaluate population status; and (3) what rules should be used to determine suitable harvests? In most cases, the answers to these questions are governed by biological characteristics of the population, public demand for the resource, budgetary constraints, and uncertainty. Management agencies must operate within the confines of an annual budget such that decisions on how to allocate finite resources to manage a particular fishery are made in the context of multiple agency and fishery objectives. However, choices pertaining to how 1 (monitoring data) and 2 (population assessment) affect the choice and performance of 3 (harvest policy) are rarely evaluated. These choices have become more critical as the demand for science-based fisheries management has increased at a faster pace than the availability of resources (e.g., funds, data, or qualified personnel) required to perform the necessary science (MSA 2007; U.S. Dept. of Commerce and U.S. Dept. of Education 2008).

The frequency and complexity of data gathering and assessment schemes are two management choices that are likely to have distinct investment tradeoffs, both in terms of biological and economic expectations. It is reasonable to expect that management performance from a complex, data-intensive scheme (e.g., statistical age-structured assessment) would differ according to the frequency with which it was applied, or in relation to a simpler, less costly scheme (e.g., fishery-independent index). However, if there were insignificant biological differences in terms of harvest policy choice and long-term system performance between schemes, rational management would suggest the use of the most cost-effective set of procedures so that limited monitoring and assessment resources could be re-allocated elsewhere (Hansen and Jones 2008). In some cases, management performance has been shown to improve (Hilborn 1979; Ludwig and Walters 1985) or have little long-term conservation implications (Cox and Kronlund 2008) when using simplified assessment procedures.

Population assessment procedures generally occur at regular time intervals, with assessment frequency being dictated, ideally, by species life history and management goals. For example, some Pacific salmon stocks are managed using in-season monitoring and assessment schemes to regularly update population status throughout the fishing season in pursuit of constant escapement harvest policies (e.g., Robb and Peterman 1997; Su and Adkison 2002). At the other extreme, multi-year catch limits have been proposed for many whale species using procedures at 5-year intervals (IWC 2007). Clearly, there is a balance between the frequency of updating (or feedback) management actions and species longevity when considering optimizing harvest, stock rebuilding time after over-depletion, costs of management, or other fishery objectives. Alternatively, simply delaying pre-defined management action (e.g., due to political opposition) has been shown to severely degrade policy performance and exacerbate undesirable circumstances (Shertzer and Prager 2006).

Alternative data collection and assessment schemes will undoubtedly influence operational management in one way or another. Using closed loop simulations to compare the tradeoffs associated with different schemes can be particularly useful for decision-makers because it highlights the potential opportunity costs associated with foregone decisions within a risk assessment framework. Here, we apply this approach to the Lake Erie walleye (*Sander vitreus*) fishery to guide management for this socially, culturally, and economically valuable fishery. Specifically, we investigate whether 1) the ordinal performance and 2) the absolute performance of candidate harvest policies change under three alternative data collection and assessment schemes across a suite of common performance measures.

Methods

Study Population

Lake Erie is the smallest of the Laurentian Great Lakes in terms of volume yet is the most productive (Beeton et al. 1999). The west basin (mean depth = 7.4 m) and central basin (18.5 m) support lucrative warm and cool-water fisheries, while the east basin (24.4 m) is dominated by cool and cold-water species. Walleye are most abundant in the west and central basins of Lake Erie (Figure 4.1) with 98% and 97% of the historical walleye harvest and effort, respectively, occurring in this area (WTG 2009). As a result, data collection, stock assessment and harvest policy management procedures are used to set harvest levels (total allowable catch, TAC) in this area. Eastern basin stocks remain small, and thus are not currently incorporated into lake-wide TACs. Walleye are exploited by a commercial gillnet fishery exclusive to Canadian waters and a recreational hook-and-line fishery mainly in United States waters. All analyses presented here focus on the management of the west and central basin walleye population.

Approach Overview

Closed-loop simulations of the entire management process were used to compare how different management procedures performed across a range of plausible conditions. The general steps included (*sensu* Punt 2006):

- Develop a model to describe the true population dynamics for the purpose of simulations, often termed operating model (OM).
- (2) Parameterize the OM using information from the most recent population assessment and best available knowledge.
- (3) Project the OM forward through time while imposing one set of candidate management procedures.
 - a. At each time step
 - i. Generate observed data from OM conditioned by population structure.
 - ii. Conduct stock assessment (SA) procedure using new observations.
 - Use results from SA procedure to inform harvest policy procedure and set catch levels (i.e., TACs).
 - iv. Apply SA informed TAC to the OM.
 - v. Use the OM to project forward one time step accounting for actual harvest.
 - b. Repeat over time horizon.
- (4) Repeat steps 2-3 many times and compile performance measures.
- (5) Repeat steps 2-4 for each set of candidate management procedures.
- (6) Repeat steps 2-5 to evaluate sensitivity to key model assumptions.

The full routine resulted in 250 individual 50-year projections from which performance metrics were then computed for 18 sets of candidate management procedures and then repeated twice to evaluate sensitivity.

Operating Model

Walleye population dynamics were simulated using a stochastic age- and spatiallystructured operating model (OM) that followed the general structure of the walleye statistical catch-at-age stock assessment model (SCA) developed in chapter 1, but was informed by updated survey information (standardized survey data; chapter 2). Model notation (Table 4.1) and equations (Table 4.2) describe the dynamics of both the OM and SCA. The OM tracked a single population of age-2 through an age-7⁺ group of walleye ('plus' symbol indicates all fish age-7 and older) through time and was implemented using AD model builder software (Fournier 2011). To facilitate comparisons among candidate management strategies, the same set of random numbers were used to generate OM stochasticity for each set of management procedures tested.

