A Quantitative Review of Cumulative Effects and Cumulative Stress

in the Laurentian Great Lakes

by

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A Thesis

presented to

The University of Guelph

In partial fulfilment of requirements

for the degree of

Master of Science

in

Environmental Science

Guelph, Ontario, Canada

ABSTRACT:

A Quantitative Review of Cumulative Effects and Cumulative Stress in the Laurentian Great Lakes

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Cumulative Effects (CE) on ecosystems resulting from anthropogenic activities have been observed qualitatively for centuries and discussed conceptually for decades, but only recently have quantitative approaches that integrate spatial and temporal scales been proposed. Quantitative characterization, however, is limited and the lack of metrics and diagnostic tools to manage CE leaves environmental assessment with unknown viability in Cumulative Effects consideration. In distinguishing between Cumulative Stress (CS) and CE, this study explores the quantitative relationship between recent projections of CS in Lake Huron and fish growth-based model measurements of CE. The results show that not only did the fish-growth based estimates of CE align poorly with CS estimates, but they appear to be confounded by uncertainties in the spatial structure of fish populations within Lake Huron. This may be due to a poor estimate of CS, the growth-based metric of CE or underlying complexity in the system that is confounding mechanistic resolution of CS and CE at this coarse ecosystem scale. Management actions taken to address CE in the face of a weak understanding of aquatic system responses to multiple, interacting stressors may be error prone and ineffective, with the potential to further degrade systems being restored. Identifying a suitable metric for CE remains a priority and should emphasize the following important criteria: 1) Integrate over space; 2) Integrate over time; 3) be responsive to cumulative stress; 4) be neither prohibitively expensive nor complex.

I'd like to dedicate this thesis to my grandfathers James William Barbour and Norman Vincent

Harris. They didn't make it to see the finished thesis but they left me their names and wives for

moral support.

Acknowledgements

I'd like to thank Soren Brothers and Paul Sibley and the rest of the NSERC CREATE team for supporting me through three years on my extended-stay MSc and Neil Rooney for this last semester. Thanks all three of you for providing me with this learning opportunity.

I'd like to thank Hafiz Maherali for inviting me into his lab as a work study back in 3rd year exposing me to research working with Chris Caruso, Stefan Weber (flowering synchrony), Gary Poon (Garlic mustard suppressing mycorrhizae) and Sabina Stănescu (Tilman's R*)

I'd like to thank Amanda Caskenette for introducing me to Kevin McCann and this thesis isn't long enough for the gratitude I've got for these last 6 years being a fly on the wall in the McCann Lab. Thank you Gabriel Gellner for teaching me how to code in Mathematica. Tyler Tunney, Colette Ward, Tim Bartley, Carmen Murall, Lauren Jarvis, Nicholas Edmunds, Carling Bieg, Laura Johnson, Marie Gutgesell, Chris Weland, James Simpson and Jordan Mailloux. Neil Rooney, Bailey McMeans, Rachel Salt, Peter Kraska and Jeremy Ramshaw we had a solid Rooney Lab. I'm missing people but I've learned a lot from conversation with each of you.

To the memorably passionate professors I've had the pleasure of learning from here at Guelph, thank you for sparking my curiosity and making these past 9 years more enjoyable; John Fryxell, Andrew MacDougall, Tom Nudds, Karl Cottenie, Andrew McAdam, Andy Gordon, Jon Warland, Steve Crawford, Andreas Heyland, Richard Manderville, John Dawson, Dan Gillis, Hung Lee, Cortland Griswold, Joseph Mokanski, Frédéric Laberge, Gerald Friars, Beren

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General Introduction

In an era of carbon taxes and global initiatives to mitigate climate change, there is growing consensus that anthropogenic stressors are affecting the structure and functioning of ecosystems and ecosystem services with small scale threats (e.g. the emission from a single car) resulting in much larger scale effects (e.g. increasing global temperature) (Schindler, 2001). There are many cars on earth but there are also many other forms of greenhouse gas cumulatively affecting global temperature as well (Solomon et al., 2009). Similarly these greenhouse gas emissions cumulatively affect earth not only driving changes in increasing temperature, but causing acid rain in high doses and global eutrophication in low doses (Vitousek et al., 1997). These cumulative effects (CE) are challenging to manage as there are both a myriad of stressors to be accounted for and multiple effects to consider including effects that can push a system into feedback loops and further undesirable effects (e.g. nutrients and eutrophication)(Allan et al. 2013). Consequently, predicting these cumulative effects for management decision-making is challenging (Araujo and Guisan, 2006).

