

AN INVESTIGATION OF LAKE ERIE YELLOW PERCH STOCK ASSESSMENT
ASSUMPTIONS

By

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A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Fisheries and Wildlife – Master of Science

2014

ABSTRACT

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The purpose of this research was to investigate two of the assumptions made in the assessment of Lake Erie yellow perch (*Perca flavescens*). In any model, assumptions have to be made in both model structure and data utilization. Testing these assumptions is important to ensure results are not being biased. In Chapter 1, I tested the assumption that each management unit (MU) in Lake Erie has a distinct yellow perch population with no mixing. I investigated the effect this assumption has on assessment and whether it could bias the results if it was being violated. I developed a statistical catch-at-age model that allowed movement between two of the MUs and evaluated how abundance estimates changed for 24 different movement scenarios. The abundance estimates differed between scenarios in unexpected and inconsistent ways, suggesting these models are sensitive to assumptions about movement. In Chapter 2, I investigated the assumption that one of the fishery independent surveys used in the stock assessment model is an unbiased indicator of trends in abundance. If these surveys are being affected by factors besides trends in abundance, the resulting index could be biased if these factors are not taken into account. I used a catch-rate standardization and model selection approach to investigate the effect of temporal, spatial, and environmental factors. Wind was incorporated using a novel approach that combined both wind direction and speed into a single parameter. The patterns seen in the standardized index of abundance from the best-fit model that incorporated other factors versus the non-standardized index were similar for both MUs; however, using a standardized index has the potential to accommodate for future changes in the environment of Lake Erie.

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ACKNOWLEDGEMENTS

I would first and foremost like to thank my advisor, Dr. Mike Jones, whose insight and guidance were instrumental in the completion of my master's program. I firmly believe that the most important aspect of graduate school is the connection with your advisor, and I consider myself lucky to have an advisor who both expanded my knowledge of the field and supported my interest in getting involved in projects in addition to my thesis work. This expanded my experience and made my graduate program much richer. I would also like to thank my committee members, Dr. Jim Bence and Dr. Brian Roth, who provided ideas and suggestions throughout the entire process. I thank the Yellow Perch Task Group, especially Megan Belore, Kevin Kayle, and Andy Cook, for providing the data. I would also like to thank Matt Catalano for assisting me with the modeling and coding in ADMB. I am also very appreciative of all the support I received from my colleagues within the MSU Department of Fisheries and Wildlife and Quantitative Fisheries Center. I also acknowledge support from the Great Lakes Fishery Commission, National Fish and Wildlife Foundation, Ricker Endowment, and Fenske Fellowship.

I would additionally like to thank all of my family and friends. The Peterson family, consisting of a computer programmer, statistician, writer, and fellow graduate student, was the perfect support group/sounding board/editor for my master's program. Kathy, Ed, Sarah, and Mary Peterson, I could not have done this without you. My friends, who forced me to relax and have fun every once and a while, and always introduced me as the friend who counts fish, to you all I am forever grateful.

PREFACE

Both Chapters 1 and 2 were written with the assumption that both would be submitted for publication in peer-reviewed journals. For this reason, both are in the first person plural narrative, even though the thesis has one author. All references are formatted in a style consistent with the North American Journal of Fisheries Management.

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INTRODUCTION

Yellow perch (*Perca flavescens*) have been an important component of the commercial and recreational fisheries in Lake Erie for over 200 years. Historically, Lake Erie fishery harvests were dominated by cisco and blue pike, but the loss of these two stocks gave way to a commercial and recreational fishery dominated by percids. Today, yellow perch remain one of the most popular fish species in the lake. All Lake Erie jurisdictions except Michigan contain a yellow perch commercial fishery and all jurisdictions except Ontario contain a recreational fishery (YPTG 2014).

The past 40 years have seen fluctuations in both the harvest and abundance of yellow perch. In the 1970s and early 1980s, commercial percid harvest was dominated by yellow perch and this reflected abundances that were among the highest on record. It is hypothesized that this was due to decreased fishing pressure and pollution (Kenyon and Murray 2001). Commercial catch declined with the collapse of the yellow perch population in the early 1990s, which Kenyon and Murray (2001) suggested was because of the dreissenid mussel invasion, overfishing, and poor weather conditions. In recent years, the perch population has recovered and again has been dominating the commercial percid catch, although recruitment continues to be variable. The recreational fishery is also prominent in Lake Erie, and tends to focus in the central and western basins, with the majority of the harvest occurring in Ohio waters, and has been variable throughout the time period (YPTG 2014).

The 2004 State of the Lake Report for Lake Erie (Tyson et al. 2009) identified many issues facing cool-water species such as yellow perch, including invasive species spread, increased exploitation, recruitment fluctuation, pathogens and parasites, and habitat loss. To

protect this valuable fish species, yellow perch are managed by an interagency quota system, with a total allowable catch (TAC) determined annually and allocated to each jurisdiction based on area. The Lake Erie Committee – which is the management body that determines the TAC – is trying to sustain the yellow perch population at a level that allows for consistent sizes of harvest (Ryan et al. 2003).

The YPTG determines a recommended allowable harvest using statistical catch-at-age (SCAA) models to assess yellow perch abundance. Lake Erie is separated into four management units (MUs) and each has a unique stock assessment model with data specific to the area. These models use a variety of data sets, including fishery-dependent catch and effort data and fishery-independent survey indices, to estimate fishing mortality and abundance. With any SCAA assessment, as with all models, there are a variety of assumptions that must be made in the creation and evaluation of the model. These assumptions are an important component of a model; if they are incorrect the conclusions drawn from the results may be biased and inaccurate. It is important to investigate assumptions for validity and re-investigate as new data become available. The goal of this research was to investigate two assumptions made in the assessment models for yellow perch.

Chapter 1 investigated an assumption in the structure of the assessment models, specifically the assumption that there is no movement of yellow perch between MUs. There is a stock assessment model for each MU in Lake Erie and each model is assumed to be independent of the others. Previous tagging work and an on-going tagging study in Lake Erie all suggest that while yellow perch do not move a lot, they do move enough to cross MU boundaries (Mraz 1952; Glover et al. 2008; A. Cook, OMNR, personal communication). I developed a stock assessment model that included movement between MUs 1 and 2 and investigated a range of

movement scenarios. Chapter 2 investigated an assumption made when using the data in the stock assessment model. The fishery independent indices are assumed to be proportional to yellow perch abundance. However, research has indicated that fishery independent survey catchability can be susceptible to changing environmental factors (Gunderson 1993; Maunder et al. 2006). By using catch-rate standardization I evaluated whether there were important factors that affect survey catch rates other than abundance and also whether the standardized index based on the model and the original non-standardized index had similar trends. I considered year, week, management unit, water temperature, depth, secchi depth, hypoxia, and wind as potential factors affecting survey catch rates. I included wind as an indicator of current speed and direction, introducing a new approach to including this factor and evaluating its potential importance.

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CHAPTER 1

DOES MOVEMENT OF YELLOW PERCH ACROSS MANAGEMENT BOUNDARIES IN LAKE ERIE MATTER FOR ASSESSING THE STOCK?

Introduction

Fisheries managers often assess the status of a fish population and then implement harvest control rules (HCRs) that, in part, reflect understanding of the biological processes governing the dynamics of the population. To perform these tasks, it is useful to have an understanding of the distribution of the population and knowledge of discrete stocks in the management area. Management units (MUs) are often defined to separate stocks and allow managers to implement different HCRs depending on the status of specific fish stocks (Halliday and Pinhorn 1990; Stephenson 1999; Reiss et al. 2009). For each MU, the population dynamics of the fish stock are assessed within its boundaries and a MU-specific harvest level is applied. However, the actual rationale for the delineation of MUs is often quite arbitrary, based on a combination of presumed stock structure and existing political boundaries. It has been suggested that these stocks should represent evolutionarily significant units (Ryder 1986), but the actual application of this is not clear (Dizon et al. 1992; Vogler and DeSalle 1992). Stock structure can be evaluated based on morphological differences (e.g., Wilson et al. 1991), the identification of genetically-distinct population sub-units (e.g., King et al. 2001), or a combination of morphology, genetics, and behaviour (e.g. Toth et al. 2012). Even when distinct stock units can be identified, there remain questions about the most appropriate scale of management: if there is some mixing of individuals among discrete stocks, should managers use a larger scale than genetic or morphological differences may imply, or use a smaller scale to manage each of these

stocks individually? Assumptions regarding the population's structure and movement among sub-populations are important components of stock assessment and fisheries management.

Fish move for a variety of reasons. Migration of fish, as defined by Lucas et al. (2001), is simply the movement by all or part of a population between sites that have differing biotic and abiotic characteristics. Using this definition, all scales of movement are included in the term migration. Marine movement tends to be well studied compared to freshwater movement; large oceanic migrations are easy to identify and can have an impressive scale, as is the case for Atlantic bluefin tuna (*Thunnus thynnus*) that travel across the ocean or most species of Pacific salmon (*Oncorhynchus spp.*) that migrate to the ocean before returning to freshwater to spawn (Block et al. 2001; Behnke and Tomelleri 2002). However, smaller scale movements that occur in freshwater environments can be just as important to the biology and survival of fish species as the spawning run of Pacific salmon. Fish migration is highly variable in space and time, and has been shown to be triggered by a variety of internal and external stimuli.

Genetic and ontogenetic factors can influence life history and migration characteristics, as seen in diadromous species of salmonids (Jonsson 1982; Näslund 1993) and the dispersal of walleye (*Sander vitreus*; Berger et al. 2012). An example of an ontogenetic trigger is a fish undergoing a spawning migration once they have reached maturity. Hunger and metabolic factors are other internal triggers of migration. The search for food and the density of prey has been argued to influence distance and speed traveled for foraging (Thomas 1977). The marginal value theorem is similar to this idea – animals will leave an area if the return rates on foraging falls below a certain value (Charnov 1976). Homing or spawning site fidelity can be a trigger as well. This movement allows fish to return to a spawning site that is known to be suitable for spawning when other sexually mature fish will also be present (Wootton 1990). This is well

documented for salmonids but this behaviour has also been seen in many freshwater fish, including lake whitefish (*Coregonus clupeaformis*; Ebener et al. 2010), white bass (*Roccus chrysops*; Hasler et al. 1969), white sucker (*Catostomus commersoni*; Werner 1979), common carp (*Cyprinus carpio*; Otis and Weber 1982), and yellow perch (*Perca flavescens*; Aalto and Newsome 1990). Predator avoidance can be considered both an internal and external trigger for migration. Alarm substances trigger a response, such as Schreckstoff in teleosts (Smith 1992) and the necromone of larval sea lamprey (*Petromyzon marinus*; Wagner et al. 2011). The presence of a predator may also trigger fish to move to refuge areas and this avoidance behaviour could be innate or learned. The opposite is true as well; prey behavior could affect the movement of its predator. This is illustrated by foraging arena theory, which asserts that a prey species can be partitioned into vulnerable and invulnerable components, and predators' success is dependent on the exchange between them (Ahrens et al. 2012). A predator may move to take advantage of a large group of vulnerable prey, or a prey species may be adapted to spend most of its time in invulnerable areas. Many factors have the potential to trigger fish movement; whether this trigger leads to short movements in search of prey or more optimal habitat or a large migration to a spawning area, this movement is important for survival.

As techniques for quantifying movement advance, we have greater ability to observe this movement and potentially its cause. Historically, managers had to rely on commercial fishery logs, recreational catch records, and small-scale mark-recovery studies to determine movement. These data require major assumptions which limit their application to fisheries management, and often movement was assumed inconsequential for freshwater species (Lucas et al. 2001). More recently, extensive tagging studies and the development of effective biotelemetry techniques (radio, acoustic or satellite technologies) are being used to evaluate the degree of movement in

many fish species and quantifying movement is an increasingly achievable goal. Kapuscinski et al. (2005) used tag-recovery data for lake trout (*Salvelinus namaycush*) in Lake Superior to estimate the different rates of movement between MUs. In Guam, acoustic telemetry was used to establish that unicornfish (*Naso unicornis* and *Naso lituratus*) remained inside a marine reserve, which is the primary management tool for Guam's reef fishery (Marshall et al. 2011). Stock assessment models can now incorporate movement rates in their evaluation of a fish stock. However, quantifying movement can be complex and costly. Extensive tagging and telemetry studies require considerable resources and time. It would be useful to identify evidence that movement is in fact important to the assessment of the stock before extensive movement studies are performed.