Several types of uncertainty were incorporated into the analysis. Structural uncertainty (or model process error) was acknowledged by applying a different set of initial conditions and population parameters used to initialize and control the OM for each simulation (Jones and Bence 2009). Each set was one Markov chain Monte Carlo (MCMC) sample of the stationary joint posterior distribution from the most recent (2008) catch-at-age stock assessment model as approximated by using MCMC with the Metropolis-Hastings algorithm (Gelman et al. 2004). Initial conditions included abundance at age in the most recent two years; two years previous was needed to calculate spawning stock size (Eq. 4.2.10 (Table 4.2 equation 10)). Parameters (and control variables; Table 4.2) governing the 'true' population dynamics included a Ricker α , β , and lognormal error terms; intercept, slope, and normal error terms for the relationship between recreational effort and abundance; catchability; vulnerability; standard deviations for

effort, catch, and CPE observations; and the spatial distribution of commercial fishing mortality (further specifics provided below). This approach allowed for two levels of recruitment (and recreational effort) uncertainty: 1) lognormal error inherent to a single MCMC sampled Ricker stock-recruitment function (mean squared error on loge scale), and 2) structural error associated with selecting a particular set of Ricker parameters (i.e., parameters were estimated from each MCMC sample of stock and recruitment to generate a time series of recruits for a given simulation; Figure 4.2). Uncertainty associated with imperfect observations (observation error) was incorporated by distorting simulated data prior to executing assessment procedures. As such, lognormal errors were applied to fishing effort (Eqs. 4.2.19-4.2.20), catch (Eq. 4.2.22), and survey CPE (Eq. 4.2.23) observations. Error in observed proportions-at-age (Eqs. 4.2.24-4.2.25) was incorporated by using a multivariate-logistic function with constant age and gear standard deviations (Table 4.1; Schnute and Richards, 1995; Cox and Kronlund 2008). Assessment uncertainty was applied by updating the OM with fishing mortality rates informed by a particular harvest policy using assessment-based estimates of abundance (Irwin et al. 2008). In effect, assessment-based fishing mortality rates were converted into TACs, which were then used in conjunction with the simulated 'true' abundance to calculate fishing mortality rates applied to the OM (Eqs. 4.2.27-4.2.28). Lognormal policy implementation error (Table 4.1) was applied to the policy-specified commercial fishing mortality rate to account for uncertainty associated with imperfect adherence to policy measures (Eq. 4.2.30).

Population dynamics were composed of recruitment and mortality processes incremented on an annual basis. Recruitment to the fishery was assumed to occur at the beginning of the year for age-2 fish with recruitment size being a Ricker function (lognormal error (Eq. 4.2.3)) of spawning stock size two years prior. An upper bound of 200 million walleye was imposed on projected recruitment to prevent unrealistically large recruitment events that resulted from extreme positive errors associated with the tail end of the lognormal distribution. Spawning stock size was a measure of the total number of eggs produced by females during the year by applying age-specific estimates of walleye maturity (Wang et al. 2009) and fecundity (Muth and Ickes 1993) to the total number of females in each age category (Eq. 4.2.10).

Total mortality consisted of removals due to fishing and deaths due to natural causes. The instantaneous natural mortality rate was assumed known and constant at 0.32 yr^{-1} . Instantaneous fishing mortality depended upon year, age, and region for each fishery. The operational harvest policy was used to set a target TAC, of which a percentage (43.1%; WTG 2009) was allocated to the commercial fishery and then distributed between regions (i.e. west and central basins; Eq. 4.2.29) according to the "recent" or "historical" spatial distribution of fishing as estimated by the most recent stock assessment (see sensitivity analysis). The "recent" period (2001-2008) corresponded to a time of initially rebuilding walleye stocks as set forth in the Lake Erie coordinated percid management strategy (Locke et al. 2005). The "historical" period (1990-2008) included all years since the beginning of conducting region inclusive fisheryindependent surveys. Summing mean weight of the catch across ages and regions resulted in total commercial yield (Eq. 4.2.26). The recreational fishery was assumed to be self-regulating by allowing the amount of recreational effort expended to be a linear function of population abundance (Eq. 4.2.20; Jones and Bence 2009). As a result, recreational fishing mortality was not explicitly set by the operational harvest policy (Eq. 4.2.21). Individual cohorts declined through time according to total mortality (Eqs. 4.2.7-4.2.8), thus assuming no population-level

emigration. The sum of all age-classes included in the OM represented total walleye abundance. Biomass was the product of abundance-at-age and mean weight-at-age, summed across ages (Eq. 4.2.9).

Catchability and vulnerability scaling parameters were used to solve for remaining OM unknowns: age- and region-specific recreational fishing mortality (Eq. 4.2.21) and survey CPE (Eq. 4.2.13); and region-specific commercial fishing effort (Eq. 4.2.19). Catchability was defined as the proportion of the population caught with one unit of fishing or survey effort (Hilborn and Walters 1992). Vulnerability was the product of gear selectivity and species availability to capture, which was used to capture differences in regional availability owing to spatial population structure.

Management Procedures

A set of management procedures – a data collection and stock assessment scheme along with the choice of harvest policy – constituted a management strategy (Table 4.3). Three different data collection and stock assessment schemes were used to assess the performance of three general types of harvest control rules: constant fishing mortality rules, feedback or state dependent fishing mortality rules, and conditional constant catch rules (Figure 4.3). Control rules specify guidelines used to adjust management based on the current assessed state of the population (Deroba and Bence 2008). In all, the combination of alternative candidate management procedures constituted the evaluation of 18 different management strategy scenarios (see Table 4.3 for descriptions).

Walleye population assessments were conducted using either a model-based approach (SCA) or a data-based approach (survey index of abundance (SI)) within the simulation framework. The SCA assessment procedure was informed by annual fishery data and survey data that was "collected" (i.e., observed from the OM with error) either annually or every third year. Details on the structure and parameterization of the SCA model are outlined in Table 4.2 and can be found in chapter 1, but in general follows that outlined in Fournier and Archibald (1982) and Deriso et al. (1985) with region- and year-specific estimates of catchability and region- and age-specific estimates of vulnerability. Population estimates were obtained by fitting the model to observed harvest, effort, survey, and age composition data for each region (Table 4.4). For the SI approach, CPE indices of relative abundance were "collected" from fisheryindependent surveys using information on simulated population size and vulnerability and catchability parameter values that were used to initialize the OM (Eq. 4.2.13). Survey catchability was based on the relationship between standardized, according to spatial, temporal, and environmental external factors (see chapter 2 for details), CPE and population abundance. Observed CPE values for each survey and region combination were then averaged to form a single annual population index.