In order to address the complexity of cumulative effects management the CREATE Great Lakes team was assembled to collaborate on interdisciplinary projects related managing cumulative stress (CS) in the Great Lakes. This thesis is an exploratory ecological study to test consistency between CS based and CE based predictive modeling in Lake Huron. In the remainder of this document I outline a case study using fishery monitoring data to assess the predictive ability of a recently published CS index (Allan et al., 2013).

When we consider a management objective such as sustainability, both pure and applied ecology address the complexity of managing CE, albeit from different perspectives. In community ecology, sustainability has a number of interpretations and consequently there are a variety of accepted metrics used in management that fall somewhere in between pure and applied realms (McMeans et al., 2016). First, community ecology tends to conceptualize whole food-webs, from top to bottom, and map the structure with measurements of function in space and time with large budgets and precise resolution. This is conservative and precise, and what forensic sciences want, but expensive and rarely feasible (Ogden, 2010). This is however what we attempt to generate with predictive modeling (Long and Chapman 1985). Conversely, applied community ecology acknowledges that entire food webs exist, but is largely interested in knowing if proposed activities are going to result in undesirable effects as determined by laws (CEAA, 2012). This approach is minimalist, but cheap and plausibly functional, if done accurately (Salt, 2013).This Project-based scope is increasingly regarded as insufficient compared to regional frameworks (Noble, 2010), but it is the standard enforced by law (e.g. CEAA, 2012; CWA, 2006). Consequently, it is favourable to use monitoring approaches that fall in between both extremes to incrementally expand minimum standards while cost remains feasible (e.g. LD 50, fish monitoring) (CWA, 2006).

Natural systems are complex. This is true of both physical and biological components of ecosystems. Habitat complexity is an example of physical complexity characterization in ecosystems which is based on which species occur (e.g. Grimes triangle (Silvertown et al., 1992), R* (Tilman, 2004)) and also how biological interactions are affected by that physical habitat (e.g. refugia) (Tunney et al., 2012). Biological complexity however is often characterized

by diversity with understandings rooted in Elton's claim that "Diversity Begets Stability" which inferred that the most stable ecosystems also tend to be the most diverse (Elton, 1958). Elton's work was later clarified by Robert May; that the stability he spoke of comes from functional diversity and not diversity alone, because of the functional redundancy it creates in feeding interactions (May, 1973). Modern continuation of this work has consisted of: further characterization of feeding interaction sub-components of foodwebs that are stabilizing (McCann, 2000); isolation of specific attributes and behaviours within these sub-components (e.g. attack rates) (Rooney et al., 2006); the role of weak interactions in stable ecosystems (McCann et al., 1998); and monitoring how changes at one part of the food web proliferate through space and time (McMeans et al., 2016).

In order to assess feeding interactions, community ecology measures the structure and function of ecosystems (McMeans et al, 2016). Structure is the biological diversity through which energy and material flows in feeding interactions (Odum, 1953). The study of structure involves tracing energy and materials (e.g. stable isotope or fatty acid analyses) from the autotrophs and heterotrophs at the base of the foodweb through the foodweb (McMeans et al., 2016). Function on the other hand is the magnitude of suitable energy resources flowing through that structure (Odum, 1953). The study of function involves taking measurements (e.g. growth rates) associated with the biological components of the ecosystem, and while it cannot inform on where the energy came from, it can inform on the amount of energy available and its quality (Francis, 1988). Monitoring is limited by feasibility often resulting in some but not all of these measurements being used and often on limited spatial and temporal scales (Salt, 2013). Consequently the coarse-scale community-level understanding almost always involves projection

and generalization of interpolation from project-based spatial and temporal scale-monitoring up to regional scale decision making (Salt, 2013; Long and Chapman, 1985).

While in a pure sense community ecology continues to describe ecosystems in their own right, circumstance has brought to light its utility in identifying threats. Although there remain conceptual and methodological challenges to integrating CE (Gunn and Noble, 2011), metrics from community ecology have been used to characterize CE in large aquatic systems (Crain et al., 2008). Given that community ecology has observed measurable changes in the structure and function of ecosystems (Crain et al., 2008; McMeans et al., 2016), threats to nature can be thought of as the underlying mechanisms that lead to those changes in ecosystems, even when mechanisms are unidentified or poorly understood (Peters and Rigler, 1995; Noble, 2010; Salt, 2013).