The movement of fish can be a concern to both managers and stakeholders. If MUs are used to manage a fish population, but the fish are moving across those boundaries, the results of the stock assessment could be biased and lead to total allowable catches (TACs) that are not reflective of the actual status of the population (Cadrin and Secor 2009; Berger et al. 2012; Molton et al. 2012). Misidentification of fish stocks can have detrimental effects on both the fish species and the fishery it supports (Pawson and Jennings 1996; Begg et al. 1999). Abundance overestimates, possibly due to movement of fish from other stocks into the MU when the population is being assessed, can lead to increased biological risk to the fish stock in the MU if a high fishing rate is used. Conversely, abundance underestimates can lead to unnecessarily low fishing rates and increased economic risk to the fisheries. Incorrectly assessing the population of the stock can be an issue for any fishery that is divided into MUs, such as yellow perch in Lake Erie, which is the focus of this study.

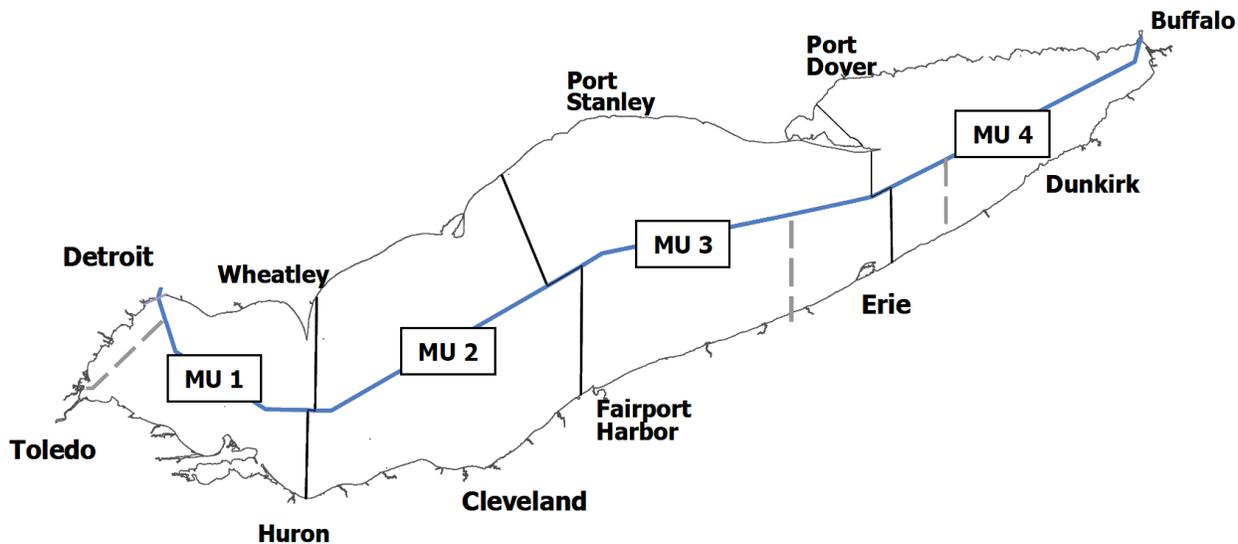


Figure 1.1. Lake Erie management units (MUs) for yellow perch.

Lake Erie is the smallest, but most biologically productive, of the Laurentian Great Lakes, and is the location of very large recreational and commercial fisheries for walleye and yellow perch. Yellow perch are found throughout Lake Erie, but are most abundant in the warmer waters of the central and western basins (YPTG 2013). The yellow perch fishery in Lake Erie is economically valuable for both commercial and recreational interests in the United States and Canada. In Ontario, yellow perch is considered to be the most valuable commercial species in the lake (Brown et al. 2009), representing 55% of the economic benefit of all fish taken in Lake Erie from 1980-1984 (Craig 1987). Recreational fishermen value yellow perch in the Great Lakes as well; in Ohio, yellow perch has been an important target species of anglers for many years. In 2012, Ohio alone logged 1.5 million angler hours in Lake Erie for yellow perch (YPTG 2013). To try to ensure the sustainability of the yellow perch fishery, the Lake Erie Committee (LEC) – a group of fishery managers from the Michigan, New York, Ohio, Ontario, and Pennsylvania agencies that have jurisdiction over Lake Erie fisheries – determines an allowable harvest level each year. Yellow perch fisheries in Lake Erie are managed as four separate MUs, from west to east across the lake (Figure 1.1), with each MU receiving a different harvest level

based on the assessed abundance of yellow perch in each unit and a target fishing mortality rate. The stock assessment models currently used assume that there is no movement of fish between MUs. A broadly representative group of Lake Erie managers and stakeholders (Lake Erie Percid Management Advisory Group: LEPMAG), while reviewing yellow perch management in Lake Erie, identified the potential for movement among MUs and its consequences for harvest policies to be a key uncertainty.

Previous research suggests many reasons for yellow perch movement. Environmental factors such as water temperature (Ferguson 1958; Engel and Magnuson 1976; Ross and Siniff 1982), light intensity (Craig 1977; Helfman 1979), and dissolved oxygen (Sandheinrich and Hubert 1984; Imbrock et al. 1996) have all been suggested to influence the movement of perch. Habitat characteristics such as availability of submerged vegetation and substrate composition or predator/prey presence and distribution, can affect yellow perch distribution as well (Fish and Savitz 1983; Eklov 1997). It has been suggested that perch do not move much and the movement they do exhibit is mostly localized (Lucas et al. 2001), with one tagging study capturing most of the released fish less than 45 km from the point of release within 60 days (Smith and Van Oosten 1939). Even though they may move moderate distances in response to environmental factors, yellow perch appear to have spawning site fidelity, returning each year to a specific spawning site (Kipling and Le Cren 1984; Aalto and Newsome 1990; Glover et al. 2008).

Recent tagging studies, particularly in Lake Michigan, have attempted to more explicitly estimate the magnitude of movement and spawning site fidelity of yellow perch. Glover et al. (2008) analyzed tagging data from 1996 to 2001 in the southern basin of Lake Michigan and in Green Bay. They inferred that yellow perch did return to the same spawning site, but movement occurred throughout the year (on average, fish were found 60.4 km away from the tagging site),

with most of the fish moving soon after spawning. Another study in Lake Michigan could not make many inferences because of tagging difficulties, but of the fish that were tagged and recovered, 27.8% were caught outside the tagging area with 8.4% over 32 km away (Mraz 1952). Yellow perch movement in Lake Erie has not been studied until recently. An on-going tagging study by the Ontario Ministry of Natural Resources (A. Cook, OMNR, personal communication) has been collecting data since 2009. Preliminary results showed that the average distance traveled by all fish recovered in the study was 24 km from the tagging area to location of recovery in the fishery harvest. Together, these tagging studies and previous research suggest that yellow perch have the potential to move across MU boundaries in Lake Erie, but will likely return to their original MU to spawn.

Statistical catch-at-age (SCAA) models are used to assess the status of the Lake Erie yellow perch population. These models rely on fishery-dependent and -independent data to estimate trends in abundance and determine the harvest rate. The MU-level assessments in Lake Erie for yellow perch effectively assume dynamics among the four units are independent of one another. Movement of yellow perch across these boundaries would be a violation of that assumption and might bias the results of the SCAA models (Punt et al. 2005; Dichmont et al. 2006; Kell et al. 2009; Kerr et al 2010). The goal of this research was to investigate if the rate of movement of yellow perch is important to the assessment of the stock. To address this goal, we developed a SCAA model for yellow perch that allows for movement between MUs and evaluated a range of movement scenarios. Specifically, we focused on evaluating the difference in abundance estimates between movement scenarios and investigating the consistency of the model's response to differing levels of movement.

Methods

Study system

Lake Erie is approximately 400 km in length and 92 km across at its widest point. It is composed of three basins, which differ considerably. The western basin is the shallowest with an average depth of just 7.3 m; it is also the most turbid, warmest and most biologically productive of the three basins. The central basin is intermediate between the other two basins, with cooler water temperatures and an average depth of 18.3 m. The eastern basin is the deepest (average depth of 24.4 m), coldest and least productive (Ryan et al. 2003). This gradient of habitat characteristics provides a suitable environment for a wide variety of species, ranging from mostly warm-water species in the western basin, to cool-water species in the central basin, and cold-water species in the eastern basin. Lake Erie is surrounded by four states (Michigan, Ohio, Pennsylvania, and New York) and one Canadian province (Ontario). Each of these jurisdictions is home to a variety of fisheries, both commercial and recreational. Walleye and yellow perch are the two main targeted fish species in the lake. In 2012, an estimated 31.5 million yellow perch and 2.5 million walleye were harvested from Lake Erie (WTG 2013; YPTG 2013).

Yellow perch can be found throughout the lake and are an important component of the Lake Erie ecosystem. Yellow perch reach sexual maturity around two to three years of age (Scott and Crossman 1973; Becker 1983; Moyle 2002). Yellow perch spawn in the spring, hiding their eggs in the shallower parts of Lake Erie within submerged vegetation or fallen brush (Brown et al. 2009). Once the eggs hatch, larvae feed primarily on zooplankton. But as they grow they undergo an ontogenetic diet shift, feeding on insects, then larger invertebrates, and finally becoming piscivorous as adults, feeding on the eggs and young of other fish, sometimes even

other yellow perch (Brown et al. 2009). They are also an important prey species for predators such as walleye and double-crested cormorants (*Phalacrocorax auritus*).

The LEC, with representatives from each authority (four states and one Canadian province), coordinates management of the yellow perch fishery. The Yellow Perch Task Group (YPTG) conducts a yearly statistical catch-at-age assessment to determine the status of the fishery. The current year's abundance and survival estimates are used to predict the abundance for the following year. Based on this prediction and the application of a harvest control rule, a recommended allowable harvest (RAH) is produced. The RAH is presented to the LEC which then decides on a TAC. For this management process, as mentioned before, Lake Erie is separated into MUs, which are used to specify areas of discrete yellow perch stocks while also acknowledging political boundaries. There are four MUs numbered from west to east. MU 1 is the western basin of the lake, MUs 2 and 3 encompass the central basin, and MU 4 is the eastern basin (Figure 1.1). The majority of the overall harvest takes place in MUs 2 and 3 (35% and 43% in 2012 respectively), with 16% of the 2012 harvest in MU 1 and only 6% in MU 4 (YPTG 2013). Each MU is assumed to be independent of the others, with unique data sets and stock assessment models.

To examine the potential effect of movement on the stock assessments, I chose to focus my analysis on two MUs: 1 and 2. MU 1 and 2 were chosen because they represent two adjacent MUs with a large combined harvest (51% of the total lake wide harvest in 2012) as well as angler harvest (77% of the total lake wide harvest in 2012) and because they were the primary target of the OMNR tagging study, which informed the estimates of fish movement used in the model.

Data

Five data sets are included in the stock assessment for each MU. These include both fishery dependent and independent data sets (Table 1.1). Commercial and angler catch and effort data are used for the fishery dependent data sets. There are also two fishery independent surveys for each MU. The OMNR and the Ontario Commercial Fisheries' Association (OCFA) partner to conduct an annual gillnet survey in each MU while Ohio conducts their own fall trawl surveys. The longest data sets begin in 1975, which is when the model starts.

Table 1.1. Data sources for the Lake Erie yellow perch stock assessment models. Includes the management unit, the names of the data source, the type of gear, the first year included in the data sets (all data goes to 2011), whether it is a fishery independent or dependent data source, and the weight (λ) of the data set in the model (used in the objective function, see Table 1.3).