A suite of harvest policies were implemented for each of three general types of control rules to supply contrast in the evaluation of alternative data collection and assessment schemes (see Table 4.3 for descriptions). Policies that impose a constant fishing mortality rate ($F_{0.1}$, $F_{0.3}$, $F_{0.5}$, and $F_{0.7}$ examined here) rule were implemented by using annual and 3-year SCA estimates of absolute abundance, with TACs being set according to equations 4.2.27-4.2.29. For the 3-year case, TAC was held constant during interim years. Alternatively, feedback policies (FB) impose

dynamic control rules, usually set as a function of some state of the fishery or population (Hilborn and Walters 1992; Deroba and Bence 2008). The feedback policy used here allowed fishing mortality to increase at intermediate population sizes for SCA procedures (Wright et al. 2005; Jones and Bence 2009) and intermediate CPE indices for SI procedures (Figure 4.3). The functional relationship developed for the SI feedback policy was constructed to match as close as possible the total allowable catch that would have resulted when using the SCA feedback policy (Eqs. 4.2.31-4.2.32). In effect, estimates of survey catchability from the most recent stock assessment model were used to make the connection between standardized survey CPE values used in the SI feedback policy and total abundance used in the SCA feedback policy. Other candidate policies that were evaluated imposed a three year moving average rule (FB3MA) and a 20% maximum annual deviation rule (FB_{20%}) to the general feedback policy, restricting year to year changes in fishing mortality in an attempt to improve harvest stability. In cases where feedback policies were used with 3-year procedures, harvest during the interim period was governed by a constant TAC rule (FB_{CC}) or a constant fishing mortality rule (FB_{CF}). The third general set of control rules evaluated, conditional constant catch (CC; Figure 4.3), maintained commercial catches at 5 million walleye unless the population fell below 15 million (SCA-based procedures) or a CPE of 3.29 (SI-based procedures) at which point a constant $F_{0,1}$ policy (or the equivalent for SI-based procedures) was initiated until recovery. A constant commercial fishing TAC of 5 million walleye was used because industry personnel have identified this as the level of harvest needed to maintain existing infrastructure.

Performance Measures

Select summary statistics from each simulation, calculated across the time horizon, were compiled to produce a distribution of expected performance for each candidate set of management procedures. Performance measures were selected to be representative of those commonly considered when conducting MSEs (Punt 1993; Butterworth and Punt 1999; Rademeyer et al. 2007), such as expectations relating to sustainability, risk, and industry stability (Table 4.5). Mean walleye abundance and age, recreational fishery CPE, and commercial fishery harvest and yield were metrics used to evaluate long-term expected conditions. Risks associated with a given policy were quantified as the percentage of years the population fell below 15 million walleye (classified as a population in "crisis"; Locke et al. 2005) and as the percentage of years the spawning stock size fell below 20% of the unfished spawning stock size. Variation associated with annual commercial harvest and total abundance was used to quantify measures of stability.

For each performance measure, policies were sequentially ranked to qualitatively compare the ordinal performance (i.e., relative selection) of policies common to annual and 3year SCA procedures ($F_{0.1}$, $F_{0.3}$, $F_{0.5}$, $F_{0.7}$, and FB; FB_{CF} for the 3-year FB policy) and between polices common to annual SCA and SI procedures (FB, $FB_{20\%}$, FB_{3MA} , and CC). Lower rankings referred to better performance (e.g., a high measure of harvest stability would be ranked low). Absolute performance metrics were also compared to evaluate quantitative differences in policy expectations and tradeoffs among the three data collection and assessment schemes. Comparisons focus on total commercial harvest, variation in commercial harvest (industry stability), and risk-based performance measures because other performance metrics evaluated had a strong positive (commercial yield) or negative (recreational CPE and average age) correlation with commercial harvest performance or because of a lack in contrast among policies (population abundance). Thus, comparisons using these performance metrics are not discussed in detail, but are presented graphically in the appendix (Figures 4.12-4.16).

Sensitivity Analysis

Sensitivity to the allocation of regional commercial fishing mortality ("recent" or "historical") was evaluated because of the influence spatial population structure had on predicted walleye population dynamics (chapter 1). The full suite of candidate management procedures was evaluated and performance metrics computed for each case. Inferences relating to study objectives were then examined for each set of results.

Results

The selection (rank order) and performance of harvest policies under three different data collection and assessment schemes was insensitive to the values used to allocate commercial fishing mortality ("recent" or "historical") between regions (Figure 4.11). This was not too surprising given that the difference between allocation arrangements was small (~4%, on average). The remaining results are presented using the "recent" allocation construct as it is more applicable to current fishery dynamics.

Selection of harvest policy

The rank order of harvest policies was influenced by the choice of a data collection and stock assessment procedure for some performance measures (Table 4.6). However, rank order was mostly unaffected for measures pertaining to population and industry stability and management risk (Table 4.6). Of those that were affected, discrepancies in rank order between annual SCA and SI procedures were considerable and prevalent (7 of 9 cases), whereas only minor discrepancies were detected between annual and 3-year SCA procedures (3 of 9 cases). Rank order was insensitive to the choice of annual and 3-year SCA procedures with regards to commercial harvest, population abundance and stability, recreational CPE, and risk-related performance measures. Only risk-related performance measures were insensitive to rank order between annual SCA and SI procedures.

Harvest policy performance

Absolute measures of policy performance were dependent upon the choice of management strategy. In general, there were performance costs associated with those policies examined utilizing annual SI and less frequent (3-year) SCA management procedures. In comparison to annual SCA procedures, annual SI procedures generally resulted in decreased performance. For example, the SI-informed FB policy resulted in a 24% decline in expected commercial harvest (Figure 4.4) and a 32% increase in commercial harvest CV (decrease in stability; Figure 4.5) compared to the SCA-informed FB policy. A similar pattern was apparent (decrease in harvest and decrease in harvest stability) between the SI procedure and SCA procedure when using the CC harvest policy. FB control rules that enforced interannual restrictions (FB_{20%}, FB_{3MA}) improved harvest stability substantially compared to the
unrestricted FB policy for SI procedures, resulting in a reversal of the comparative performance between annual SI and SCA procedures. Although apparent for harvest stability, this reversal was not evident for other performance measures. Management risk (Figures 4.6-4.7) also increased when using SI-procedures for all but one policy evaluated (FB, slight decrease). The CC policy provided the highest amount of risk associated with attaining an undesirable population state.

The application of 3-year SCA procedures resulted in minor to modest effects on policy performance when compared to annual SCA procedures. Total commercial harvest increased with higher constant F_x policies for both annual and 3-year SCA procedures, but the distribution of results remained similar between procedures across F_x policies (Figure 4.4). The relative performance of the 3-year SCA procedure was comparatively worse at higher constant F policies, resulting in a lower median harvest for the F_{0.7} policy compared to the annual SCA procedure. Despite the minor SCA procedure – F_x policy interaction for total commercial harvest, stability in commercial harvest remained fairly constant across constant F_x policies for each procedure, though the 3-year SCA procedure was less stable than the annual SCA procedure (increase in CV of ~13%) and the distribution of results were more variable (Figure 4.5). Regardless of SCA assessment timing, FB policies performed most similarly to the constant F_{0.3} policy. Still, the 3-year FB_{CC} (or FB_{CF}) policy did slightly better (worse for FB_{CF}) in terms of commercial harvest and slightly worse (better) in terms of stability in harvest than all three of the annual-based FB policies (FB, FB20%, and FB3MA) which performed

similarly. For both SCA procedures, policies with higher expected levels of commercial harvest were associated with a higher risk of achieving an undesirable population state (Figures 4.6-4.7). There was slightly higher management risks associated with the 3-year procedure compared to the annual procedure despite the fact that, for some policies, the 3-year procedure had lower expected harvests. The exception to this was the 3-year feedback policy with constant fishing mortality during interim years (FB_{CF}) which maintained low management risk, comparable to annual SCA FB policies.