In the Great Lakes watershed, early historical observations of anthropogenic ecosystem changes were made by Pehr Kalm ("Peter" Kalm in some publications) in the 1700s when he noted the loss of ungulates, birds and fish from the unchecked over-harvest-for-export (Moberg et al., 2015) to meet the bio-economic demand of protein-starved pre-potato famine Europe (Kalm, 1770). In the 1800's, Malthus characterized the underlying mechanism of this observation as the differential growth rates of humans and the resources on which we feed; when a population's growth is exponential and the underlying resources are not, resource scarcity ensues (principle of population) (Malthus, 1888). Applying the modern concept of a meta-population to synthesize Kalm and Malthus's work expanded to a global scale, no colonial redistribution of harvest pressure (Moberg et al., 2015) can avoid the underlying principle of population. Given that

population growth has continued to outpace natural resources, the mechanism identified by Malthus has continued and the breadth of observations of ecosystem responses like Kalm's have increased (GLRI, 2011; Allan et al., 2013).

Recent examples of large lake ecosystems being anthropogenically compromised include the change from large fish to all small fish from overfishing as seen in Lake Victoria, Africa and which is common to many tropical lake systems (Witte et al., 1991). These large-scale collapse patterns also occur when we alter the physical components of the ecosystem as seen in the desertification of the Aral Sea due to severe water loss from diversion projects to support agriculture in a naturally arid region (Micklin, 2007). In some cases both physical disruption and overfishing combine to cause foodweb collapse in large lake ecosystems as is the case in the Tonlé Sap, Cambodia which suffers from severe fishing pressure and damming (Kummu and Sarkkula, 2008). Given that there are people relying on the services provided by these ecosystems, (e.g. The majority of Cambodia's dietary protein comes from Tonlé Sap Fisheries), there are incentives to predict undesirable human impacts (Sokhem and Sunada, 2006). In order to develop predictive models for the management of threats on effects (e.g. collapse) in these lake ecosystems, management diagnostics needs to be developed and characterized based on the observations in the system (Rigler and Peters, 1995).

Single stressor-effect interactions in aquatic systems are numerous and well characterized including: reduced fish size and reduced age-at-maturation effects resultant from overfishing (Pauly et al. 1998); stunted fish growth rates resultant from heavy metal contamination (IIes and Rasmussen, 2005); Salmonid predator refugia resultant from temperature stress (Tunney et al.

2012); entire regime-shifting eutrophication effects resultant from nutrient stress that drives changes to turbidity/light regimes (Tilman, 2004) and whole-system production for all subsequent biological interactions (Scheffer et al., 2001). Not only are all of the aforementioned single stressor-effect threats present in the Great Lakes, but they are occurring simultaneously as Cumulative Stress (CS) (Allan et al, 2013). Similarly there have been significant changes in fish communities as seen in both total catch and species composition in Great Lakes fisheries (GLRI 2011).

As Rigler and Peters (1995) outlined, the mechanism and the observations are independent, consequently, the cumulative context of a CS mechanism does not change that CE and single-stressor effects are indistinguishably observed as changes in the structure and function of ecosystems in metrics (McMeans et al., 2016). This is whether or not the effects have characterized underlying mechanisms relating to a stress or a threat. CS has two forms that are defined by two independent approaches related in that they are the same when CE, CS and all the relevant threats are understood in context as they appear in metrics (Long and Chapman 1985). CS based management involves the speculative characterization of CS using individual threats perceived to be of a sufficiently high dose to be poison as "All things are poison and nothing is without poison; only the dose makes a thing not a poison"(Paracelsus and Weke, 1965) to contribute to the CS (Allan et al., 2013). CE based management involves the speculative (without CE metrics for context) characterization of CS using the spatial distributions of effects to infer distributions of locations of likely underlying stressors within the context of where the effects are happening, but with little resolution on details of the underlying mechanism for predictive models and management applications (e.g. banning a stressor) (Long and Chapman

1985).