MU	Name	Gear	First Year	Independent or Dependent?	Weight
1	Ontario commercial catch and effort	Gillnet	1975	Dependent	1.0
1	Ohio commercial catch and effort	Trapnet	1975	Dependent	0.7
1	Angler catch and effort	Sport	1975	Dependent	0.9
1	Partnership survey catch-per-effort	Gillnet	1990	Independent	1.0
1	Ohio fall survey catch-per-effort	Trawl	1990	Independent	1.0
2	Ontario commercial catch and effort	Gillnet	1975	Dependent	1.0
2	Ohio commercial catch and effort	Trapnet	1989	Dependent	0.7
2	Angler catch and effort	Sport	1987	Dependent	0.9

Table 1.1 (cont'd)

2	Partnership survey catch-per-effort	Gillnet	1990	Independent	1.0
2	Ohio fall survey catch-per-effort	Trawl	1990	Independent	0.9

Assessment model incorporating movement

Automatic Differentiation Model Builder (ADMB; Fournier 2012) software was used to construct and fit the statistical-catch-at-age model. ADMB is an optimization tool for non-linear statistical modeling and is the same software used by the YPTG for conducting their annual assessments. Our stock assessment model estimates yellow perch population dynamics beginning in 1975 and is age-structured, covering five age classes (2, 3, 4, 5, 6+) for both MU 1 and 2 (Table 1.2 and 1.3). Fishery effort data and CPE from fishery independent surveys provides the information for estimating fishing mortality and abundance. The natural mortality rate is assumed to be constant and known ($M=0.4 \text{ yr}^{-1}$). Biomass was calculated as the product of the observed mean weight-at-age and the estimated abundance-at-age (Eq. 1.3.11). The mean weights-at-age for both MUs were obtained from the fishery independent surveys.

The model itself was a modification of the model currently used for yellow perch management in Lake Erie. Instantaneous fishing mortality was defined as the product of observed fishing effort, catchability, and selectivity (Eq. 1.3.5). Catchability is estimated as a free parameter and reflects the relationship between the catch rate and the true population size. In our model; catchability for each data set was determined using a ‘constrained random walk’ approach (Wilberg et al. 2010). This approach allowed the catchability to be time-varying and is becoming increasingly common in statistical catch-at-age models (Fournier et al. 1998; Wilberg and Bence 2006). The catchability could gradually change over time in either direction to reflect

differences in the factors that affect catchability, including changes in management, gear, angler behavior, or changes in fish distribution, without having to define the specific factors. This parameter was calculated for each year by multiplying the previous year's catchability by the previous year's process error deviation (Eq. 1.3.3 and 1.3.4). The error deviations were assumed to be log-normally distributed. The deviations were also penalized in the objective function for large changes, which resulted in an approximate coefficient of variation for catchability over time of 10%. Selectivity is another free parameter that encompasses both the gear selectivity and the species availability in the area of capture. Age-specific selectivity for each data set was calculated relative to a fully selected age, and no functional form was assumed, resulting in five different selectivity curves for each MU (three fishery-dependent data sets and two fishery-independent surveys). Fishing and natural mortality were used to calculate total mortality (Eq. 1.3.6). Total mortality was converted to survival, which was then used to estimate abundance (Eq. 1.3.7-1.3.10). For the fishery-independent surveys, catchability and selectivity were used with the estimated abundance to predict the survey catch-per-effort (Eq. 1.3.13).

The use of multiple data sources requires an assumption about the relative quality of different data sets. A weighting factor (λ) was used to control the amount of influence each data set had on the fit of the model (Table 1.1). The weighting factors are assumed to be inversely proportional to the observation and process error variance associated with each data source. These weights were determined by the YPTG using an expert opinion approach, where Lake Erie managers and assessment biologists considered different attributes of the data set such as spatial and temporal coverage, sampling technique, and fishing methodology to evaluate the relative quality and assign a weighting factor (YPTG 2012).

To incorporate fish movement into the two stock assessment models, we adjusted the standard SCAA equation used to estimate abundance. In a standard statistical catch-at-age model, abundance is determined by the previous year's abundance and the previous year's survival estimates. For our analysis, this equation was divided into two equations, spawning area abundance (Eq. 1.3.8-1.3.9) and vulnerable abundance (Eq. 1.3.10).

Spawning area abundance is defined as

$$N_{m,y+1,a+1} = N_{m,y,a} (\gamma_{x,z=1} S_{m=1,y,a} + \gamma_{x,z=2} S_{m=2,y,a}) \quad (1.3.8)$$

where $N_{m,y,a}$ was the abundance at MU m , year y , and age a ; $\gamma_{x,z}$ was the movement proportion where x is the starting MU and z is the destination MU; and $S_{m,y,a}$ was the survival in MU m at the current age and current year. This equation assumed that the yellow perch that moved out of the current MU were affected by the mortality that occurred in the other MU during the fishing season before the fish returned to the original MU to spawn. This equation reflected the observed spawning site fidelity of yellow perch.

Vulnerable abundance is defined as

$$Nv_{m,y,a} = (N_{m=1,y,a} \gamma_{x=1,z}) + (N_{m=2,y,a} \gamma_{x=2,z}) \quad (1.3.10)$$

where $Nv_{m,y,a}$ is the vulnerable abundance at MU m , year y , and age a . This abundance was used to describe the fish population in MU m during the fishing season. The movement parameter (γ) and the spawning area abundance were used to calculate this abundance. The movement parameter in both these equations represents the proportion of fish that travel from one MU to another after spawning into an area vulnerable to fishing during the year. The vulnerable

abundance is then used in the calculation of estimated catch using Baranov's catch equation (Eq. 1.3.12) and the calculation of the estimated survey abundance index (Eq. 1.3.13). For each movement scenario, the parameter γ was fixed for each MU and assumed to be constant for all ages and all years for both the spawning area and vulnerable abundances.

Table 1.2. Description of symbols in Table 1.3 describing the base assessment model.

Symbol	Description
Subscript Indicators	
m	Management unit (1 and 2)
y	Year (1975-2011)
a	Age (2-6+)
f	Fishery (commercial gillnet, commercial trapnet, recreational angler)
i	Survey (Ontario, Ohio)
x	Starting MU (1 and 2, used in movement value below)
z	Destination MU (1 and 2, used in movement value below)
Assumed Values	
M	Instantaneous rate of natural mortality (0.40 yr ⁻¹)
λ_f	Weight for fishery catches (Table 1.1)
λ_i	Weight for survey index catch rates (Table 1.1)
λ_q	Random walk catchability penalty (scaled so standard deviation of catchability deviations was ~0.1)
$\gamma_{x,z}$	Movement proportion, x is the starting MU and z is the destination MU (e.g. $\gamma_{1,2}$ is the proportion of fish from MU 1 that traveled to MU 2 while $\gamma_{1,1}$ is the proportion of fish from MU 1 that stayed in MU 1), assumed to be fixed and constant across ages and years
Observed Data	
$C_{m,y,a,f}$	Annual numbers of yellow perch caught at age by fishery and MU
$I_{m,y,a,i}$	Survey abundance index at age
$E_{m,y,f}$	Fishery effort
$W_{m,y,a}$	Mean weight
Estimated Parameters	
$R_{m,y}$	Recruitment
$G_{m,a}$	Initial abundances at age (>2) in first year
$q_{m,y=1975,f}$	Initial catchability coefficient for each fishery
$q_{m,y=1990,i}$	Initial catchability coefficient for each survey
$\varepsilon_{m,y>1975,f}$	Random walk catchability deviations for each fishery

Table 1.2 (cont'd)

$\varepsilon_{m,y>1990,i}$	Random walk catchability deviations for each survey
$S_{m,a,f}$	Selectivity at age for each fishery
$S_{m,a,i}$	Selectivity at age for each survey
Calculated Parameters	
$q_{m,y>1975,f}$	Catchability coefficient for each fishery following the first year
$q_{m,y>1990,i}$	Catchability coefficient for each survey following the first year
$F_{m,y,a,f}$	Instantaneous fishing mortality rate
$Z_{m,y,a}$	Instantaneous total mortality rate
$S_{m,y,a}$	Survival rate
$N_{m,y,a}$	Spawning area abundance at age
$Nv_{m,y,a}$	Vulnerable abundance at age
$B_{m,y}$	Total biomass
$\hat{C}_{m,y,a,f}$	Model predicted catch at age
$\hat{I}_{m,y,a,i}$	Model predicted survey abundance index at age
n	Sample size of objective function components

Table 1.3. Equations for population and observation submodels used in the yellow perch assessment model.

Equation	Reference
Population Submodel	
Recruitment and initial numbers at age	
$N_{m,y,a=2} = R_{m,y}$	(1.3.1)
$N_{m,y=1975,a>2} = G_{m,a}$	(1.3.2)
Random walk catchability	
$q_{m,y+1,f} = q_{m,y,f} e^{\varepsilon_{m,y,f}}$	(1.3.3)
$q_{m,y+1,i} = q_{m,y,i} e^{\varepsilon_{m,y,i}}$	(1.3.4)
Mortality and survival rates	
$F_{m,y,a,f} = q_{m,y,f} S_{m,a,f} E_{m,y,f}$	(1.3.5)
$Z_{m,y,a} = M + \sum_f F_{m,y,a,f}$	(1.3.6)
$S_{m,y,a} = e^{-Z_{m,y,a}}$	(1.3.7)

Table 1.3 (cont'd)

Population dynamics

$$N_{m,y+1,a+1|a<6} = N_{m,y,a}(\gamma_{x,z=1}S_{m=1,y,a} + \gamma_{x,z=2}S_{m=2,y,a}) \quad (1.3.8)$$

$$\begin{aligned} N_{m,y+1,a=6} &= N_{m,y,a=5}(\gamma_{x,z=1}S_{m=1,y,a=5} + \gamma_{x,z=2}S_{m=2,y,a=5}) \\ &+ N_{m,y,a=6}(\gamma_{x,z=1}S_{m=1,y,a=6} + \gamma_{x,z=2}S_{m=2,y,a=6}) \end{aligned} \quad (1.3.9)$$

$$Nv_{m,y,a} = (N_{m=1,y,a}\gamma_{x=1,z}) + (N_{m=2,y,a}\gamma_{x=2,z}) \quad (1.3.10)$$

$$B_{m,y} = \sum_a N_{m,y,a}W_{m,y,a} \quad (1.3.11)$$

Observation Submodel

$$\hat{C}_{m,y,a,f} = \frac{F_{m,y,a,f}}{Z_{m,y,a}}(1 - S_{m,y,a})Nv_{m,y,a} \quad (1.3.12)$$

$$\hat{I}_{m,y,a,i} = q_{m,y,i}S_{m,a,i}Nv_{m,y,a} \quad (1.3.13)$$

Table 1.4. The objective function. Calculated by summing weighted individual log-normal likelihood components (f). The final likelihood (F) was penalized by sample size.

Equation	Reference
$f = \lambda_f \sum_{y,a} \left[\ln \left(\frac{C_{m,y,a,f}}{\hat{C}_{m,y,a,f}} \right) \right]^2$	(1.4.1)
$f = \lambda_i \sum_{y,a} \left[\ln \left(\frac{I_{m,y,a,i}}{\hat{I}_{m,y,a,i}} \right) \right]^2$	(1.4.2)
$f = \lambda_q \sum_{y,a} \left[\ln(\varepsilon_{m,y,f}) \right]^2$	(1.4.3)
$f = \lambda_q \sum_{y,a} \left[\ln(\varepsilon_{m,y,i}) \right]^2$	(1.4.4)
$F = \frac{n}{2} \ln \left(\frac{2\pi \sum f}{n} \right) + \frac{n}{2}$	(1.4.5)

We fit the model to observed harvest, effort, and survey data. The objective function is the log-likelihood for each data source penalized by the sample size (Table 1.4). The expert opinion

weights are used to effectively scale the error variance of each data source to that estimated for the two partnership surveys, the two commercial gillnet data sets, and the MU 1 Ohio survey which all received the highest quality rating by the expert opinion approach.

Movement scenarios

We investigated 25 different movement scenarios with two time series (MU 1 and MU 2) of 37 years, with the movement parameter for each scenario ranging from 0% to 40% in increments of 10% for each MU (e.g., Scenario 1: MU 1=0%, MU 2=0%; Scenario 2: MU 1=0%, MU 2=10%; Table 1.5). The OMNR tagging study results suggested an average travel of 24 km over one to two years' time. Lake Erie is 388 km across and the MUs are approximately 84-100 km wide, so a distance of 24 km could move a not insignificant amount of fish into an adjacent MU, but yellow perch do not appear to be traveling all over the lake. The range of movement used in this study was informed by the OMNR tagging study and previous tagging studies, but because of the lack of extensive data we included larger amounts of movement (30 and 40%) as well as more moderate amounts of movement in the range.

