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**Acoustically derived fish size-spectra within a lake and the statistical power to detect
environmental change.**

Derrick Tupper de Kerckhove^{*a}, Brian John Shuter^{a,b}, and Scott Milne^c

^{*}Corresponding author: fish.research@gmail.com

^aDepartment of Ecology and Evolutionary Biology,

University of Toronto,

Toronto, Ontario, M5S 3B2, Canada

^b brian.shuter@utoronto.ca

^c smilne@milnettechnologies.ca

Running Head: Acoustically derived size-spectra indicators

Abstract

Fisheries acoustic surveys are increasingly being used to monitor the abundance of fish stocks yet their adoption as a tool to monitor changes in community size-spectra have not been well explored. In this study we use a series of historical acoustic surveys of the pelagic zones of three arms of Lake Opeongo to determine if acoustically derived size-spectra indicators (slope and height) can be effectively measured and used as a monitoring tool. Acoustic size spectra indicators were successfully measured for every survey, and resembled the same indicators found in netting surveys. From 2005 to 2009 the slope of the size-spectra became shallower, likely due to a decrease in abundance in schooling prey fish. Estimates of sources of survey variation including fish size estimates and inter-basin differences were low ($<10\%$ coefficients of variation) suggesting that monitoring programs would detect annual changes in the size-spectra slopes ranging from 2% to 15% within 10 years. Size-spectra heights did not change very much over the time-series of surveys. Using Lake Trout fishery data from Lake Opeongo we estimate that sources of natural variation in size-spectra at the population level could be much higher, and potentially require longer monitoring periods. We noted from our study that standardized surveys and data analyses are critical if acoustically derived size-spectra are to be adopted as a monitoring tool. We also suggest that size-spectra be calculated through echo-integration rather than echo-counting methods because in this study echo-counting led to lower estimates of abundance and size-spectra indicators which are likely under-estimates of the true fish community's abundance.

Keywords: size spectrum; fisheries acoustics; power analysis; echo-integration; echo-counting; Lake Trout; Cisco

Introduction

Monitoring of environmental change is rarely achieved through the study of the ecosystem as a whole because in all but the simplest and smallest systems it is extremely difficult to observe all ecosystem components (FAO 1999). Effective monitoring is instead typically conducted through the study of a set of indicators that are assumed to represent the main components of the environment that require management (Rice 2000; Rice and Rochet 2005; de Kerckhove 2015). Therefore, indicators are often selected depending on their management context, as well as their ability to accurately represent ecosystem characteristics. One of the earliest examples of an aquatic indicator are the fisheries reference points (e.g. Maximum Sustainable Yields) which were based on simple representations of fish population dynamics. Over time, a broad set of indicators (e.g. Index of Biotic Integrity, Habitat Suitability Index, Relative Ascendancy, Abundance Biomass Curves) has been developed to monitor aquatic systems (see Fulton et al. 2005 and Minns et al. 2011 for thorough reviews of marine and freshwater indicators, respectively).

The use of size-spectra as a diagnostic tool for monitoring ecosystem health is a relatively recent innovation in marine (Bianchi 2000; Rochet and Trenkel 2003) and freshwater (Emmrich et al. 2011; Murry and Farrell 2014) environmental indicators. In this methodology, a negative and linear log-log relationship between abundance (or biomass) and body size in a community of organisms is found to be conserved across many orders of magnitude in body size, and often across large spatial and temporal scales (Kerr 1974; Dickie et al. 1987; White et al. 2007). The ubiquity of this relationship is attributed to fundamental allometric relationships between body size, metabolism, predator-prey dynamics and abundance (Gillooly et al. 2001; Brown et al. 2007; Andersen et al. 2009). Therefore, changes in the log-log relationship typically reflect

external pressures that shift the community away from an established equilibrium (Bianchi et al 2000). In marine systems, changes to size-spectra have been examined mainly in the context of fisheries pressures on large individuals (Rice and Gislason 1996; Bianchi et al 2000), however in freshwater systems a greater emphasis has been placed on changes in habitat quality (Holmgren and Appelberg 2000; De Leeuw et al 2003; Emmrich et al 2011). As the abundance of size classes are altered through external pressures, the slope and height of the log-log relationship shifts, which contributes indicators that can be monitored over time. Typically the slope of size-spectra relationships is thought to relate mainly to the trophic structure of the ecosystem and the height to overall productivity (Murry and Farrell 2014). While this relationship is most commonly described as a linear regression on a log-log scale, other non-linear relationships (i.e. Pareto distributions) have also been used (Emmrich et al. 2011) and are gaining popularity. Size-spectra in aquatic ecosystems are most often derived from netting data which in fisheries are usually selected from commercial trawl catches (Bianchi et al 2000; Nicholson and Jennings 2005) or scientific index gill netting surveys (Emmrich et al. 2011; Chu et al. 2015 in this same issue). Unfortunately, both these methods have drawbacks. Trawl data is usually reported in one overall biomass and abundance measure for each haul, and as such the biomass of individual body size classes must be estimated rather than directly measured (Bianchi et al 2000). Gill netting catches are often reported per fish, which simplifies the measurement of the size spectra, however, unless well calibrated, netting data can be size selective in multiple ways. First, the size of the fish can determine its swimming speed and its fit in the available mesh sizes which introduces selectivity in rates of net encounter and fish entrapment, respectively (Rudstam et al. 1984). Second, large fish are suspected to be poorly represented in standard netting surveys (Pope et al. 2005; Emmrich et al. 2012), especially if they reside in deeper sections of the lake