Tradeoffs between diverse, and often competing, measures of policy performance were conditional on the choice of a data collection and assessment scheme. Key tradeoffs between measures of median commercial harvest and risks associated with an undesirable population state (Figures 4.8-4.9) or to median recreational catch rates (Figure 4.10) were comparatively more favorable for annual SCA procedures than for 3-year SCA procedures when using constant F_x policies. For example, annual SCA procedures resulted in less risk for the same amount of harvest (or more harvest at the same risk level; Figure 4.8) as that for 3-year SCA procedures while also increasing stability (Figure 4.9). For FB policies, tradeoffs were generally more favorable for annual and 3-year SCA procedures over SI procedures. Both SCA procedures allowed for similar amounts of increased harvest over that expected using the SI procedure while maintaining a comparable risk level (Figure 4.8). Thus, there was no clear loss in terms of harvest and risk tradeoffs between annual and 3-year SCA procedures. Similar performance tradeoffs were identified between SCA-based FB policies and constant $F_{0.3}$ policies. Tradeoffs

associated with CC policies provided the largest contrast between competing performance measures and were substantially different than those for FB or constant F_x policies.

Discussion

Fisheries management is fraught with tough decisions, most of which are made with little, and highly uncertain, information in an attempt to balance conflicting fishery objectives (e.g., desire for the highest possible commercial harvest and increasing the number of recreational angler trips). One imperative decision is the selection of a harvest policy to guide rational management (Quinn and Deriso 1999; Deroba and Bence 2008), which was shown here to be conditional on the specific data collection and population assessment scheme used to define policy parameters. The use of alternative schemes had considerable influence on the expected performance of candidate policies, implying that policies that best meet stakeholder objectives will depend upon the selection of data collection and population assessment procedures.

In general, annual SCA procedures outperformed the other procedural schemes and provided the overall best balance between harvest and risk-related tradeoffs. However, there was only a small loss in performance when less rigorous/costly procedures were used. If, for example, less frequent population assessments were implemented, the resulting savings in management cost could be used to increase survey sample sizes (chapter 2), improve walleye habitat, further model development and testing, or commit to other research needs (Locke et al. 2005). This is not a pathological example or obscure set of circumstances as there were comparatively small differences in terms of harvest – risk tradeoffs (Figures 4.8-4.10) between annual and 3-year SCA procedures, suggesting that alternative uses of assessment resources

warrants examination. Indeed, there are other implicit tradeoffs associated with practical fisheries management, such as opportunity costs that were not a formal part of this analysis. The results presented here do provide quantitative measures (or mathematical expectations) of real decision tradeoffs between conflicting biological and fishery related management objectives, allowing decision-makers to avoid the common pitfalls associated with qualitative (or individual decision-maker) expectations driving the perceived best management strategy (Plous 1993; Hammond et al. 1999; Butterworth et al. 2010). Ultimately, selecting a harvest policy can be a difficult task; especially when population abundance is driven primarily by recruitment, as is the case for Lake Erie walleye, because moderate contrasts in fishing mortality are just not that influential on long-term population dynamics.

In addition to biological and fishery performance, managing authorities must also consider information costs (i.e., expense associated with acquiring policy parameters) and stakeholder understanding when developing a management strategy (Hansen and Jones 2008). Complex procedures (e.g., age-structured estimates of absolute abundance; SCA) tend to be more data intensive, costly to implement, and less transparent than comparatively simpler procedures (e.g., survey index of relative abundance; SI). In some cases, very little has been gained in terms of long-term policy performance when using complex, model-based procedures over simple, data-based procedures (Hilborn et al. 2002; Cox and Kronlund 2008). This can result from having survey data that tracks population trends well or from the use of misleading fishery data, supplying biased information to model-based assessments (Apostoloki and Hillary 2009). For Lake Erie walleye, policy performance was by and large reduced when informed by survey index (SI) rather than SCA-based management procedures. One possible reason is that the two surveys, each with different survey designs, used to index walleye population status have exhibited different short-term trends in abundance (chapter 2), increasing uncertainty associated with population status; this has been shown to affect harvest policy performance (Katsukawa 2004). If age-structured data are available, it may better to do an age-structured assessment (Butterworth and Punt 1999), especially when the population has been dominated by large year classes (Cooke 1999), as has been the case for Lake Erie walleye more recently. Moreover, it is much more difficult in practice to define survey-based control rules for TAC-managed fisheries compared to rules based on procedures that estimate absolute measures of population abundance and fishing mortality (Hilborn et al. 2002; Cox and Kronlund 2008).

The use of data-based procedures to set harvest policy parameters has received more attention recently (Cox and Kronlund 2008; Apostoloki and Hillary 2009; Pomarede et al. 2010). In contrast, much less attention has been devoted to evaluating how the frequency of population assessments influences harvest policy choice. Certainly, species life history will play a role in deciding the periodicity (e.g., season, year, or every so many years) of candidate assessment cycles in order to capture major shifts in population dynamics, particularly for populations driven strongly by recruitment dynamics. Fully recruited Lake Erie walleye (age-2 and older) have moderate annual survival rates (mean = 0.61 yr^{-1}) and longevity (~20 years), suggesting that 3-year cycles may be adequate for this species. Although for most performance measures the 3-year SCA procedures evaluated here performed moderately worse than comparable annual SCA procedures, there was one case (FB_{CF}; 3-year feedback policy with constant fishing mortality during interim years) where assessment timing made little difference. For the analysis of this policy, interim year TACs were set according to the interim constant fishing mortality rate (as

specified by the policy) and "true" population abundance. Yet, in practical applications some other information about relative or absolute population size (e.g., a fishery-dependent index or estimates from a tagging program) will be needed to inform this type of policy during interim years. The FB_{CF} policy was evaluated here not because of practicality, but rather as basis from which to infer general characteristics between annual and 3-year SCA procedures. Further evaluations of this type of control rule, including uncertainty associated with setting interim year TACs, are needed.