Evaluation of results

The estimated spawning area abundance in both MUs was the focus of our comparison of the different movement scenarios. The complete time series was analyzed for trends but the terminal abundance (abundance in the final year) was primarily used to compare scenarios. Changes to key parameters, particularly catchability, were also used to compare scenarios. We additionally considered the sensitivity of the model to the starting values used.

We looked at the last five years' abundance estimates for each scenario to determine if the terminal abundance for a specific scenario relative to the rest of the scenarios' terminal

abundance estimates reflected the patterns seen at the end of the time series. Eight scenarios did not; these were the scenarios with 30 and 40% movement from MU 2 to MU 1 with at least 10% movement from MU 1 to MU 2. These discrepancies between the terminal abundance patterns across the scenarios and the last 5-year patterns across the scenarios did not make a difference to the final conclusions drawn from the results, and they will be discussed but not presented. We also investigated the patterns in the catchability estimates for the different data sets.

For the presentation of the results, the 25 scenarios are organized into five groups. For each group, the movement from MU 1 to MU 2 is constant, while each individual scenario in the group has a different rate of movement from MU 2 to MU 1.

Table 1.5. Movement scenarios.

Scenario	Movement from MU 1 to MU 2 (%)	Movement from MU 2 to MU 1 (%)
1	0	0
2	0	10
3	0	20
4	0	30
5	0	40
6	10	0
7	10	10
8	10	20
9	10	30
10	10	40
11	20	0
12	20	10
13	20	20
14	20	30
15	20	40
16	30	0
17	30	10
18	30	20
19	30	30
20	30	40

Table 1.5 (cont'd)

21	40	0
22	40	10
23	40	20
24	40	30
25	40	40

Results

Comparison of the different movement scenarios

When movement from MU 1 to MU 2 was low, estimated abundance in both MUs was similar to that obtained when there was no movement (10% maximum discrepancy; Table 1.6). The two scenarios within 10% of the no-movement scenarios for the abundance estimates of both MUs were when movement from MU 1 to MU 2 was 10% and movement out of MU 2 was 0% or 40% (scenario 6 and 10, respectively). However, scenario 10 was not consistent across the time series in its difference from the no-movement scenario. Looking at the most recent five years, scenario 10's MU 1 abundance was much lower than the no-movement scenario until the final year. Scenario 6 was the only scenario consistently close to the no-movement scenario for both MU 1 and MU 2 abundances.

Table 1.6. Terminal spawning area abundance estimates by management unit for each of the movement scenarios with the percent change from the no-movement scenario (scenario 1) specified.

Scenario ($\gamma_{1,2}, \gamma_{2,1}$)	MU 1 abundance (millions of fish)	% Change from scenario 1	MU 2 abundance (millions of fish)	% Change from scenario 1
1 (0,0)	23.24	0	43.37	0
2 (0,10)†	19.26	-17.1	40.64	-6.3
3 (0,20)†	15.99	-31.2	42.57	-1.8
4 (0,30)†	14.98	-35.6	45.50	4.9
5 (0,40)	16.42	-29.4	47.75	10.1
6 (10,0)*†‡	25.58	10.0	44.73	3.1
7 (10,10)†	20.62	-11.3	39.05	-10.0

Table 1.6 (cont'd)

8 (10,20)†	17.40	-25.1	39.32	-9.3
9 (10,30)†	20.77	-10.6	45.07	3.9
10 (10,40)*†‡	21.95	-5.6	41.80	-3.6
11 (20,0)	32.50	39.8	38.41	-11.4
12 (20,10)	26.18	12.6	31.98	-26.3
13 (20,20)*	22.42	-3.5	33.07	-23.8
14 (20,30)*	22.76	-2.1	34.38	-20.7
15 (20,40)	25.77	10.9	35.90	-17.2
16 (30,0)	30.87	32.8	49.08	13.2
17 (30,10)	27.24	17.2	29.54	-31.9
18 (30,20)	20.47	-11.9	32.59	-24.9
19 (30,30)	25.76	10.9	33.08	-23.7
20 (30,40)	27.85	19.8	32.87	-24.2
21 (40,0)	28.52	22.7	49.32	13.7
22 (40,10)	20.77	-10.6	30.90	-28.8
23 (40,20)	16.12	-30.6	31.44	-27.5
24 (40,30)*	21.38	-8.0	29.89	-31.1
25 (40,40)	30.82	32.6	26.32	-39.3

* scenarios with MU 1 abundance estimates within 10% of the no-movement scenario

† scenarios with MU 2 abundance estimates within 10% of the no-movement scenario

‡ scenarios with MU 1 and MU 2 abundance estimates within 10% of the no-movement scenario

At higher levels of movement, the trends seen in the abundance estimates do not suggest a consistent response to changes in movement. Focusing on MU 1 abundance, estimates were erratic with increasing movement in either direction (Figure 1.2). The estimates tended to increase with increasing movement from MU 1 to MU 2, which is what would be expected. As more fish leave MU 1 the model estimates a higher MU 1 abundance in the spawning area to explain the catch seen during the vulnerable time, after the fish have traveled to MU 2. However, there are exceptions to this trend at the highest levels of movement (e.g. scenario 22-24). Looking at movement from MU 2 to MU 1, the MU 1 estimates tended to decrease with increasing movement, which again would be expected, but this became more erratic when movement out of MU 1 was increasing as well. Focusing on MU 2 abundance, estimates seemed relatively insensitive to increasing movement out of MU 2 when movement out of MU 1 was

low (e.g. scenarios 2-10; Figure 1.2). When movement out of MU 1 increased, MU 2 abundance estimates tended to be lower, as expected, but there were exceptions at the highest levels of movement (e.g. scenario 16 and 21). There were some trends, but no consistent patterns in abundance across the different levels of movement for MU 1 or MU 2.

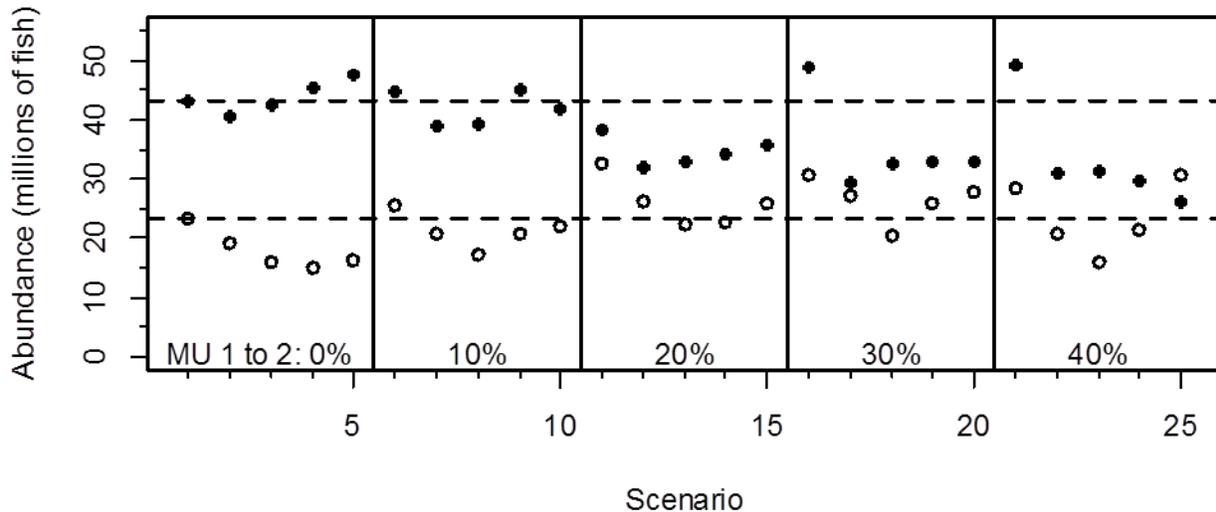


Figure 1.2. Terminal spawning area abundance for MU 1 (white circles) and MU 2 (black circles). Dashed lines are abundance estimates from a no-movement scenario (lower line is MU 1, upper line is MU 2). Each panel contains 5 scenarios with the same movement from MU 1 to MU 2, with increasing movement from left to right.

Changes in estimates of other parameters in the model, specifically catchability, appeared to be driving some of these inconsistent patterns of abundance, again in erratic ways. Fishery catchability seemed to be more sensitive to high levels of movement than the fishery-independent surveys. In five high movement scenarios (scenarios 9, 16, 21-23), fishery catchability was estimated to be multiple orders of magnitude higher than all other estimated catchabilities (Figure 1.3). Generally, MU 1 fishery catchability tended to decrease with increasing movement from MU 2 to MU 1, but there were exceptions in addition to the scenarios with extremely large values (e.g. scenario 12). MU 2 fishery catchability seemed relatively

insensitive to increasing movement out of MU 2, with the exception of scenario 9. The fishery independent survey catchabilities showed less erratic results (Figure 1.4 and 1.5). MU 1 survey catchabilities tended to increase with increasing movement out of MU 2 while MU 2 survey catchabilities tended to decrease. However, there were some exceptions at higher levels of movement (e.g. scenario 10 Ohio survey catchability).

Sensitivity of model to starting values

The model was sensitive to the starting values for catchability in many of the movement scenarios. The starting values used by the 'no-movement' model (original YPTG stock assessment starting values) were insufficient for many of the higher movement scenario models to obtain convergence. Often a specific starting value needed to be used, sometimes obtained by the results of a similar scenario (if convergence was achieved) or by using a number of iterations testing a variety of starting values. All models eventually achieved convergence, as indicated by all parameter gradients fulfilling the derivative criterion and no error messages in the output.

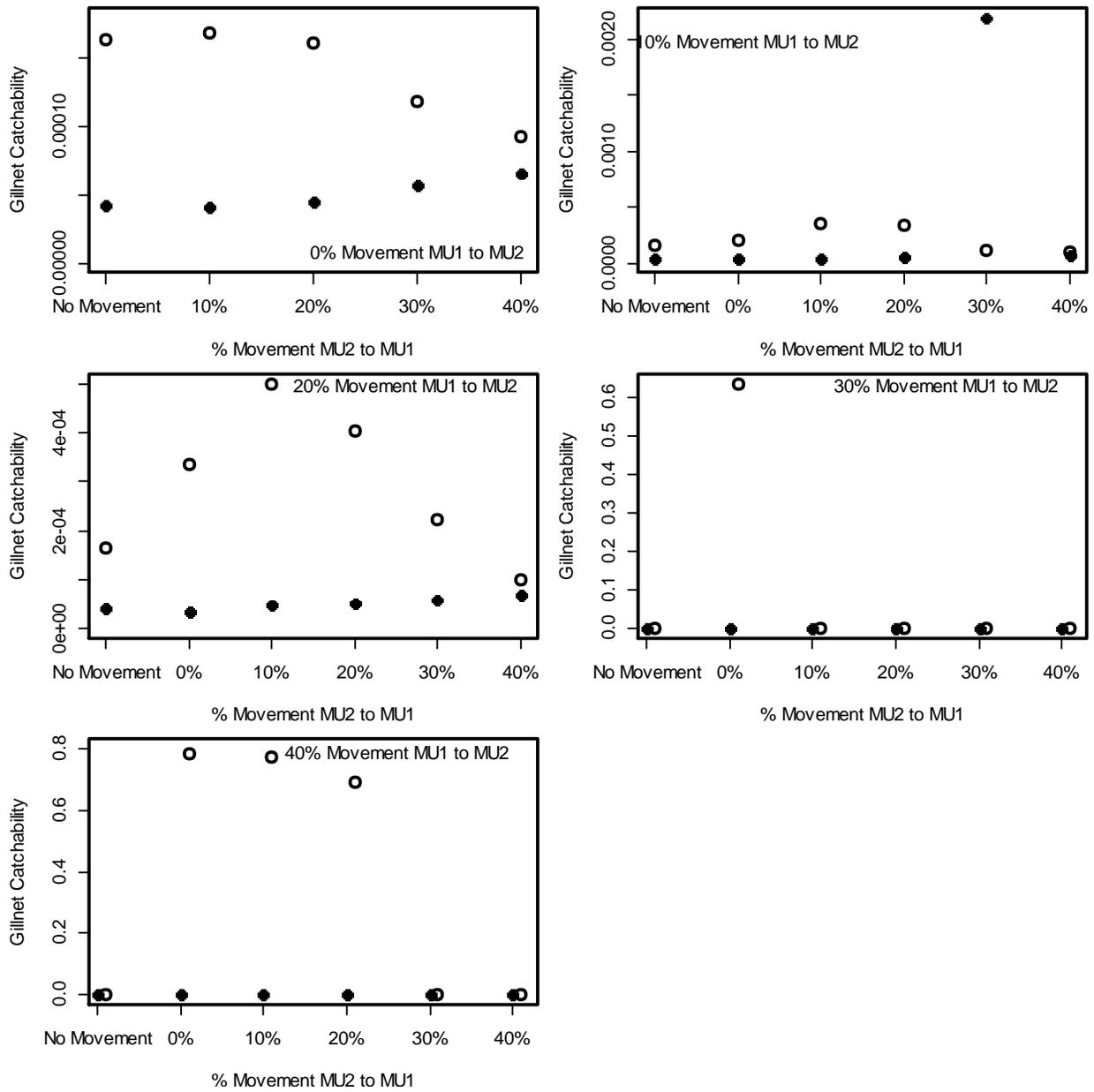


Figure 1.3. Gillnet catchability for MU 1 (white circles) and MU 2 (black circles) for the 25 different movement scenarios grouped by the amount of movement from MU 1 to MU 2. No movement is the scenario with 0% movement between MUs. Note the scale for each of these plots is different and some of the points in the panels are offset.