which are less efficiently sampled (although note that Emmrich et al. 2012 generally found strong correlations between gill net catches and acoustic abundance estimates across 18 European lakes). A promising method to overcome the drawbacks of trawls and gill nets in measuring size-spectra is the use of fisheries acoustic surveys (Simmonds and MacLennan 2005). Fisheries acoustic technology has advanced rapidly over the last 20 years to the point where robust and relatively unbiased estimates of fish size distributions can be obtained from simple surveys. Although standard acoustic methodologies are not yet well suited to identifying different species, in size-spectrum analyses a knowledge of an organism's species is not required, only its size. Despite recent work on validating acoustic measurements of fish size and abundance in lakes with gill netting surveys (Emmrich et al. 2012), there has been very little research on the utility of acoustic derived size-spectra (although see Wheeland and Rose 2015a in this same issue).

Even if acoustically derived size-spectra could be easily and robustly measured, it would remain important to test its utility as an indicator of environmental change. Many modern indicators have been discovered through the retrospective analysis of long time series of ecological data (e.g. more than 50 years). While these studies may reveal novel relationships, there is no guarantee that they will have the statistical power to answer management questions over more relevant and typically shorter time-periods (e.g. less than 10 years; Nicholson and Jennings 2004; Maxwell and Jennings 2005; Jones and Petreman 2012). Instead, each indicator must be evaluated for its ability, under diverse sources of natural or survey variation, to detect a meaningful change. For example, due to high natural variation even annual changes in abundance that exceed 20% can take over 10 years of monitoring to detect in some fish populations (Maxwell and Jennings 2005; Budy et al. 2007). Despite this low power,

management recommendations are sometimes made based on a lack of change in an indicator. Peterman (1990) noted 142 management decisions in 160 fisheries studies demonstrating no change to an indicator with only one test of statistical power. As a partial measure of abundance, the size-spectra could be susceptible to the same lack of power. Nicholson and Jennings (2004) retrospectively examined size-spectra in an ocean fishery and noted that to have detected the historical decline in slope and height would have taken 30 and 14 years, respectively. In this paper we examine the use of fisheries acoustic surveys as a method for deriving size-spectra in three arms of a single lake (Lake Opeongo). We approach this question from three main directions. First we compare trawl, gill netting and acoustic data collected over the same time period to ensure they describe a similar distribution of fish sizes per survey as well as examine the potential error in fish size associated with each acoustics measurement. We tailor our trawl and netting surveys to be less susceptible to the bias mentioned above. Second we analyze a series of annual lake wide surveys from 2005 to 2010 to calculate the slope and height of the fish size spectra and compare them among surveys, years and lake arms. Third, we use 75 years of creel data to recreate the annual size-spectra of a Lake Trout (*Salvelinus namaycush*, Walbaum) population in Lake Opeongo which has gone through large changes in size-at-age and abundance due to the introduction of pelagic prey fish and the dynamics of a local recreational fishery (Matuszek et al. 1990; Shuter et al. this volume). From these three approaches we are able to assess three sources of variation in acoustically derived size-spectra indicators: 1) the ‘error’ associated with estimating the size of individual fish, 2) fine-scale spatial variation in fish size distributions within the lake at a given point in time, and 3) natural changes in fish size-structure over time for both the Lake Trout population, and the Lake Opeongo fish community. Using these sources of variation, we estimate the length of time it would take to detect different

rates of change in the community size-spectra slope and height in Lake Opeongo (following Nicholson and Jennings 2005 and Jones and Petreman 2012).

Materials and Methods

Study Area

The study was conducted on Lake Opeongo in Algonquin Park (Ontario, Canada) which is a long term aquatic study system for the Harkness Fisheries Laboratory operated by the Ontario Ministry of Natural Resources and Forestry. The lake is oligotrophic with a maximum depth of 51 m and a surface area of 58 km². Its pelagic zone contains mainly Cisco (*Coregonus artedii* Mitchill), Yellow Perch (*Perca flavescens* Mitchill), Lake Whitefish (*C. clupeaformis* Mitchill), Burbot (*Lota lota*, Linnaeus) and Lake Trout. The lake is separated into three arms (East, North and South) which are connected through shallow corridors (< 5 m deep) that allow fish movement throughout the year but likely deter the exchange of pelagic and coolwater species in the summer time. Consequently, the three arms are often sampled independently, even though the populations are not known to be fragmented.