There are many types and configurations of control rules that are used to define harvest policies and guide rational fisheries management (Deroba and Bence 2009). Harvest policies evaluated in this analysis were chosen to facilitate comparisons between alternative data collection and assessment procedures while representing some of the more common types of control rules in use today (e.g., constant fishing mortality, feedback or state dependent, and conditional constant catch). Because of innate differences in the definition of and application of policy parameters among alternative data collection and assessment procedures, comparing the relative performance of these procedures can be difficult. As such, interim year fishing mortality rates for 3-year procedures were held constant (as previously discussed) and every effort was made to match, using empirical relationships, feedback policies based on relative abundance (survey index CPE; SI procedures) with those based on absolute abundance (SCA procedures). For applications where supporting empirical data to define candidate CPE-TAC policy relationships is lacking (i.e. estimates of absolute abundance and fishing mortality), survey index information is typically used to inform future exploitation in relative terms only and thus is typically used in an adaptive management framework (Apostolaki and Hillary 2009). Although,

Cox and Kronlund (2008) applied a survey index management procedure to directly set annual TACs by estimating a harvest policy scaling parameter and an autocorrelation parameter using multiple linear regression on historical catch limits and survey indices.

There is growing evidence to suggest that Lake Erie walleye may emigrate from the quota management area (west and central basin proper) to the east basin (Wang et al. 2007; Zhao et al. 2011) and up the Detroit river corridor (Wang et al. 2007). Both operating and assessment population dynamic models developed here assumed no emigration (or immigration) was occurring. The number and extent of regional tagging studies is increasing on Lake Erie, shedding light on both inter- and intra-lake walleye movement. Some of the critical questions that remain relate to spawning site fidelity (do emigrants return and contribute to the local spawning stock?) and to movements in relation to the quota management zone (is there age-, sexor season-specific differences in the extent and duration of this movement?). In any case, current assumptions about population closure should not affect comparative results, though they could systematically influence absolute measures of performance.

Results presented here provide a basis from which to test further candidate management procedures. For example, an SI-based procedure that applied a smoothing function to survey indices over short time durations (Cox and Kronlund 2008) may perform better than the simple SI procedure evaluated in the current analysis. Or, perhaps a set of procedures that utilize complex SCA assessments to statistically capture triennial changes in catchability or selectivity with simple and easily interpretable SI procedures during interim years would perform favorably. The latter approach would certainly not yield much in terms of economic savings, but it may have substantial benefit in terms of increasing process transparency. Further analyses could also

investigate alternative assumptions about the recreational fishery. The current belief, albeit somewhat controversial, is that the recreational fishery is linearly self-regulating (recreational effort follows a linear function of population abundance). Given the contention, other competing beliefs (e.g., a logistic relationship or other asymptotic function) should also be evaluated to see how results are affected. It would also be advantageous to extend the current OM to explicitly include the costs associated with different management procedures. The resulting "bioeconomic" model could be used to directly evaluate the end costs and benefits of using simpler or less frequent assessments. Lastly, results from this work describing the relative performance of alternative management procedures should be interpreted within the context of those particular policies evaluated here, and not broadly inferred to all situations and circumstances. For example, only one set of policy parameters was evaluated for feedback control rules, so to make general conclusions about feedback versus constant F policies (in general or for Lake Erie walleye) would be inappropriate.

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APPENDIX 4A

Main Tables and Figures

Symbol	Description	Value						
Index var	iables (levels)							
а	Age $(2-7^{+})$							
y	Year							
, f	Fishery (commercial = 1; recreational (OH) = 2; recreational (MI) = 3)							
S	Survey (Ontario = 1; Ohio/Michigan = 2)							
r	Region (west basin = 1; central basin = 2)							
ОМ	Actual (simulated) value from operating model							
AM	Assessed (estimated) value from population assessment							
State and	control variables							
Ν	Abundance							
F	Fishing mortality							
Ζ	Total mortality							
М	Natural mortality	0.32						
С	Fishery catch							
Ι	Survey CPE							
Р	Proportions at age							
E	Fishing effort							
TAC	Total allowable catch							
В	Biomass (kgs)							
Y	Yield (kgs)							
Α	Allocation of F (by region) and TAC (by fishery)	MCMC (region); 0.431 (f=1)						
λ	Data source weight (relative to standard data source)							
Ŕ	Recruitment (simulated)	MCMC						
R	Intermediate year recruitment projectioin							
Ġ	Initial abundance for the most recent two years	MCMC						
É	Fishing effort (simulated)	MCMC (f>1)						
É	Recreational fishing mortaltiy (simulated)							
S	Spawning stock size (# eggs)							
т	Maturity	0.32, 0.88, 0.99, 1, 1, 1						
f	Fecundity (1000s of eggs/female)	7, 57, 106, 155, 204, 328						
W	mass (kgs)	0.75, 1.08, 1.42, 1.7, 1.91, 2.51						
n	Sample size (# years data)							

Table 4.1.—Description of symbols used in operating and assessment models. Values used to drive simulations were either explicitly established or taken as a sample from the joint posterior distribution (MCMC) associated with the most recent statistical catch-at-age stock assessment.

Table 4.1.—(cont'd).

Ĉ	Predicted catch	
Î	Predicted survey CPE	
\widehat{P}	Predicted proportions at age	
N ^{eff}	Effective sample size	
σ_{f}	CV for fishery catch (σ_{std} / λ_f)	
σ_s	CV for survey CPE (σ_{std} / λ_s)	
σ_{ϵ}	Standard deviation for effort deviations $(\sigma_{std} / \lambda_{\epsilon})$	
Structural	Parameters	
R	Recruitment	
G	Initial abundance in the first year	
q	Catchability	MCMC
V	Vulnerability	MCMC
$\sigma_{\it std}$	CV for standard data source (Ontario survey)	
Distributi	onal Parameters	
α	Ricker alpha	MCMC
β	Ricker beta	MCMC
τ	Recruitment process error	
σ_{τ}	Standard deviation for recruitment error	MCMC
η	Intermediate year recruitment projection error	
σ_r	Standard deviation for recruitment projection error	0.38
ε	Effort deviations	
ν	Effort observation error	
σ_{ν}	Standard deviation for effort observation error	MCMC
γ	Intercept for recreational E to N relationship	MCMC
δ	Slope for recreational E to N relationship	MCMC
К	Process error for recreational E to N relationship	
σ_{κ}	Standard deviation for recreational E to N error	MCMC
φ	Fishery catch observation error	
$\sigma_{m{\phi}}$	Standard deviation for fishery catch observation error	MCMC
ψ	Survey CPE observation error	
σ_{ψ}	Standard deviation for survey CPE observation error	MCMC
ω	Proportions at age observation error	
σ_{ω}	Standard deviation for proportions at age observation error	0.2, 0.2, 0.2, 0.2, 0.2, 0.2
ξ	Policy implementation error	
σξ	Standard deviation for implementation error	0.05