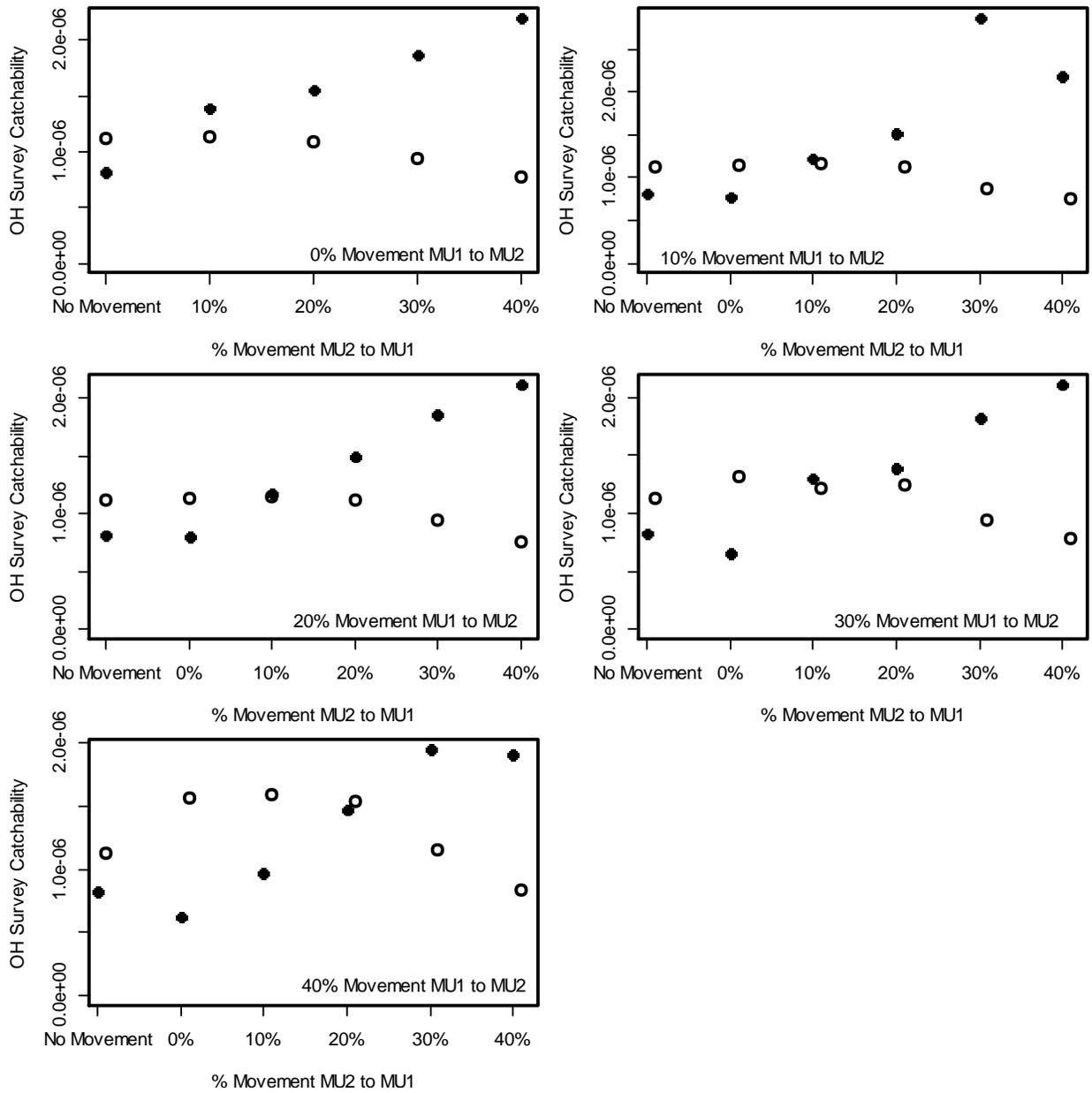


Figure 1.4. OH survey catchability for MU 1 (white circles) and MU 2 (black circles) for the 25 different movement scenarios grouped by the amount of movement from MU 1 to MU 2. No movement is the scenario with 0% movement between MUs. Note the scale for each of these plots is different and some of the points in the panels are offset.

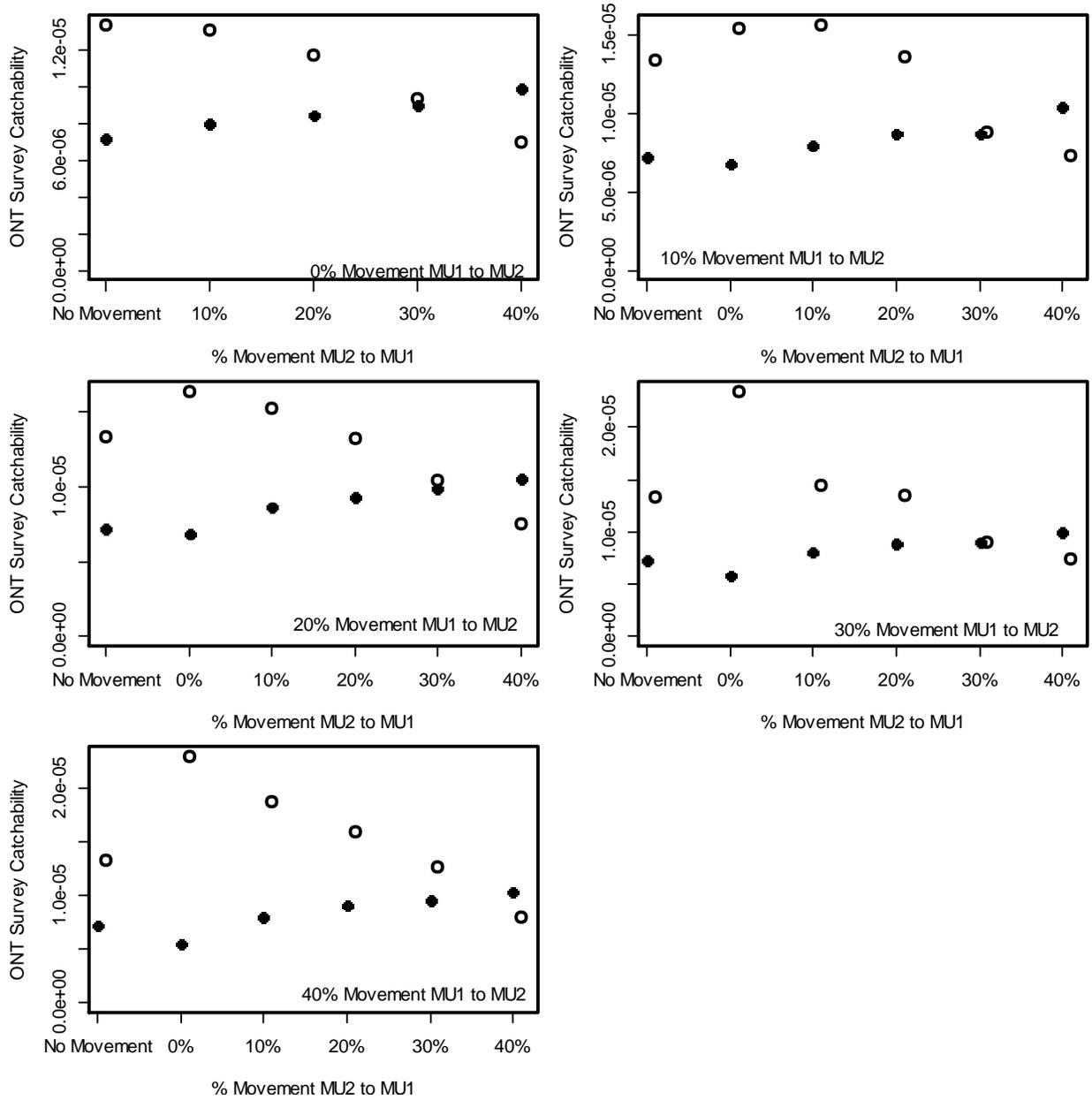


Figure 1.5. ONT survey catchability for MU 1 (white circles) and MU 2 (black circles) for the 25 different movement scenarios grouped by the amount of movement from MU 1 to MU 2. No movement is the scenario with 0% movement between MUs. Note the scale for each of these plots is different and some of the points in the panels are offset.

Discussion

Consistency in the way the model responds to the movement parameter

The Lake Erie yellow perch models appear to be very sensitive to assumptions of non-zero movement. Except in very low movement scenarios, the models do not respond consistently to different rates of movement and appear to be confounding abundance estimates and catchability to explain the observed catch when movement was assumed. We attempted to evaluate the confounding of parameters by assuming catchability was fixed at the values estimated in the no-movement scenario. This approach resulted in non-convergence for the majority of the movement scenarios; further supporting the idea that catchability is being used to explain observed catch and that these models are sensitive to movement assumptions.

Assumptions of the movement model

There are assumptions underlying the conclusions and implications of this research below: that these results can be applied to all of Lake Erie, that yellow perch exhibit spawning site fidelity, and that movement is constant across years and ages. The models used in this research only covered the western half of Lake Erie (MU 1 and MU 2). This was an exploratory analysis and these two MUs represent a large amount of the lake-wide harvest for both the commercial and recreational fisheries, so it seemed appropriate to adopt this simplification for our analysis. However, it is possible that if all four MUs were included in this analysis we would see different patterns in the results. Adding MUs would also increase the complexity and amount of overall movement in the model which would most likely increase problems with model convergence.

This analysis also assumed that yellow perch spawn in their ‘home’ MU, move during the fishing season, and return to their ‘home’ MU to spawn again. This is consistent with the evidence of spawning site fidelity found in the literature (Kipling and Le Cren 1984; Aalto and Newsome 1990; Glover et al. 2008). However, site fidelity is still an understudied characteristic of yellow perch, particularly in Lake Erie, and it is possible that this assumption is not representative of the biology of Lake Erie yellow perch. If this assumption is being violated, these results would not accurately represent the stock assessment model’s response to the assumption of non-zero movement.

The movement parameter in this analysis is assumed constant across ages and years. It is possible that incorporating a more specific movement pattern into the model would be better able to accommodate movement or would better reflect actual conditions in the lake. A fixed parameter was used because there has been little evidence to suggest what an age-specific movement pattern for yellow perch would be. A constant yearly pattern was used for model simplicity; however there has been some research into environmental factors that change temporally that could affect the distribution and movement of yellow perch, such as the presence of hypoxia (Roberts et al. 2009). Adding this complexity could likely increase convergence issues and could not be justified based on existing knowledge.

Management implications

If yellow perch are moving across MU boundaries, the current MU stock assessment structure may not be sufficient to assess abundance accurately at the MU level unless movement between MUs is very low. At higher levels of movement, these stock assessment models have difficulty both finding best-fit parameters and fitting the data in a consistent way. Both catchability and abundance appear to be used to fit the data in a confounded and unpredictable

manner. If movement is quantified in the future and more than approximately 10% of the stock is moving across MUs, it may be necessary to consider an alternate assessment model structure. Further, if movement is occurring, it is possible that the current stock assessment models are giving biased estimates that do not accurately reflect the status of the yellow perch population.