Acoustic Data Collection and Analysis

Acoustic surveys have been conducted on the three arms annually since 1999, although only since 2005 has a generally consistent protocol been followed. All surveys used in this study (2005, 2006, 2007, 2009) adhered to the Great Lakes Standard Operating Protocol (Parker-Stetter et al. 2009). All surveys were conducted at night beginning at least 1 hour after sunset in late July or August with two surveys per year conducted in 2007 and 2009 (except for the North Arm in 2009). Acoustic data was collected with a Simrad EY500 or EK60 circular 7° x 7° split-beam 120 kHz transducer (Kongsberg Maritime, Kongsberg, Norway) mounted facing downwards from aluminum poles affixed to the mid-ship of survey vessels (see Table 1 for the

echosounder operation settings used in the appropriate Kongsberg Maritime software). A 100 m long Elementary Distance Sampling Unit (EDSU) was justified as an appropriate horizontal distance to balance the effects of spatial auto-correlation at local scales and preserve variance at global scales. All data was analyzed by 1 m depth bins because fish in Lake Opeongo are suspected to vertically distribute themselves by size at night. Systematic transects were followed at a speed of 5.5 km/hr across the pelagic zones (i.e. depth > 5 m) either as zig-zags for surveys between 2005 and 2007, or parallel tracks with 500 m spacing for 2009 (see Simmonds and MacLennan 2005, pg. 313). Random selections of EDSUs were collected to compare the two survey designs and no differences in abundance estimates were found between the two patterns. All raw hydroacoustic data were processed using Echoview® (Myriax Software Pty. Ltd. version 5.2.70) following recommendations in the software manual and standard data-analysis procedures (Parker-Stetter et al. 2009). All echograms were first examined to identify and remove bad data regions due to electronic noise, cavitation and bottom intrusion within the analysis area. All data within 5 m from the surface were excluded from the analysis to minimize noise from wave action and the transducer's ring down interference from the transducer. Estimates of the magnitude of background noise at 1 m were obtained from passive listening with each transducer but were not completed for every survey prior to 2009. Fortunately, the available noise estimates prior to 2009 were low in magnitude and variation so an average estimate was used for the EY500 transducer. Using a Time Varied Gain data generator in Echoview®, the predicted noise was first modelled and then removed from the acoustic backscatter (Sv) and target strength (TS) data for each transducer by linear subtraction. Minimum Sv and TS thresholds of -60 dB and -54 dB respectively were applied to the analysis. .

Single target densities were considered to be unbiased as they did not exceed Sawada's N_V of 0.01 (the number of fish per acoustic sampling volume, Sawada et al. 1993).

Size Spectra Analysis

The abundance of different size-classes of fish was estimated on a lake arm wide basis which allowed us to compare changes in size-spectra indicators among surveys. There are two possible methods to estimate the abundance of size-classes: echo-counting and echo-integration.

Although echo-integration is a standard procedure (Parker-Stetter et al. 2009), other researchers may choose to count single targets to assess different proportions of size-classes within a lake (e.g. Wheeland and Rose 2015a in this issue). For both methods, the single targets need to be grouped as individual fish, instead of assigning multiple fish counts to one fish that remained within the acoustic beam for multiple pings. A fish track detection module in Echoview® was used with all defaults and the following modification: minimum number of pings = 1, minimum number of single targets = 1, and maximum gap between single targets = 3 pings. Fish track regions will thus represent all single targets including those fish which only appeared once in the acoustic beam. After exporting the fish track single targets, Love's (1971) equation was used to convert the target strength (in dB) of each single target to a fish size (length in mm). While other equations exist that are more specifically tested for the fish species found in Lake Opeongo (Parker-Stetter et al. 2009), Love's was verified for Lake Trout in Lake Opeongo (Middel 2005) and its generality would likely lead to it being used in a standard protocol across many different systems. Once fish sizes were estimated, fish size classes were created from a logarithm of base 2 of the fish size with a width of half a log2 unit (e.g. 5, 5.5, 6, 6.5...). In the echo-counting method, the counts of fish found in each size class and at each 1 m depth bin were normalized (i.e. fish count divided by the class width in real numbers), and then scaled up to a lake arm wide

estimate using the ratio of the surveyed volume to lake volume for each corresponding depth bin (Appendix 1). A danger of the echo-counting method is that biases from target co-incidence may inflate the perceived size of the fish leading to higher abundances for large size classes (Soule et al. 1995) and miss some of the smaller size classes that are not selected by the single target detection algorithm. Echo-integration mitigates these biases by using the fish size class distributions per depth bin as a means of partitioning the average echo backscatter per EDSU (Parker-Stetter et al. 2009). The final abundance estimate is therefore driven more by the average echo in each sampling unit than by counting individual fish. Similarly to echo counting, the abundance estimate was normalized and the survey estimate was scaled up to a lake arm wide estimate. We generated both the echo-counting and echo-integration estimates and compared the two using a two-tailed paired sample t-test.

The equation of the size spectra line was calculated by an ordinary least squares linear regression between the logarithm of base 2 of the normalized fish abundance (dependent variable) with the logarithm of base 2 of the mid-point of the fish size classes (independent variable). Note however, that the first size class was not used in the regression. Because the acoustic data has a minimum size threshold, there is no guarantee that the smallest size class abundance accurately characterizes the number of fish in the lake. In all cases, the excluded size class included fish smaller than 32 mm. From the regression line the slope was retained as an indicator along with the height which was defined as the y-value of the point on the regression line at a log₂ size class estimate of 7 (observed as the typical mid-point of the fish size distribution). The slope and height was calculated for every survey. We used a two-factor ANOVA to test the effect of the survey year and basin on the size-spectra slope or height. An ordinary least-square linear

regression was also conducted between the indicators and the year to look for trends over the time period.