Reference	Equation	Source
Population me	<u>odel</u>	
(4.2.1)	$N_{y,a=2} = R_y$	AM
(4.2.2)	$N_{y=1978,a>2} = G_a$	AM
(4.2.3)	$\acute{R}_y = \alpha S_{y-2} e^{-\beta S_{-2y} + \tau_y}; \ \tau_y \sim N(0, \sigma_\tau^2)$	OM
(4.2.4)	$\tilde{R}_{y} = \hat{R}_{y} e^{\eta_{y}}; \ \eta_{y} \sim N(0, \sigma_{\eta}^{2})$	AM
(4.2.5)	$Z_{y,a} = M + \sum_{r} \sum_{f} F_{y,a,r,f}$	OM, AN
(4.2.6)	$F_{y,a,r,f} = q_{r,f} v_{a,r,f} E_{y,r,f} e^{\varepsilon_{y,r,f}}; \varepsilon_{y,r,f} \sim N(0, \sigma_{\varepsilon}^2)$	AM
(4.2.7)	$N_{y+1,a+1 a<7} = N_{y,a}e^{-Z_{y,a}}$	OM, AN
(4.2.8)	$N_{y+1,a=7} = N_{y,a=6}e^{-Z_{y,a=6}} + N_{y,a=7}e^{-Z_{y,a=7}}$	OM, AM
(4.2.9)	$B_{y} = \sum_{a} N_{y,a} w_{y,a}$	OM, AM
(4.2.10)	$S_y = \frac{1}{2} \sum_a N_{y,a} f_a m_a$	OM
(4.2.11)	$F_{y,a,r,f} = F_{y,r,f} v_{a,f}$	OM
(4.2.12)	$C_{y,a,r,f} = \frac{F_{y,a,r,f}}{Z_{y,a}} (1 - e^{-Z_{y,a}}) N_{y,a}$	OM
(4.2.13)	$I_{y,a,r,s} = q_{r,s} v_{a,r,s} N_{y,a} e^{-(0.75 \cdot Z_{y,a})}$	OM
(4.2.14)	$P_{y,a,r,f} = \frac{C_{y,a,r,f}}{C_{y,r,f}}; P_{y,a,r,s} = \frac{I_{y,a,r,s}}{I_{y,r,s}}$	ОМ
Observation r	nodel	
(4.2.15)	$\hat{C}_{y,a,r,f} = \frac{\hat{F}_{y,a,r,f}}{\hat{Z}_{y,a}} (1 - e^{-\hat{Z}_{y,a}}) \hat{N}_{y,a}$	AM
(1 2 1 ()	$\hat{\boldsymbol{\rho}} = \hat{c}_{y,a,r,f}$	43.4

Table 4.2.—Model equations used in catch-at-age operating (OM) and assessment (AM) models.

(4.2.16)
$$\hat{P}_{y,a,r,f} = \frac{c_{y,a,r,f}}{\hat{c}_{y,r,f}}$$
 AM

(4.2.17)
$$\hat{I}_{y,a,r,s} = \hat{q}_{r,s} \hat{v}_{a,r,s} \widehat{N}_{y,a} e^{-(0.75 \cdot \hat{Z}_{y,a})}$$
AM

(4.2.18)
$$\hat{P}_{y,a,r,s} = \frac{I_{y,a,r,s}}{\hat{I}_{y,r,s}}$$
 AM

(4.2.19)
$$\acute{E}_{y,r,f=1} = \frac{F_{r,f}A_r}{q_{r,f}} e^{v_{y,r,f}}; v_{y,r,f} \sim N(0, \sigma_v^2)$$
 OM

(4.2.20)
$$\hat{E}_{y,r,f>1} = \begin{bmatrix} \gamma + \delta N_y + \kappa_y \end{bmatrix} e^{\nu_{y,r,f}}; \kappa_y \sim N(0, \sigma_{\kappa}^2) \\ v_{y,r,f} \sim N(0, \sigma_{\nu}^2)$$
 OM

(4.2.21)
$$\dot{F}_{y,a,r,f>1} = q_{r,f} v_{a,r,f} \dot{E}_{y,r,f>1}$$
 OM

(4.2.22)
$$C_{y,r,f} = (\sum_{a} C_{y,a,r,f}) e^{\varphi_{y,r,f}}; \varphi_{y,r,f} \sim N(0, \sigma_{\varphi}^2)$$
 OM

(4.2.23)
$$I_{y,r,s} = (\sum_{a} I_{y,a,r,s}) e^{\psi_{y,r,s}}; \psi_{y,r,s} \sim N(0, \sigma_{\psi}^2)$$
 OM

(4.2.24)
$$P_{y,a,r,f} = \frac{e^{\left[lnP_{y,a,r,f} + \omega_f - \frac{1}{5}\sum_a \left(lnP_{y,a,r,f} + \omega_f\right)\right]}}{\sum_a e^{\left[lnP_{y,a,r,f} + \omega_f - \frac{1}{5}\sum_a \left(lnP_{y,a,r,f} + \omega_f\right)\right]}}$$
 OM

(4.2.25)
$$P_{y,a,r,s} = \frac{e^{\left[lnP_{y,a,r,s} + \omega_s - \frac{1}{5}\sum_a (lnP_{y,a,r,s} + \omega_s)\right]}}{\sum_a e^{\left[lnP_{y,a,r,s} + \omega_s - \frac{1}{5}\sum_a (lnP_{y,a,r,s} + \omega_s)\right]}}$$
 OM

(4.2.26)
$$Y_y = \sum_a \sum_r C_{y,a,r} w_{y,a}$$
 OM

Policy implementation

(4.2.27)
$$TAC_y = \frac{F_y^{AM}}{Z_y^{AM}} (1 - e^{-Z_y}) N_y^{AM}$$
 OM

(4.2.28)
$$TAC_y = \frac{F_y^{OM}}{Z_y^{OM}} (1 - e^{-Z_y}) N_y^{OM}$$
 OM

(4.2.29)
$$TAC_{y,f=1} = \frac{F_y^{OM}}{Z_y^{OM}} (1 - e^{-Z_y}) N_y^{OM} A_{f=1}$$
 OM