The framework of this analysis could also be applied to other managed fish populations that use a similar multi-MU approach when levels of movement are hypothesized. It would be useful to re-do this analysis using a lower, narrower range of movement to investigate if more modest changes in movement lead to different results. It is possible the issues with convergence and erratic results at the higher levels of movement are because those levels of movement are enough higher than the ‘true’ movement that the model had a hard time finding the parameter estimates that would accommodate unrealistically high rates of movement. Also a general investigation into using different ways to incorporate movement into this type of MU structure could aid the management of yellow perch and other fish species that may be moving across management boundaries.

There are a variety of ways to incorporate movement; one approach that has been evaluated for other stocks would be to aggregate MUs into one stock assessment model. Previous simulation work on other fish species compared a ‘pooled’ assessment approach to a separate assessment approach and found that even with modest amounts of movement, which is likely the case for yellow perch, aggregated stock assessment models performed better than separate models (Ying et al. 2011; Guan et al. 2013; Li et al. in press). However, an aggregated approach does not take into account different productivities of different areas. If there are separate stocks that are subject to different fishing rates and histories, even if there is mixing occurring, using an

aggregated assessment can lead to biased results (Cope and Punt 2007; Kell et al. 2012; Hart et al. 2013).

Another option for Lake Erie yellow perch would be to continue to separate the lake into MUs but allocate the catch and survey data to its actual source population, making each dataset population-specific (Powers and Porch 2004; Guan et al. 2013). Guan et al. (2013) found this approach to have low estimation bias compared to other approaches. However, it can be difficult to implement in practice and would require a high investment into sourcing fish with uncertain benefit. This approach utilizes additional data, such as tagging and otolith microchemistry, which tends not to be readily available for all commercially harvested fish species.

The model structure used in this research explicitly allowed for movement between MUs as opposed to a ‘pooled’ or separate approach, but there are other ways to include movement. A simulation study for lake whitefish used a similar model structure, except the stock assessment used the ‘true’ mixing rate, and they found this approach performed well in some scenarios but not all (Li et al. in press). Alternatives to this movement model have been explored in the literature, such as specifying movement of fish before recruitment (Cope and Punt 2011), specifying movement into and subsequent spawning in another area (Ying et al. 2011), or allowing movement with no relationship between spawning and fishing area (Guan et al. 2013). These may be further avenues of research for Lake Erie yellow perch stock assessment models.

This research shows that the current Lake Erie yellow perch stock assessment models are sensitive to movement assumptions and ignoring movement has the potential to lead to biased results. However, there is still a lot of uncertainty about yellow perch movement and it is not clear what approach should be taken to account for movement in the assessment of the stock.

This is an economically and culturally valuable resource and uncertainty in the stock assessment leads to uncertainty in the management of this species. Future work needs to focus on reducing this uncertainty to ensure appropriate management of yellow perch in Lake Erie.

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CHAPTER 2

STANDARDIZATION OF CATCH-PER-EFFORT DATA FOR YELLOW PERCH IN LAKE ERIE: EFFECT OF WIND CONDITIONS ON SURVEY INDICES

Introduction

Stock assessment techniques use a variety of data sources to estimate the dynamics of an exploited fish population. Generally, data sets include commercial catch or recreational harvest and effort data, which are assumed to be proportional to abundance. However, it has been frequently shown that this relationship may not be accurate (Beverton and Holt 1957; Harley et al. 2001). Fishery data are inherently biased by the distribution of fishing effort and the fact that it is a targeted effort. Walters and Maguire (1996) concluded from the analysis of the northern cod (*Gadus morhua*) collapse that when commercial catch per unit effort (CPE) is assumed to be proportional to abundance, there is increased risk of overestimating the stock size. Accounting for this bias has been a popular topic of research. Stock assessment models now tend to include a measure of both the catchability of the fishing gear as well as the age-specific vulnerability of fish to the fishing gear.

Fishery-independent surveys are also used as data sources and are often assumed to provide a less biased indicator of abundance (Kimura and Somerton 2006; Link et al. 2008). These surveys can vary from trawls and gillnets to baited hooks and traps, and include indirect methods such as acoustic telemetry. These surveys are generally designed to be representative of the population, as opposed to fishery-dependent sources that tend to target heavily-populated or more vulnerable to harvest areas. They are therefore assumed to show trends similar to those of the actual population. However, even fishery-independent surveys are susceptible to factors other

than the abundance of the fish stock that can influence catch rates (Gunderson 1993; Maunder et al. 2006).

Many factors that have the potential to influence the catch rates of a survey can vary over time. Location and season can influence catch rates (Punt et al. 2000; Deroba and Bence 2009). Berger et al. (2012) found that water clarity and surface water temperature affected survey catch rates of walleye (*Sander vitreus*) on the United States side of Lake Erie. Water clarity and depth have been shown to affect the catchability of ruffe (*Gymnocephalus cernua*) and young pikeperch (*Stizostedion lucioperca*) in the Netherlands (Buijse et al. 1992). Temperature can influence swimming performance in an area (Wardle 1983), as well as affect abundance, (Hart et al. 2011), both of which can affect survey catch rates. Perry et al. (2000) observed that stronger winds and tides with reduced sunshine increased the catch rates of smooth pink shrimp (*Pandalus jordani*). Arreguin-Sanchez (1996) reviewed several studies that illustrated the potential variability in survey data resulting from a variety of factors including water temperature, tidal cycles, time of day of the survey, and wind strength. By adjusting for factors that have an impact on survey catch rates you can obtain a more accurate representation of the trends in the abundance of a fishery.

A common way to adjust a survey index to account for factors besides abundance is catch-rate standardization (Gavaris 1980; Kimura 1981; Harley et al. 2001; Hinton and Maunder 2004; Yu et al. 2011; Berger et al. 2012). There are many different approaches to catch-rate standardization, but it usually involves constructing and fitting a model of CPE that includes the effects of environmental factors as well as spatial factors such as location of the survey and water depth (Maunder and Punt 2004). Historically, each vessel's fishing power was determined relative to a standard fishing vessel (Gulland 1956; Beverton and Holt 1957), but more recent

methods use statistical tools such as generalized linear models (GLMs; Gavaris 1980), spatial generalized linear models (s-GLMs; Nishida and Chen 2004), generalized additive models (GAMs; Bigelow et al. 1999), and generalized linear mixed models (GLMMs; Berger et al. 2012). For each technique it is important to identify the needed explanatory variables for the fishery in question (Maunder and Punt 2004).

Even though many recognize the need for catch-rate standardization, not many fisheries incorporate it into their stock assessments. Yellow perch (*Perca flavescens*) in Lake Erie are managed as four separate management units (MUs). A stock assessment is performed for each of these MUs annually to inform managers about the status of the population. Each of these models use two fishery-independent surveys, a trawl survey in U.S. waters and a gillnet survey in Canadian waters. The stock assessments for MUs 1-3 use a fall Ohio trawl survey. The trends seen in this trawl survey are given a higher weight in the assessment, meaning the model relies more heavily on them to evaluate the status of the yellow perch population. The index is assumed to be an unbiased indicator of the trends in yellow perch abundance. However, trawl surveys are susceptible to the effects of environmental factors as are other surveys (e.g., water temperature: Smith and Page 1996; water clarity: Buijse et al. 1992). As described in Chapter 1, many environmental factors potentially affect the distribution of yellow perch in Lake Erie. The trawl survey records include water transparency, water temperature, and dissolved oxygen, all of which have been shown to influence catch in the lake (Hartman 1972; Ryder 1977). Accounting for these factors could potentially increase the accuracy of the trends seen in the survey and subsequently the results of the stock assessment.

Wind condition is another environmental factor that can influence trawl surveys because it is a measureable indicator of water current speed and direction (Engas 1994; Perry et al. 2000;

Bolle et al. 2001; Poulard and Trenkel 2007). Queirolo et al. (2012) investigated the effect of wind condition on trawl geometry, and found that both net spread and variability in the contact of the footrope with the seabed were significantly affected by wind speed and direction. However, this environmental variable is rarely included in trawl CPE standardization because wind speed and direction are not often recorded and the relationship between wind and trawl geometry is difficult to determine. Lake Erie is surrounded by a number of climate observation stations, along with a few weather buoys in the lake, which record wind speed and direction. Therefore, for the yellow perch fishery in Lake Erie, wind can be included in catch rate standardization and improve the accuracy of the abundance index derived from the survey data.

Wind condition, as well as other factors such as dissolved oxygen, temperature, and water turbidity, will be included as potential influential factors in this investigation. Environmental factors need to be investigated to determine which significantly contribute to the standardized index for the Ohio trawl survey, and then after taking these into account, the temporal index can be extracted as a more unbiased estimate of the trends in abundance. The objectives of this study are to 1) develop an approach to converting wind speed and direction observations into a single parameter appropriate for this analysis; 2) develop a model for CPE that includes environmental factors using a GLM; 3) use model selection to identify the significant factors of the best-fit model; and 4) extract the year-by-MU effect from the best-fit model and compare the trends of the standardized index to the original non-standardized trends derived from the CPUE data.

Methods

Study site

Lake Erie is the southernmost, shallowest, and most biologically productive of the Great Lakes. Lake Erie is home to a large commercial fishery and is a popular destination for recreational anglers. Yellow perch and walleye are the two main targeted species in this lake, and both are managed by the Lake Erie Committee. Lake Erie, yellow perch, and the management of yellow perch are described in more detail in Chapter 1. Yellow perch in each of four MUs are evaluated yearly using a statistical catch-at-age model that incorporates fishery-dependent and fishery-independent data.

Survey data

The survey data used in this analysis were provided by the Ohio Department of Natural Resources (ODNR). The survey data used in the yellow perch stock assessment models start in 1990 and continue through the present. Each fall, the ODNR performs a bottom trawl survey (September through the first week of November) in the Ohio waters of Lake Erie. This involves towing a flat-bottom semi-balloon otter trawl with a 10.7-m head rope and 13-mm bar mesh in the cod end through the water at a specific location for a short period of time (5-10 minutes). These surveys are used in MUs 1-3, in addition to a gillnet survey performed by the Ontario Ministry of Natural Resources and Ontario Commercial Fisheries' Association partnership in Canadian waters, to provide fishery-independent indices of abundance for the stock assessment models for these three management units. The trawl site location is determined using a double-stratified random sampling approach (K. Kayle, ODNR, personal communication). Lake Erie is divided into 2.5 minute grids. The grids sampled are stratified by ports (Vermillion, Lorain, Cleveland, Chagrin, Fairport/Perry, and Astabula/Conneaut). The grids are then stratified by

depth contour (5, 10, 15, or 20 m) and three grids per depth and location are sampled. Many of the trawls measure environmental data: dissolved oxygen, turbidity of the water, and temperature. To include wind observations in our standardization model, we needed to know the starting and ending location of the trawl, or the bearing at which it trawled, as well as the wind direction, in order to determine the wind direction relative to the direction of the trawl. For MUs 2 and 3, this information was noted in the catch data, so the data for these two MUs were used in the analysis. Only the trawl data that included environmental records were used; all other observations were omitted. The final data set included 241 observations from 1997 to 2011 with no observations for 1998, 1999, and 2006. The location of the trawls is shown in Figure 2.1.



Figure 2.1. Trawl locations.

Objective 1: Converting wind observations into a single wind parameter for each trawl

Hourly wind observations for direction and speed were obtained from 22 stations around the lake. This data was gathered from the National Oceanic and Atmospheric Administration's National Climatic Data Center (NCDC). For each trawl date per station, a half-daily average wind vector was calculated. This method is similar to the way the NCDC provides daily wind summaries in its Local Climatic Data product (called the resultant wind speed and direction) and how Poulard and Trenkel (2007) included wind in their investigation of its effect on survey indices. The half-daily wind vector was calculated by converting all wind observations from 12 hours before the trawl end time into Cartesian coordinates. The sum was then obtained for the X and Y components of the coordinates and the angle of the resultant vector and average resultant length were computed and converted back to polar coordinates. The angle was the resultant wind direction. The length divided by the number of observations was the resultant wind speed.