Sources of Variation: Fish Size Estimate

Trawl and gill netting programs were conducted along with acoustic surveys in 2010 to compare fish size-frequency distributions from each method. A pelagic trawl for small lakes (length = 13.6 m, headline = 7.16 m, wing mesh = 38.1 mm, outer codend mesh = 38.1 mm, trawl heart mesh = 19 mm, inner codend mesh = 9.5 mm) was deployed with simultaneous acoustic surveying from the same vessel following linear transects in the South Arm in July and September. A gill netting program was conducted in the South Arm through-out September 2010 including over 60 2-hour sets of suspended pelagic nets between the surface and 20 m using single (50 m x 2 m with either 7, 19, 25 or 38 mm stretched mesh sizes) and multimesh (25 m x 6 m with 7, 13, 19, 25, 32, and 38 mm stretched mesh sizes) gill nets. During this time a full acoustic survey of the South Arm was conducted for which the analysis only focussed on depth bins that were sampled by the gill nets. All fish captured were measured for their fork length and identified to species. The net catches were converted to target strength using Love's (1971) equation, and compared to acoustic surveys using a non-parametric Wilcoxon signed-rank test. All acoustic surveys and data analyses were completed following the same methods as presented above.

A source of variation in acoustically derived size-spectra is the estimate of the target strength for each fish surveyed by the acoustic beam. Depending on the orientation of the fish, the target strength can be inflated or under-estimated. For single targets that only appear in one ping, there isn't a direct method to ascertain the uncertainty of that estimate. However, some fish swim within the acoustic beam for multiple pings, and their size is determined using the average target

strength. Using all the 2007 data, we selected fish tracks with at least 2 pings and calculated the standard deviation of the target strength. To determine how this potential variation influenced the size-spectra indicators, the size of each fish observed in each 2007 survey was randomly assigned a new value by sampling from a normal distribution with a mean equal to its observed target strength and a general standard deviation estimated from all fish tracks with two pings or greater. Following this re-assignment of fish sizes, the same process as above was used to calculate the size-spectra for each survey. This process was iterated 1000 times for each survey, and the standard deviations of the estimated slope and height values were calculated.

Sources of Variation: Survey Estimate

Although the community of fish within Lake Opeongo is not believed to be fragmented into sub-populations, individuals are distributed among three arms. It is not clear whether the size-spectra will be equivalent among arms or even between different basins within an arm. We calculate the standard deviation of the slope and height among the arms, and between the east and west end of each arm.

Sources of Variation: Population Dynamics

The Lake Trout population in Lake Opeongo has been monitored through a creel program of the recreational fishery since 1936. The anglers are interviewed for information on their catch and effort, and morphometrics and aging structures are collected from the harvested fish. Using this information the population structure of the Lake Trout can be recreated using a Virtual Population Analysis (VPA). The methodology for this analysis, as well as more detail on the creel program, is presented in Shuter and colleagues (2015) in this same issue. In that analysis, only fish aged 7 to 13 and older were modelled because the accuracy surrounding the ageing and catchability of the other age groups was low. In this analysis, we were not concerned with a

wholly accurate recreation of the Lake Trout population, but instead wanted to capture the potential variation in age classes over a time period where the population and individual body sizes have grown considerably. We were also interested in observing whether the size-spectra indicators were sensitive to these changes in Lake Trout population structure. We loosened the restrictions on the ages and used the same VPA analysis software (NOAA Fisheries Toolbox, 2010, VPA / ADAPT version 3.4.5) and parameters presented in Shuter and colleagues (2015) to estimate the abundances of age classes from 2 to 30 years old from 1936 to 2010. We used the creel results to estimate the average Lake Trout fork length at age for each age class at each survey year. With the stock and fish sizes we were able to recreate the size spectrum indicators for a single species using the same size classes and methodology presented above. The natural variation of the slope and height from the Lake Trout time series can be calculated in two ways following Nicholson and Jennings (2004). First, a model smoothing function can be applied to the time-series, and the standard error can be estimated from the residuals. We used the *loess* smoothing function in *R* (R-Core Team 2014). However, smoothing functions may give biased estimates of the variance, and so we also followed a second option and calculated a difference-based variance estimator recommended by Gasser and colleagues (1986) with the form:

$$\hat{\sigma}^2 = \frac{2}{3(T-2)} \sum_{t=3}^T (0.5y_{t-2} - y_{t-1} + 0.5y_t)^2$$

where σ^2 is the variance, T is the length of the time-series, and y is the slope or the height of the size-spectra. It is important to note that the size of young Lake Trout is equivalent to older Cisco and Lake Whitefish, which are much more abundant in Lake Opeongo. Therefore, these population specific estimates will be much more variable because the size-spectra will not be anchored at lower size classes by multiple species. However, the exercise is valuable because it allows us to measure the higher end of the expected variation in the size-spectrum indicators. For

a more representative estimate of annual variation in the community size-spectrum, we calculated the residual variation from the ordinary least-square linear regression between the acoustically derived size-spectra indicators and the year (introduced above).