(4.2.30)
$$F_{y,f=1}^{OM} = F_y^{OM} e^{\xi_y}; \ \xi_y \sim N(0, \sigma_{\xi}^2)$$
 OM

Feedback (state dependent) (4.2.31)

AM, OM

$$\begin{array}{ll} F_y^{AM} = 0.1 & \mbox{if } N_y < 15 \\ F_y^{AM} = 0.02 N_y - 0.2 & \mbox{if } 15 \leq N_y < 20 \\ F_y^{AM} = 0.0075 N_y + 0.05 & \mbox{if } 20 \leq N_y < 40 \\ F_y^{AM} = 0.35 & \mbox{if } N_y \geq 40 \end{array}$$

(4.2.32)		AM, OM
	$TAC_y = 0.373CPE_y$	$if CPE_y < 3.29$
	$TAC_{y} = 0.576CPE_{y} - 0.67$	$if 3.29 \le CPE_{y} < 6.58$
	$TAC_{v} = 0.422CPE_{v} - 0.342$	$if 6.58 \le CPE_{v} < 23.35$
	$TAC_y = 1.068CPE_y - 14.732$	$if CPE_y \ge 23.35$
	(N _y and TAC _y are i	n millions)

Table 4.3.—Candidate data collection, population assessment, and harvest policy management procedures. Each management strategy scenario examined included the choice of a single type of harvest control rule (feedback, FB; constant F, F_x ; and conditional constant catch, CC) informed by one of three data collection and assessment schemes. Abbreviations include: F = instantaneous fishing mortality; N = total estimated population abundance; TAC = total allowable catch; CPE = catch-per-effort; and M = millions.

	Management Procedure	e		
Data Collection	Population Assessment Harvest Policy		Scenario	Description
Annual				
Fishery and survey	Catch-at-age (SCA)	FB	1	F set according to N (see Fig. 3, eq. 4.2.31)
		(FB _{20%})	2	same as above except F not allowed to deviate more than 20% from year to year
		(FB _{3MA})	3	same as two above except F set by averaging the most recent three years
		$(F_{0.1}, F_{0.3}, F_{0.5}, F_{0.7})$	4-7	F constant at 0.1, 0.3, 0.5, and 0.7 levels
		(CC)	8	F set so TAC=5M unless N<15M at which point $F_{0.1}$ is applied
Survey	Survey index (SI)	FB	9	F set according to survey CPE (see Fig. 3, eq. 4.2.32)
		(FB _{20%})	10	same as above except F not allowed to deviate more than 20% from year to year
		(FB _{3MA})	11	same as two above except F set by averaging the most recent three years
		(CC)	12	F set so TAC=5M unless CPE<3.29 at which point the equivalent of $F_{0.1}$ is applied
Triennial (suvey); Ar	nnual (fishery)			
Fishery and survey	Catch-at-age (SCA)	(FB _{CC})	13	F set according to N (Fig. 3, eq. 4.2.31); TAC adjusted every third year and constant during the interim
		(FB _{CF})	14	F set according to N (Fig. 3, eq. 4.2.31); TAC adjusted every third year with constant F during the interim
		$(F_{0.1}, F_{0.3}, F_{0.5}, F_{0.7})$	15-18	F constant at 0.1, 0.3, 0.5, and 0.7 levels; TAC adjusted every third year and constant during the interim

Table 4.4.—The statistical catch-at-age assessment procedure estimated population parameters by minimizing the posterior negative log likelihood calculated by summing weighted individual normal and log-normal likelihood and prior components for all source combinations. Highest posterior density estimates minimized this function.

Reference	Components	Source
(4.4.1)	$n_{r,f} ln \frac{\sigma_{std}}{\sigma_f} + \frac{\sigma_f}{2\sigma_{std}^2} \sum_{y} \left[ln \left(\frac{C_{y,r,f}}{\hat{C}_{y,r,f}} \right) \right]^2$	$r_{1,2}; f_{1,2,3}$
(4.4.2)	$n_{r,s} ln \frac{\sigma_{std}}{\sigma_s} + \frac{\sigma_s}{2\sigma_{std}^2} \sum_{\mathcal{Y}} \left[ln \left(\frac{I_{\mathcal{Y},r,s}}{\hat{I}_{\mathcal{Y},r,s}} \right) \right]^2$	<i>r</i> _{1,2} ; <i>s</i> _{1,2,3}
(4.4.3)	$n_{r,f} ln \frac{\sigma_{std}}{\sigma_{\varepsilon}} + \frac{\sigma_{\varepsilon}}{2\sigma_{std}^2} \sum_{y} \left[\varepsilon_{y,r,f} \right]^2$	$r_{1,2}; f_{1,2,3}$
(4.4.4)	$-\sum_{y} N_{r,f}^{eff} \sum_{a} \left[P_{y,a,r,f} \ln\left(\hat{P}_{y,a,r,f}\right) \right]$	$r_{1,2}; f_{1,2,3}$
(4.4.5)	$-\sum_{y} N_{r,s}^{eff} \sum_{a} \left[P_{y,a,r,s} \ln \left(\hat{P}_{y,a,r,s} \right) \right]$	<i>r</i> _{1,2} ; <i>s</i> _{1,2,3}

Table 4.5.—Performance statistics used to evaluate tradeoffs among candidate management strategies. Statistics were calculated by averaging over the 50-year time projection for each simulation and management scenario combination.

Perfomance statistics	Description						
N (#)	Mean population abundance						
N stability	CV of population abundance						
Harvest (#)	Mean commercial harvest						
Harvest stability	CV of commercial harvest						
Yield (kgs)	Mean commercial tield						
CPE (#/angler hr)	Mean receational catch-per-effort						
Age composition (%)	Mean age						
% years $N < 15M$	Percentage of years abundance falls below 15 mi						
% years SSS < 20% SSS _{unfish}	Percentage of years spawning stock size falls bek						
	20% of the unfished spawning stock size						

Notes: CV = coefficient of variation

Table 4.6.—Ranked performance of harvest policies for each performance measure evaluated. The first policy set is used to compare annual SCA (SCA_A) to annual SI (SI_A) procedures. The second policy set is used to compare annual SCA to triennial SCA (SCA_T) procedures. Lower numbers refer to higher rankings and better performance.