Queirolo et al. (2012) have shown that wind speed and direction can affect water currents, which in turn can affect the geometry of the trawl. This suggests that the important component of the wind observation is the one that is perpendicular to the trawl. This perpendicular component was calculated for each resultant wind observation by transforming the angle of the resultant wind vector to the angle relative to the trawl. We calculated the length of the perpendicular component of the resultant wind vector by multiplying the resultant wind speed by the sine of the new wind angle (Figure 2.2).

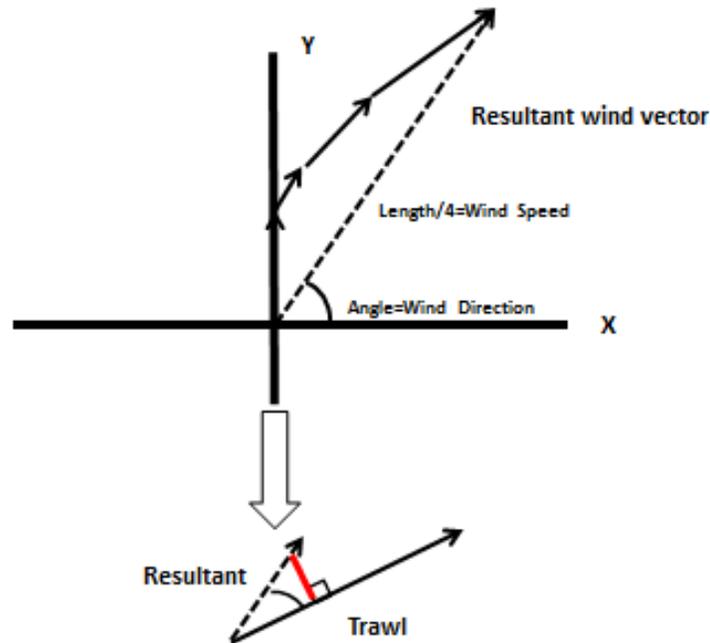


Figure 2.2. Illustration of wind parameter calculation. Each wind observation is converted into a vector. Then the resultant vector is calculated from all of the wind observations within the 12 hours before the trawl occurred (dashed line). The angle of this resultant vector is the half-daily wind direction. The length of this vector divided by the number of observations is the half-daily wind speed. Then the angle of the resultant vector is transformed to be relative to the trawl direction. Then we multiply the half-daily wind speed by the sine of the transformed angle, this gives us the length of the perpendicular component of the resultant wind vector (red line).

To interpolate the wind observation data over the trawl locations we used the spline interpolation routine in the ArcGIS software package (version 9.2, 2007, ESRI Inc., USA). Interpolation takes known values from one or more locations (weather stations) and uses them to estimate a value at a location where no measurement was taken (trawl locations). The locations and values from the known locations are used to weight those observations and create a surface of predicted parameter values for the space between the observations. We used this technique to identify a wind observation surface for each trawl observation. For each climate station we had calculated the perpendicular component of the resultant wind vector for each specific trawl time.

The interpolated value was the perpendicular component at each trawl location. The result was used as the wind parameter for catch-rate standardization.

Objective 2: Catch-rate standardization model

We used a GLM to standardize the Ohio trawl survey for yellow perch in Lake Erie using the log(CPE) as the dependent variable. A GLMM was used to investigate the inclusion of random effects (year-by-week, MU-by-week, and year-by-week-by-MU interactions). Using a backward selection approach, random effects that deteriorated model fit of the full model (i.e. any effect that increased the Akaike's information criterion corrected for small sample sizes, AIC_c , by more than two), were dropped before the fixed effects were analyzed (Deroba and Bence 2009; Berger et al. 2012). Since all random effects were dropped from the model using this approach, a GLM was then used to investigate the fixed effects. Fixed effects included in this model were year (y), week (w), MU (m), water temperature (t), Secchi depth (s), water depth (d), presence of hypoxia (h), wind observation (n), and the interaction between MU and year.

The fully parameterized model with lognormal error is

$$\begin{aligned} \ln(CPE_{ywmtsdhn}) \\ = \mu + \alpha_y + \alpha_w + \alpha_m + \alpha_t t + \alpha_s s + \alpha_d + \alpha_h + \alpha_n n + \alpha_{ym} \\ + \epsilon_{ywmtsdhn} \end{aligned}$$

where μ is the overall mean; α_i are the parameter coefficients for the fixed effects i ; and ϵ_i is the residual error term. The specific effects are the factors described above. The `glmulti` package in the R statistical computing environment is used for all analyses (Calcagno 2013; R Core Team 2013).

Objective 3: Model selection

The full model and all nested models (models with fewer parameters) were evaluated using the AIC_c (Akaike 1973; Burnham and Anderson 2002). The model selected as best had the lowest AIC_c value. However, models within 2 AIC were considered to be very similar in terms of goodness of fit. In this case, top models were model-averaged to get the best fit parameter estimates. The relative importance of each factor was determined by the number of top models that included the factor. Factors that were included in a large number of top models were presumed to be more important to model fit. Year, management unit, and the interaction between these effects were included in all models because these were required to extract the standardized index. The number of possible models in the model selection process was 64.

Objective 4: Comparison of the standardized and non-standardized index

To compare the standardized and non-standardized indices we extracted the yearly MU index of abundance from the model. The standardized index, \hat{p}_{ym} , was calculated as $\hat{\alpha}_y + \hat{\alpha}_m + \hat{\alpha}_{ym}$. In this way we extracted a standardized yearly index for each MU, which we then compared to the non-standardized index computed from the raw CPE data.

Results

The wind values that resulted from the interpolation ranged from 0.01 to 6.46 m/s with a mean value of 2.20 m/s (Figure 2.3). Approximately 75% of the wind parameter values were less than 3 m/s. We speculate this reflects the protocol for the ODNR trawl survey that specifies they will not go out on the water in high wind conditions. However, these protocols do not take into account wind conditions before the trawl, which could explain the substantially higher wind parameter values making up the other 25% of our results. This wind parameter was not

correlated by more than 20% with any of the other factors used in the full model (Pearson's rank correlation).

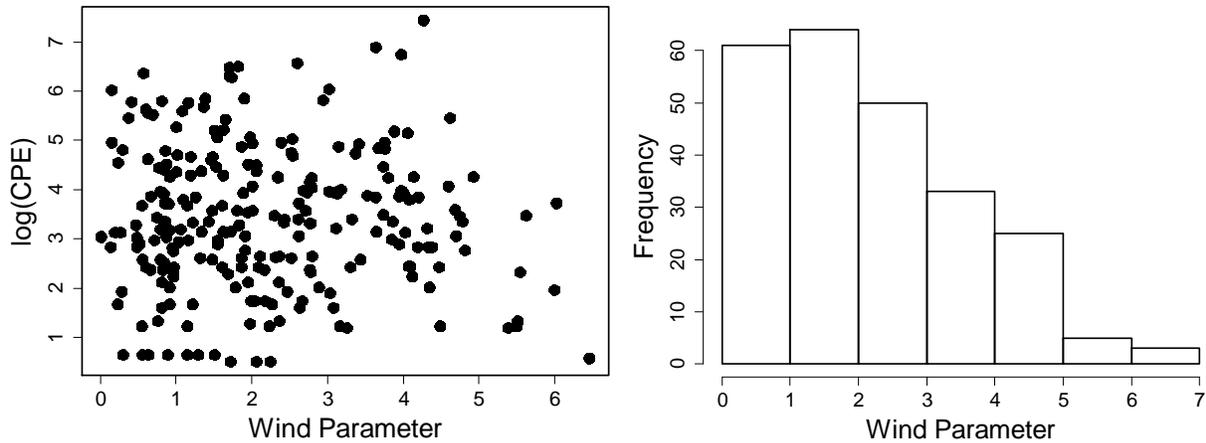


Figure 2.3. Wind interpolation results. Panel A is the catch rate versus the wind parameter and panel B is the frequency distribution of the wind parameter itself.

None of the random effects investigated in the model selection procedure appreciably increased the fit of the model. Therefore, only fixed effects were used in the final model selection. There were 64 possible models compared using AICc. The top five models were within two AICc units of each other, thus we concluded that each of these was a plausible model of trawl catch rate. To account for each of these top models, we used a model-averaging approach to determine the included effects and their corresponding parameter estimates. An analysis of using a wider range of AIC values revealed that this small AICc range yielded similar results (and the same conclusions) to a model that included all possible models.

The final averaged model included categorical and continuous environmental variables in addition to the effect of year, management unit, and the interaction between the two (Table 2.1). The importance of each variable was determined by the number of top models in which it was included and the parameter estimate itself (Table 2.1). The most important variable was water

depth, which was included in all five top models. This categorical variable had a positive relationship with the catch rate, with the depth strata of 15 m having the strongest effect. This affect is visible looking at a box plot of the data (Figure 2.4). Catch rates were also associated with, in order of importance, the presence of hypoxia (positive), water temperature (negative), and the wind parameter (negative).

Table 2.1. Factors included in the final model. Table includes parameter estimates, standard deviations, and the number of models the parameter was included in out of the top five models within 2 AIC that were used in the final averaged model.

Factor	Estimate	Standard Deviation	# Models
Wind	- 0.0156	0.031464	1
Temperature	- 0.0286	0.047645	2
Presence of Hypoxia	0.4906	0.484881	3
(Intercept)	3.1938	1.004445	5
Water depth (10)	0.4325	0.303348	5
Water depth (15)	1.2188	0.30848	5
Water depth (20)	0.9988	0.324869	5

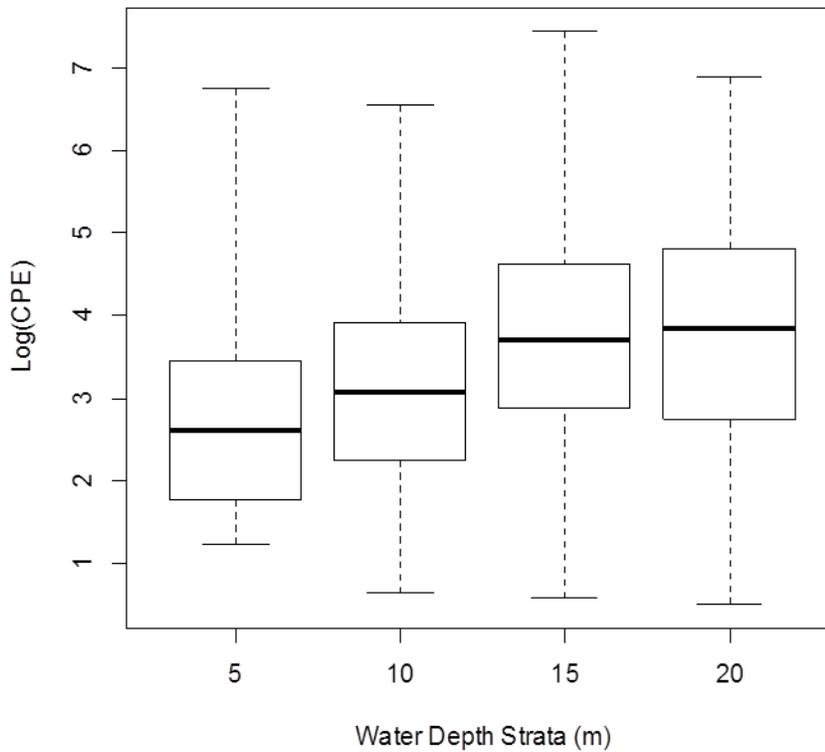


Figure 2.4. Boxplot of yellow perch catch-per-effort grouped by water depth.

Model diagnostics were used to investigate the goodness of fit for the final averaged model. The plot of observed versus expected (Figure 2.5a) shows that this model does seem to reduce the variance in the data, with the exception of very low and very high CPE values where there appears to be evidence of lack of fit. The expected values do appear to satisfy the assumption of constant variance (Figure 2.5b). There also appears to be no trend in the residuals, suggesting the model was specified correctly (Figure 2.5c), and they appear to be normally distributed on the log-normal scale, fulfilling the assumption of normality (Figure 2.5d).