Effectiveness of Detecting Change

Following Jones and Petreman (2012) we modelled the statistical power of the acoustically derived size-spectrum indicators to monitor environmental change in Lake Opeongo using a Monte Carlo simulation. This method was referred to in Jones and Petreman (2012) as a gauge of an indicator's effectiveness at detecting a press perturbation (i.e. a steady decrease or increase in the indicator). This exercise incorporates the three sources of variation (σ) we measured, the mean value of the indicator ($\bar{y}$) as well as the expected rate of change in the indicator value over time. Using this method we apply a consistent annual rate of change to the indicator (c) and determine if a linear regression would be able to detect the trend through time (T) over a range of 4-50 years. The indicator value is randomized for each year using:

$$\hat{y}_T = UNorm(\bar{y} - (\bar{y} * (T - 1) * c), \sigma)$$

where *UNorm* is a random sample from a normal distribution with a mean of $\bar{y} - (\bar{y} * (T - 1) * c)$ which is the change in indicator over time, and a standard deviation of σ which is the variation associated with the measurement of the indicator (natural and/or survey derived). This equation simulates a data point for each year of a 50 year time series that represents the indicator. With each additional year, a linear regression is conducted to determine if the change in the indicator can be detected (i.e. if the p-value of the line is < 0.05). After ten thousand iterations, the percentage of statistically significant regression lines for each year represents the *a posteriori* power estimates of the indicator. Thus we can determine after how many years of monitoring a change in the indicator would be successfully detected.

This simulation was run for a set of values for the annual rate of change in the size-spectrum slope and height comprising 2%, 5%, 10% and 15% using the individual and cumulative sources of variation from the fish-size estimates, surveys and population dynamics.

Results

Sources of Variation in Size-Spectra Indicators

The acoustic surveys generally detected broader ranges in fish sizes than both the trawl and gill netting surveys (Figure 1). Using a Wilcoxon ranked-sign test, about half of the individual trawl hauls were statistically indistinguishable from the acoustic data, but the other half demonstrated high peaks in the netting data for particular size classes. The peaks in abundance spanned a narrower size-class in the gill netting data than the trawl data. However, in the trawl surveys, both the acoustic and netting data demonstrated a shift in size in higher target strengths as the Cisco grew from July to September (Figure 1A,B). Using the 2007 single-targets grouped into fish tracks with more than one detection, we found that with a square-root transformation the standard deviations in target strength were normally distributed with a mean of 1.06 and a standard-deviation of 0.5. Therefore, fish sizes were estimated by selecting a randomized standard deviation from this distribution and adding it to each observed target strength from the fish tracks in the 2007 surveys. Using this technique, the co-efficient of variation for the slope and height of the size-spectra per survey in 2007 ranged between 2.5 to 3%, and 0.5 to 0.7%, respectively.

The abundance estimates for pelagic fish in Lake Opeongo were within the range of findings from other studies (Matuszek et al. 1990; Milne et al. 2005; Vascotto 2006) and greatly influenced by the seasonal abundance of Cisco and Yellow Perch, whose population sizes are more than order of magnitude higher than any other species. The comparison of echo-counting

with echo-integration estimates (Figure 2A) indicated that echo-counting often generates a much lower abundance estimate than found using echo-integration. However, the size-spectra indicators were consistently and significantly different between echo integration and echo counting (Figure 2B). Size-spectra intercepts and slopes were consistently of a lower magnitude for echo-counting estimates by 6.2 ($t=14.3$, $df=17$, $p < 0.001$) and 0.23 ($t=-5.3$, $df=18$, $p < 0.001$), respectively.

Size-spectra for Lake Opeongo were characteristic of aquatic size-spectra elsewhere with a negative slope on a linear regression between $\log_2$ fish size and $\log_2$ fish abundance (Figure 3). While all the regression lines were significant and the standard errors associated with the size-spectra indicators were low (Table 2), there is clearly a non-linear pattern across the size-classes. Smaller fish sizes tended to be more abundant than the predicted line, while larger size classes were less abundant, leading to a pattern that resembled a sigmoidal curve. Further, small size classes varied in their presence in different arms. Both the North and East Arm had a majority of surveys in which the 5 or 5.5 $\log_2$ fish size classes were absent, whereas they were always well represented in the South Arm. Despite these observations, there were no significant differences in slope or height among the arms within years. The coefficient of variation for surveys across the different arms was low at 4% for slopes and 3% for height. Dividing the transects within arms into east and west end surveys led to much higher coefficients of variation (i.e. 20% to 30%) yet it was clear from the size spectra curves that large size classes had a greater chance of not being observed if deep basins were not adequately surveyed. There were significant difference among years of survey for the slope ($F_{3,6} = 4.8$, $p < 0.05$) but not height. From 2005 to 2009 the size-spectra slopes in Lake Opeongo became shallower at an average rate of 8% a year ($R^2 = 0.7$, $p < 0.05$; Figure 4), with a coefficient of variation of 7.6%.