Performance Measures	Co Har	om. vest	Com. H (C	larvest V)	% Y N <	ears 15M	% Years < 20% SS	s SSB SB _{unfis}	_h Abun	dance	Abun (C	dance V)	Recreational CPE		Age Composition		Co Yie	en. eld
Policy set 1	SCA	SI _A	SI _A SCA _A SI _A		SCA _A SI _A SCA _A SI _A		SCAA	A _A SI _A SCA _A SI _A		SCA _A SI _A		SCA _A SI _A		SCA _A SI _A				
FB FB ₂₀	2 3	3 4	3 4	4 2	1 2	1 2	1 2	1 2	3 4	2 1	3 2	3 1	3	3 2	4	2 1	2 3	3 4
FB _{3MA} CC	4 1	2 1	2 1	3 1	3 4	3 4	3 4	3 4	2 1	3 4	4 1	4 2	4 2	4 1	2 1	4 3	4 1	2 1
Policy set 2	SCAA	SCA _T	SCAA	SCA _T	SCAA	SCA _T	SCA _A S	SCA _T	SCAA	SCA _T	SCAA	SCA _T	SCAA	SCA _T	SCAA	SCA _T	SCAA	SCA _T
FB	3	3	5	5	2	2	2	2	3	3	2	2	2	2	3	2	3	4
F _{0.1}	5	5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	5	5
F _{0.3}	4	4	2	2	3	3	3	3	2	2	3	3	3	3	2	3	4	3
F _{0.5}	2	2	3	4	4	4	4	4	5	5	4	4	4	4	4	4	2	2
F _{0.7}	1	1	4	3	5	5	5	5	4	4	5	5	5	5	5	5	1	1



Figure 4.1.—The west basin (WB), central basin (CB), and east basin (EB) geomorphologic regions of Lake Erie have distinct bathymetric and water quality attributes. The main walleye population occurs in the west and central basins.



Figure 4.2.—Alternative relationships for walleye stock size and age-2 recruitment dynamics. The best fitting three parameter (alpha, beta, error) Ricker stock-recruitment function (solid line) from the most recent SCA assessment model (points) was one possible realization of the true dynamics. Others (e.g., dashed lines) were developed (one for each simulation using MCMC; see text for details) to illustrate uncertainty associated with defining an underlying stock-recruitment relationship.



Figure 4.3.—Selected harvest policies that were used to translate assessment information (estimated population abundance (SCA), panel A; standardized survey CPE (SI), panel B) into an allowable fishing mortality rate (F), which was then used to derive total allowable catch (TAC). In application, TAC was obtained directly from survey CPE (T.3.32; shown against F here to facilitate visual comparisons). Specific control rules (see Table 4.3) were used to describe alternative feedback (FB - solid line, panel A and B), constant fishing mortality (F_x - dotted line, panel A), and conditional constant catch (CC - dashed line, panel A) types of harvest policies.



Figure 4.4.—Plots show the distribution of mean commercial harvest (# of age-2 and older) over a 50-year time horizon for each set of management procedures. Alternative types of harvest control rules that were evaluated included constant fishing mortality (F_x , where x is the mortality rate; top panel), feedback (FB, see figure 4.3 for graphical representation; middle panel), and conditional constant catch (CC; bottom panel) based policies that were informed by either an annual or 3-year statistical catch-at-age (SCA) or an annual survey index of abundance (SI) set of management procedures (see Table 4.3 for details). Subscripts associated with FB policies

refer to restricting annual deviations in fishing mortality to no more than 20% of the previous year (FB_{20%}); fishing mortality set by moving average according to the three most recent years (FB_{3MA}); a constant catch employed during interim (non-assessment) years (FB_{CC}); and the fishing mortality rate held constant during interim years (FB_{CF}). Box plots indicate the median (line within the box), the 25th and 75th percentiles (lower and upper box boundaries, respectively), the 10th and 90th percentiles (lower and upper error bars, respectively), and observations below the 10th and above the 90th percentiles (open circles).



Figure 4.5.—Stability in commercial harvest for alternative sets of management procedures. Plots show the distribution of the variation (coefficient of variation; CV) in commercial harvest over a 50-year time horizon. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.



Figure 4.6.—Risk that population size declines to an undesirable level for alternative sets of management procedures. Plots show the distribution of the mean percentage of years that walleye abundance falls below 15 million (age-2 and older) over a 50-year time horizon. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.



Figure 4.7.—Risk that the population is below a standard reference point for alternative sets of management procedures. Plots show the distribution of the mean percentage of years that walleye spawning stock size is less than 20% of the unfished spawning stock size over a 50-year time horizon. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.



Figure 4.8. Tradeoff between levels of commercial harvest and the risk associated with falling below a population reference point for alternative data collection and assessment procedures using constant fishing mortality rate (F_x ; top panel) and feedback (bottom panel) policies. Tradeoffs associated with conditional constant catch policies have been superimposed (single symbols, bottom panel). Points represent the median value from the distribution of simulated results.



Figure 4.9. Tradeoff between levels of stability in commercial harvest (coefficient of variation; CV) and the risk associated with the population falling to an undesirable level for alternative data collection and assessment procedures using constant fishing mortality rate (F_x ; top panel) and feedback (bottom panel) policies. Tradeoffs associated with conditional constant catch policies have been superimposed (single symbols, bottom panel). Points represent the median value from the distribution of simulated results.



Figure 4.10. Tradeoff between levels of commercial harvest and recreational catch-per-effort (CPE) for alternative data collection and assessment procedures using constant fishing mortality rate (F_x ; top panel) and feedback (bottom panel) policies. Tradeoffs associated with conditional constant catch policies have been superimposed (single symbols, bottom panel). Points represent the median value from the distribution of simulated results.

APPENDIX 4B

Additional Policy Performance Comparisons



Figure 4.11.—Sensitivity of select performance measures to the spatial allocation of commercial fishing mortality (following "recent" or "historical" trends; see text details). Shown are results based on feedback (FB) harvest control policies for each of three data collection and assessment schemes (annual SCA, annual SI, and 3-year SCA). The ordinate represents multiple scales. Box plots and abbreviations follow the same convention laid out in Figure 4.4.



Figure 4.12.—Plots show the distribution of mean walleye abundance (# of age-2 and older) over a 50-year time horizon for alternative sets of management procedures. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.



Figure 4.13.—Stability in population size for alternative sets of management procedures. Plots show the distribution of the variation (coefficient of variation; CV) in walleye abundance over a 50-year time horizon. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.



Figure 4.14.—Plots show the distribution of mean recreational catch-per-effort (CPE) over a 50year time horizon for alternative sets of management procedures. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.


Figure 4.15.—Plots show the distribution of mean age (# years) in the population over a 50-year time horizon for alternative sets of management procedures. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.



Figure 4.16.—Plots show the distribution of mean commercial yield over a 50-year time horizon for alternative sets of management procedures. Panels, box plots, and abbreviations follow the same convention laid out in Figure 4.4.

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