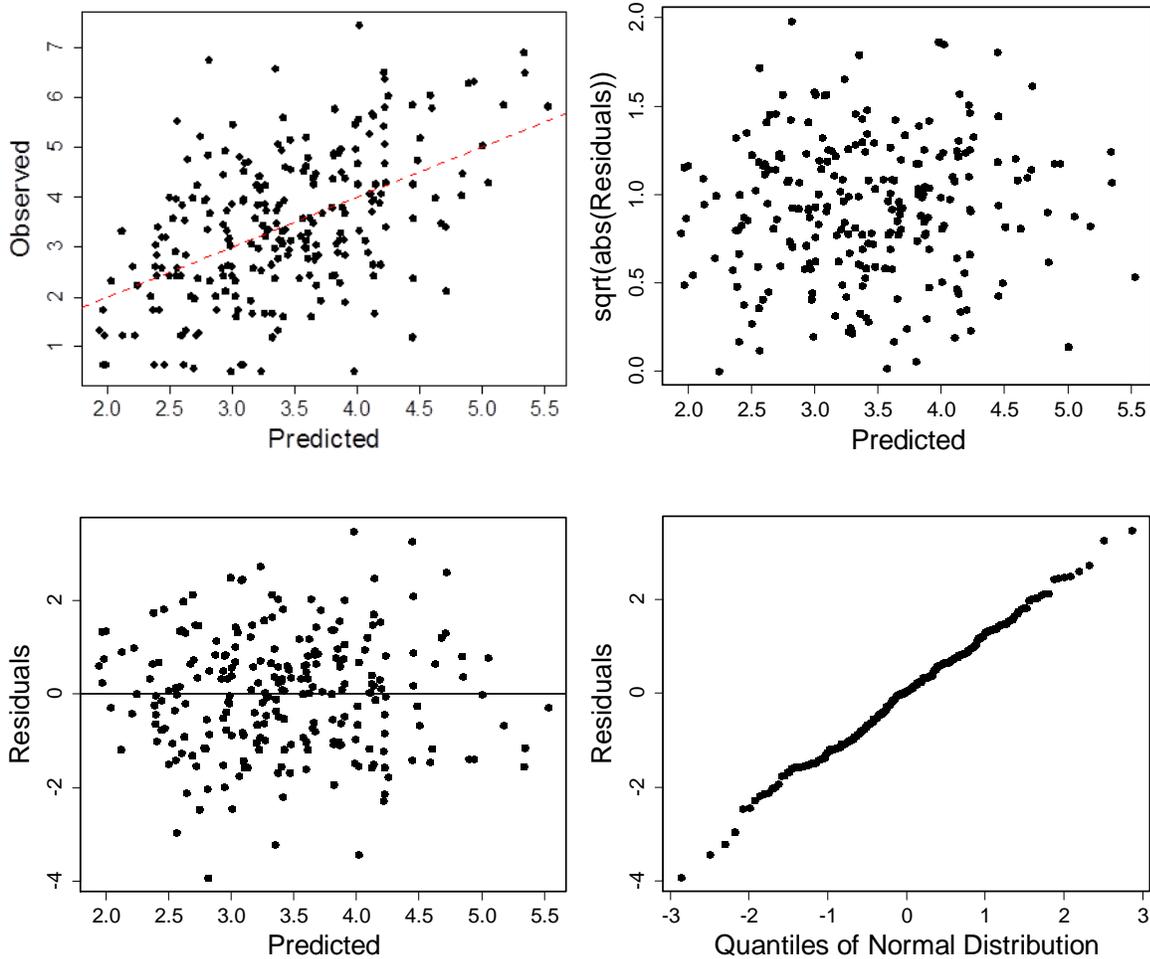


Figure 2.5. Model diagnostics. Panel A shows the observed versus predicted from the final averaged model. Panel B suggests the model fulfills the assumption of constant variance with expected values. Panel C investigates the trends in residuals. Panel D shows the residuals are normally distributed on the log-normal scale.

The coefficients for the annual differences by management unit ($\hat{\alpha}_y + \hat{\alpha}_m + \hat{\alpha}_{ym}$) from the final averaged model were extracted and used to develop standardized indices. These standardized indices of yellow perch abundance were then compared to the non-standardized indices from the Ohio trawl catch rate data. Each MU was investigated separately because the stock assessments that use these data are also separated by MU. In general, the MU 2 patterns were the same for both the standardized and non-standardized indices (Figure 2.6). The indices are relative so the constant difference in scale between them is not important. Both indices predicted the same trends of increasing and decreasing yellow perch abundance. Rankings were very similar, for example the lowest MU 2 index in the time series occurred in 2010 for both indices, and 2008 and 2005 were the two highest ranked years for both indices. MU 3 indices were not as similar. For most years the trends in abundance were the same, but the indices predicted different trends between 2000 and 2004 (Figure 2.6). The standardized index predicted a decreasing trend throughout the time period while the non-standardized index increased in 2002. The rankings also had more discrepancies. The lowest ranked year for the non-standardized index was 1997 while the lowest ranked year for the standardized index was 2004. In more recent years the rankings and trends were very similar. In the case of the Ohio trawl survey for yellow perch, there does not appear to be a consistent temporal trend in the deviation of the standardized index from the non-standardized index for either MUs 2 or 3.

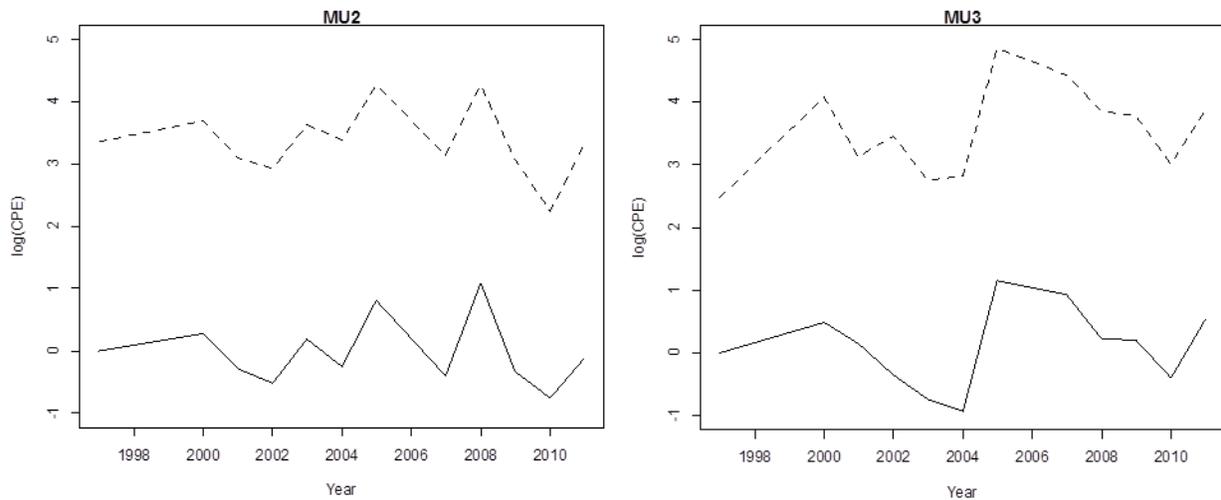


Figure 2.6. Standardized (solid) versus non-standardized (dashed) indices of yellow perch abundance for MU 2 and 3.

Discussion

Fishery-independent surveys are important components of stock assessment models. They are given a lot of weight in the overall assessment model for yellow perch in Lake Erie and can influence the estimated abundance produced by the stock assessment models, which are then used for setting total allowable catches (TACs). It is therefore vitally important that these indices of abundance are unbiased by environmental factors that are also changing over time other than actual changes in the yellow perch population. Our analysis suggests that environmental factors including water depth, the presence of hypoxia, temperature, and wind can influence the catch rates of the fall trawl survey performed by the ODNR. While the standardized index that accounts for these factors generally showed the same trends as seen in the non-standardized index for both MUs 2 and 3, there were a few years in the MU 3 index where the standardized index suggested trends that were the opposite direction as the non-standardized index. If the yellow perch population was actually decreasing instead of increasing, the stock assessment models could produce overestimates of the size of the stock, which in turn would lead to incorrectly increasing TACs, or vice-versa. Using the standardized index allows the model to

account for future inconsistencies that may arise in the survey data that are not caused by changes in abundance.

Water temperature, water depth, presence of hypoxia, and wind were all influencing factors for Lake Erie yellow perch trawl survey catch rates. Water depth was the most important factor of these four factors. As the depth strata increased from 5 m to deeper, catch rates also increased, with a depth of 15 m having the strongest positive effect. Not accounting for any other factors, the mean catch rate for each depth strata increases as the depth increases. Water depth, particularly bottom depth, has been shown to affect CPE data for yellow perch (Bacheler et al. 2011) and is corroborated by our findings. This affirms the approach used for the ODNR; having the samples stratified by depth is a valuable component of the survey. Future work could involve taking a closer look at the interaction between this important factor and temporally and spatial factors, such as year and MU, that may also contribute to the observed catch-rate. If one of the MUs had more 15 m depth samples in a certain year would it have a higher catch rate?

The presence of hypoxia was another important factor, included in three of the top five models. Hypoxic conditions had a positive influence on catch rates of yellow perch. The highest catch rate in the data set took place in hypoxic conditions. Of the 241 observations, 22 (9%) took place in hypoxic conditions. Of those 22, nine (41%) were in the upper quantile of catch rates for the entire data set. This is a counterintuitive relationship according to the low tolerance levels of yellow perch for hypoxia reported in previous studies (Moore 1942; Brown et al. 2009). This could be explained by yellow perch moving to avoid hypoxic conditions and concentrating into groups near the edges of these areas. A trawl is not a static sample, it moves through the water, meaning it could travel through a hypoxic area and then sample the aggregated fish on the

outside. Hypoxic conditions can also increase the physiological stress of the fish, leading to reduced gear avoidance capacity and higher catch rates.

Temperature and wind were also influential, though to a lesser degree. In the case of temperature, the negative estimate suggests increasing temperature decreased catch rates. Temperature observations from our data ranged from 7.9 °C to 21.8 °C. Yellow perch generally prefer cool temperatures (<20.1 °C; McCauley and Read 1973), and it is possible in Lake Erie they prefer even cooler temperatures, particularly in the fall (when the trawls are done) and the lake is still warm and just beginning to cool down. Wind was an influencing factor in only one of the top five models. The negative relationship suggests that increased wind speed perpendicular to the trawl does negatively affect the performance of the trawl.

Wind is not often included in catch rate standardization and the way it is included differs among the few studies that have investigated this environmental effect. We used an approach that relied on wind speed and direction observation from weather stations. In most cases, these weather stations were a large distance away from the trawl locations and we interpolated from only 22 locations, at most, around the lake. This approach, while valid, does provide an opportunity for increased error or noise to be included in our parameter estimates. The range of wind estimates was also restricted by the protocols in place for the Ohio trawl survey. But even with this lack of site-specific data and the trawl protocols, wind was still included as an influencing factor in the final averaged model. While it is possible that this approach captured some other factor or that wind would not be significant with a more accurate measurement, this result suggests it should not be ignored as a potentially important factor in catch rate standardizations, for yellow perch and other species that are surveyed using trawl gear. The approach described here was used because only region-wide wind observations are available.

However, in addition to the need for interpolation, this limited the analysis to trawl records that included trawl bearings and that occurred on days where wind observation data was available. A more effective approach would be to include current speed and direction as an environmental variable measured for each trawl or even some measure of the trawl geometry itself (such as trawl spread). This would provide much more accurate measures of this potential source of bias in the trawl survey.

Recognizing that there are environmental factors that can affect catch rate besides changes in abundance of the targeted species has led to an increased interest in catch rate standardization (Maunder and Punt 2004). It is common to use the available site-level measurements of factors such as water depth, water temperature, or the presence of hypoxia. For yellow perch, these factors did affect the catch rates. But it is important when designing the surveys themselves to also think about what other factors might affect catch rates. In the case of yellow perch, current, as indirectly measured from wind data, may be having a negative effect on trawl catch rates, but having the actual current measurement would give us a clearer look at that effect.

Lake Erie yellow perch surveys are susceptible to the influence of environmental factors besides changes in fish abundance. The catch rate standardization described here is a way to account for a variety of these environmental factors, but it is limited by the information that is available. These surveys could be improved by incorporating our understanding of yellow perch ecology and how they are influenced by changes in their environment. This knowledge can be used to inform future sampling approaches, such as requiring the measurement of current speed and other factors at trawl locations, as well as future catch rate standardizations. This will increase the accuracy of our stock assessment models and better inform management of the

status of fish populations, enabling them to make decisions that will protect the fish and fisheries for years to come.

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