The recreation of Lake Trout size spectra for ages 2 to 30 from 1936 to 2010, demonstrated that the size-spectra slope and height had changed over the 74 year period (Figure 5A,B). Slopes initially steepened until the 1960s, after which they became shallower up to 1990, at which point they reached a plateau. The trends in height were slightly different, with little change until 1960, a steep rise until 1990 where they too reached a plateau. These changes appear to match increases and plateaus in the abundance of age 2 and 3 Lake Trout over the time series (Figure 5C). We focussed on the slope as it appeared to be a much more sensitive indicator of change in the Lake Trout population. The coefficient of variation over the time-series associated with these changes using the Gasser and colleagues (1986) equation was 12% for the slope although the *loess* smoothing function identified much higher variation among the residuals ($>100\%$). The three phases of the time series {1936:1960, 1960:1990, 1990:2010} each demonstrate different rates of change in the slope {-8%, 10%, 0%} and larger coefficients of variation {41%, 57%, N/A}.

Effectiveness of Detecting Change

In the press perturbation simulation, we ran twenty-four scenarios that corresponded to the rates of change (2% to 15% annual change) and sources of variation (2% to 114% coefficients of variation) identified in our acoustic and creel analyses for the slope of community and population size-spectra (Table 3). The sources of variation included a range of potential values for natural variation from both low, medium and high estimates from the acoustic data from 2005 to 2009, the Gasser and colleagues (1986) estimates, and the *loess* smoothing function estimates, respectively. Generally, low sources of variation (i.e. fish sizes, or between lake arms) resulted in even small annual changes in slope being detected within 10 years of monitoring. The levels of variations observed in the acoustically derived slopes from 2005 to 2009 were small enough to

permit detection of all rates of change $\geq 2\%$ within 10 years. The estimated natural variation in Lake Trout-only slopes had a much stronger effect on the length of time required to detect a change. Coefficients of variation in the slope greater than 40% would prevent even large annual changes (e.g. 15%) from being detected within 10 years.

Discussion

Acoustic surveys conducted on Lake Opeongo as part of annual abundance surveys provided appropriate data for estimating the size-spectra of the pelagic fish community. The change in size-spectra slopes since 2005 to 2009 reflected the known decreases in abundance in small bodied fish (i.e. Cisco, young Lake Trout) experienced in Lake Opeongo over the last decade (Shuter et al. 2015 this issue). Changes in height were more stable over the recent short time-series indicating that overall productivity in Lake Opeongo has not greatly changed. The sources of variation estimated from our set of acoustic surveys were generally low ($<10\%$ co-efficient of variation) and simulation modelling using these values suggested that even small changes in the community's size structure (e.g. annual change of 5% in slope) could be effectively monitored within 10 years or less. Compared to other aquatic indicators (e.g. abundance, density, growth rates) our measured coefficients of variation were very low (Nicholson and Jennings 2004; Fulton et al. 2005; Jones and Petreman 2012). These results encourage adoption of acoustic surveys as a broadscale tool for monitoring the state of pelagic fish communities, (and support the findings of Wheeland and Rose 2015a in this issue). However, we noted strengths and weaknesses in our methodology that should be addressed in the design of a standard protocol if acoustically derived size-spectra are to be widely adopted. Further, we note our analysis of the creel data revealed the possibility of much higher sources of variation in pelagic systems lacking large populations of prey fish species (e.g. Lake Trout – freshwater shrimp systems). However,

community size-spectra will generally be much more stable than single-species spectra if higher abundances of prey at lower body sizes anchor the curve. It is beyond the scope of this study to evaluate if single-species spectra would be a useful monitoring tool, but it is clear that they'd be susceptible to high natural variation. A general result from our analysis is that to successfully implement an acoustically derived size-spectra monitoring program, reducing sources of survey variation will be a top priority. We found that coefficients of variation exceeding 50% greatly limit the ability to detect even large annual changes in size-spectra indicators.

The estimate of body length from the measured target strength of an ensonified fish is well supported in the literature to be a robust metric (Love 1971; Simmonds and MacLennan 2005; Parker-Stetter et al. 2009). While the 2010 netting and trawl data did not match the concurrent acoustic surveys perfectly, it is more likely the mismatch is due to size selective characteristics of netting rather than error from the acoustics. Gill nets are known to be size selective for Cisco (Rudstam et al. 1984) which were the most abundant pelagic fish in the lake. The 19 mm gill nets caught the most Cisco and are expected to be most efficient for 90 mm fish lengths (Rudstam et al. 1984), which may explain the large peak at that size class in our results (see target strength - 46 dB corresponding to 90 mm fish in Figure 1C). The trawl surveys caught a broader ranges in fish sizes, however, the operational depth of the trawl was estimated and therefore not measured with depth sensitive sensors on the net mouth, and so we cannot be certain it was sampling exactly the same space as the acoustic data. Regardless, the variation from errors in fish size is likely low. Among surveys it is therefore important to follow the echosounder calibration procedures carefully, and use a common target-strength conversion to fish size equation (e.g. Love 1971).

The results of our surveys suggest that a standardized protocol in both the survey transects and the data analysis methodology is critical to keeping sources of variation low. The surveys conducted on Lake Opeongo followed the same zig-zag transect design for 2005 to 2007, and only shifted to a parallel transect design in 2009. Both of these transect arrangements ensured a broad coverage of the lake arms, and thus kept the variation between surveys low. Note that in 2009 two surveys spaced within a week from each other were conducted on the South and East arms (Table 3), and the slope and height of these surveys were very similar. When subdividing the transects into East and West groups, the variation in the size-spectra estimates rose sharply because larger fish classes were not observed unless the transects covered the deepest basin. Therefore, the objective of monitoring programs should be to set up broad lake coverage with a standard set of transects to be followed on each survey. Our surveys were generally scheduled at the same month (August) each year. Annual surveys in the same season or month are likely important as pelagic fish may grow and die at high rates over the summer months. Our dataset contained a few surveys in July and one in September, and generally we observed steeper and higher size-spectra early in the season which became shallower and lower over the summer. This pattern would match the high mortality of Cisco whose population falls by over a million individuals over the summer time (de Kerckhove, unpublished data).

The method of data analysis for measuring the size-spectra should be standardized. We found that echo-counting estimates were not equivalent to echo-integration, and so should be avoided or at least never directly compared to echo-integrated results. Echo-counting size spectra slopes were consistently shallower, which is explained by the effects of target co-incidence which would over-estimate the abundance of large fish and under-estimate the abundance of small fish. Further, we recommend that the final estimates in abundance and fish size distributions are

always given on a lake-wide basis to avoid confusion between surveys. Finally, the size-spectra indicators should be selected based on the goals of the monitoring program. The linear regression used in our surveys are consistent with the standard expectations of a size-spectra indicator. However, we noted that the arrangement of most of our data-points appeared to be non-linear, resembling sigmoidal curves. If the change in the intermediate size classes was deemed to be important, indicators derived from Pareto distributions may be more appropriate (Emmrich et al. 2011). The non-linear aspect of our size-spectra may be due to the time of year the surveys were conducted. The linear relationship between abundance and body-size is based upon a yearly average, and does not exclude the possibility that pulses run through the size-classes over time (Datta and Blanchard 2015 *this issue*). Further, size-spectra typically exhibit a long tail that deviates from the linear relationship representing large and rare individuals (Bianchi et al 2000). An important limitation of our study design was that the upper 5 m of the water column was not surveyed. Other surveys (acoustic and netting) on Lake Opeongo have suggested that smaller bodied fish (young of year Cisco and most Yellow Perch ages) reside near the surface. Due to the acoustic interference near the face of the transducer and the high probability of boat avoidance at shallow depths (Wheeland and Rose 2015b), it is difficult to accurately survey this depth range. We noted that the small size classes were missing from many of the East and North arm surveys. This may be due in part to the smaller fish being distributed at shallower depths. Further efforts should be devoted to integrating horizontally mounted transducers to simultaneously collect surface estimates of fish size and density (Djemali et al. 2008; Godlewska et al. 2012). In conclusion, acoustically derived community size-spectra indicators show promise as a useful tool for broadscale monitoring of freshwater pelagic fish assemblages. Variation in size-spectra estimates can be kept low through proper survey designs, yet relatively small changes can be

detected within 10 years of surveying. Further exploration of this methodology should be conducted, including determining how to deal with historical data, which may not have been collected with standardized protocols, as well as investigating whether acoustically derived size-spectra are a good tool for comparing the ecological status of different communities.

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Table 1 – The parameters and settings for the EY500 and EK60 surveys on Lake Opeongo between 2005 and 2009.

Hydroacoustic Parameters	Transducers	
	EY500 (2005-2007)	EK60 (2009)
Absorption coefficient	0.004 dB/m	0.004 dB/m
Sound Speed	1465 m/s	1465 m/s
Frequency	120 kHz	120 kHz
Beam Type	Split	Split
Pulse Duration	Short	0.128 ms
Bandwidth	Auto	NA
Sample Interval	NA	0.023
Transmitted Pulse Length	0.1 ms	NA
Wavelength	0.0122 m	NA
Transmit Power	63 W	300 W
Transducer Gain	NA	25.91 dB
Target Strength (TS) Gain	24.9 dB	NA
Acoustic Volume Backscatter (Sv) Gain	26.5 dB	NA
Area Backscatter (Sa) Correction	-1.05	-0.53
Athwartship Beam Angle	7.12°	6.91°
Alongship Beam Angle	7.09°	6.96°
Athwartship Offset Angle	-0.035°	-0.04°
Alongship Offset Angle	-0.1°	-0.07°
Mean Sv Noise Estimate	-131.67 dB	-137.88 dB
Mean TS Noise Estimate	-164.40 dB	-168.77 dB
Sv Analysis Threshold (dB)	-60	
TS Analysis Threshold (dB)	-54	
Elementary Distance Sampling Unit (m)	100	
Vertical Depth Bin (m)	1	

Table 2 – Dates and location of surveys on Lake Opeongo for measuring the size-spectra indicators of the pelagic fish community.

Arm	Year	Date	Slope		Height	
			Estimate	Standard Error	Estimate	Standard Error
East	2005	08-Aug	-4.94	0.30	13.53	0.57
	2006	16-Aug	-4.28	0.62	12.96	1.31
	2007	04-Jul	-4.38	0.25	12.74	0.53
	2007	01-Aug	-4.43	0.44	13.08	0.94
	2009	18-Aug	-3.69	0.31	13.67	0.80
	2009	24-Aug	-3.73	0.31	13.44	0.77
North	2005	10-Aug	-4.92	0.29	13.51	0.56
	2006	15-Aug	-4.61	0.62	12.63	1.20
	2007	09-Jul	-4.51	0.34	12.33	0.66
	2007	31-Jul	-4.03	0.40	13.71	0.97
	2009	27-Aug	-4.01	0.57	14.20	1.36
South	2005	07-Aug	-4.56	0.57	14.77	1.32
	2006	14-Aug	-4.11	0.42	13.46	0.97
	2007	03-Jul	-4.41	0.76	12.65	1.53
	2007	30-Jul	-3.92	0.59	13.77	1.41
	2009	16-Aug	-3.81	0.42	13.91	1.02
	2009	21-Aug	-3.99	0.30	13.77	0.73
	2010	23-Sep	-3.82	0.47	11.22	0.97

Table 3 – Simulation of the number of years of monitoring it would take to detect an annual change in slope of the size spectra ranging from 2% to 15% under different sources (and magnitudes) of variation.

Source of Error	Standard Deviation	Co-efficient of Variation	Years to Detection			
			2%	5%	10%	15%
Fish Size Estimate	0.10	2.6%	8	< 4	< 4	< 4
Spatial Surveys	0.18	4.0%	10	6	< 4	< 4
Natural (Acoustic derived)	0.34	7.6%	14	8	5	< 4
Low Natural (Creel derived)	0.52	11.6%	18	11	7	6
Medium Natural (Creel derived)	2.58	57.3%	> 50	29	18	14
High Natural (Creel derived)	5.11	113.6%	> 50	44	28	22

Figure Captions

Figure 1 Comparison of acoustic (black bars) and netting (grey bars) estimates of fish length distributions (depicted as acoustic target strengths) in Lake Opeongo in 2010. A) July trawl estimate, B) September trawl estimate, C) September gill netting estimate.

Figure 2 Comparison of abundance (A) and size-spectra slope (B) estimates for the three arms of Lake Opeongo from 2005 to 2009 using echo-counting and echo-integration. The line represents the 1:1 line of equality.

Figure 3 Selected size-spectra regressions of $\log_2$ abundance (y-axis) to $\log_2$ fish body length (x-axis) for different years and lake arms in Lake Opeongo.

Figure 4 Acoustically derived size spectra slopes (A) and height (B) in Lake Opeongo from 2005 to 2009. The dotted line represents the average indicator value per year, and the points represent the different lake arms: triangle = North; square = East; circle = South.

Figure 5 Lake Trout size-spectra slopes (A) and heights (B), and abundances (C) for ages 2 to 30 from 1936 to 2010. Note that the size-spectra indicators are derived from the results of a Virtual Population Analysis and that the solid line represents ages 2 and 3, and the dotted line represents ages 4 to 30.

Figure 1 Comparison of acoustic (black bars) and netting (grey bars) estimates of fish length distributions (depicted as acoustic target strengths) in Lake Opeongo in 2010. A) July trawl estimate, B) September trawl estimate, C) September gill netting estimate.

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Appendix 1 – Depth specific volumes (m³) of the lake arms of Lake Opeongo

Depth (m)	South Arm	North Arm	East Arm
1	17371511	13794202	17977980
2	16846557	13406649	17411334
3	16083312	12798833	16548181
4	15083400	12292810	15814803
5	13977712	11845161	15225368
6	13029531	11375489	14692450
7	12168627	10867191	14093535
8	11413493	10299023	13556885
9	10674118	9552237	13029534
10	9942851	8680738	12475042
11	9435514	8106505	11890795
12	8967088	7532462	11274013
13	8475316	6965909	10637437
14	7935089	6431385	10007969
15	7452524	5897656	9426719
16	7008634	5384928	8872759
17	6592806	4890637	8339118
18	6186390	4367843	7783659
19	5818964	3839114	7263055
20	5526189	3355874	6762143
21	5221986	2909244	6252351
22	4957070	2509156	5762748
23	4702737	2159362	5262668
24	4429147	1853066	4773855
25	4146063	1588873	4309926
26	3858438	1361790	3890279
27	3581346	1152267	3528673
28	3325088	990942	3170626
29	3075366	849455	2805086
30	2820695	738284	2455558
31	2577010	652003	2172027
32	2363636	569955	1935638
33	2152253	495818	1690705
34	1946838	424152	1440682
35	1734353	368880	1196107
36	1532595	320873	968660
37	1341236	278903	714155
38	1174348	241485	444774
39	1011774	206618	266428
40	854502	171292	148704
41	711926	136519	50514

42	601732	108588	18135
43	502224	83383	7713
44	395846	56311	1768
45	313837	30656	14
46	252546	8258	
47	164440	242	
48	56015		
49	6852		
50	1726		
51	319		

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