Management of CS in the Great Lakes involves predictive modeling and characterization of CS as the basis for protection of ecosystem services (Allan et al. 2013). This is because just like the Tonlé Sap, Lake Victoria and the Aral Sea, the local economy benefits from the Great Lakes with (GLRI, 2011) and adverse effects such as ecosystem collapse have undesirable consequences beyond effects on ecology (e.g. economic, aesthetic etc.) (Allan et al., 2013). There are a variety of ecosystem services provided by the Great Lakes including drinking water, ecotourism and fisheries CEs resultant from CS in the Great Lakes (GLRI, 2011). Given the variety of ecosystem service interests for stakeholders, policy related to CE management in the Great Lakes uses a variety of parameters including both CS and CE based methods of characterizing CS. Examples of CS based policies include; Restoration initiatives (GLRI, 2011), Harvest Quotas (Fryxell et al 2010), Canadian Environmental Assessment Act (CEAA, 2012), OMAFRA agricultural setbacks (Nutrient Management Act, 2002), MOECC and USEPA Areas of Concern (USEPA, 2012). Examples of CE based policies include: Ontario Clean Water Act (CWA, 2006), The Ontario Wetland Evaluation System (OWES, 2013). There has been a recent movement towards using ecosystem indicators (e.g. Large Mobile Consumer (LMC) structure and function (Salt, 2013)) as the basis for regional metrics to expand beyond these project-based monitoring programs (Noble, 2010; McMeans et al., 2016)

The Goal of this thesis is to test the hypothesis that growth parameters of large mobile consumers are affected by cumulative stress in ecosystems. In order to test this hypothesis, I quantify the growth rates and maximum lengths of three large mobile consumers in Lake Huron. I then test

for relationships between the growth parameters and metrics of cumulative stress proposed by

Allen *et al.* (2013) for the Lake Huron ecosystem, with the prediction that growth rate

parameters will be negatively affected by cumulative stress.

<u>Chapter 1 Cumulative Effects and Cumulative Stress in Lake Huron</u>

Introduction

In order to meet the demands of an ever-growing population, human development is occurring at an unprecedented rate (Grimm et al. 2008). The environmental effects of this development are at once apparent but challenging to quantify. On the one hand, environmental managers have focused on the quantification of stressors resulting from development, with lesser focus on measuring the effects of these stressors on the structure and functioning of ecosystems. In contrast, ecologists have developed tools for measuring the structure and functioning of ecosystems, but these tools are often impractical for applied purposes. This disconnect is even more apparent when it comes to moving beyond simple cause-effect relationships in the environment to the effects of stressors on the structure and functioning of ecosystems. What is needed are practical metrics that can be employed in the assessment of stressor effects that reflect the state of ecosystems functioning.

Environmental management involves consideration of multiple individual stressors (CEAA, 2012). These stressors are typically quantified and ranked individually based on their predicted effects. One crucial issue for management is whether stressor effects are cumulative. The concept of cumulative effects arose in 1979 (Penek, 1979) and has been described as when individually minor effects, occurring together in space or time, result in cumulative effects (Canter, 1999). By this definition, any single stressor input applied to an open system can interact with other inputs from other sources within the system and result in effects beyond what is foreseeable from the viewpoint of the single stressor input. These interactions can be additive, synergistic and/or inhibitory all at once with complex feedbacks and thresholds ultimately resulting in changes to the system (De groot et al. 2002). Typically, stressors are categorized into

functional groups such as toxics, runoff from land, invasive species, fisheries, coastal development, climate change and aquatic habitat information and can be further lumped together as summary indices of cumulative stressors (CS) (Figure 1; e.g. Allan et al., 2013). These CS parameters are born of necessity rather than built from first principles because of the use of hazardous toxicants by industry needing to be managed, making assumptions on spatial and temporal uncertainty of CS in an attempt to provide mechanistic insights to management. There are, however, significant challenges to quantifying CS. First, there is variation in our ability to quantify individual stressors (or common groups of stressors, e.g. chemical stressors). While the field of ecotoxicology has developed standard approaches to quantifying chemical stressor effects (Newman, 2009), the same cannot be said for many other stressors such as invasive species, for example. Further, combining these different groups of stressors into one common currency of cumulative stress is a challenging task (Halpem et al. 2008). Despite these challenges, Allan *et al.* (2013) developed a defensible measure of cumulative stress for the Great Lakes ecosystem. What still needs to be developed, however, is a measurement of the effects of these CS on the ecosystem, or the cumulative effects (CE).
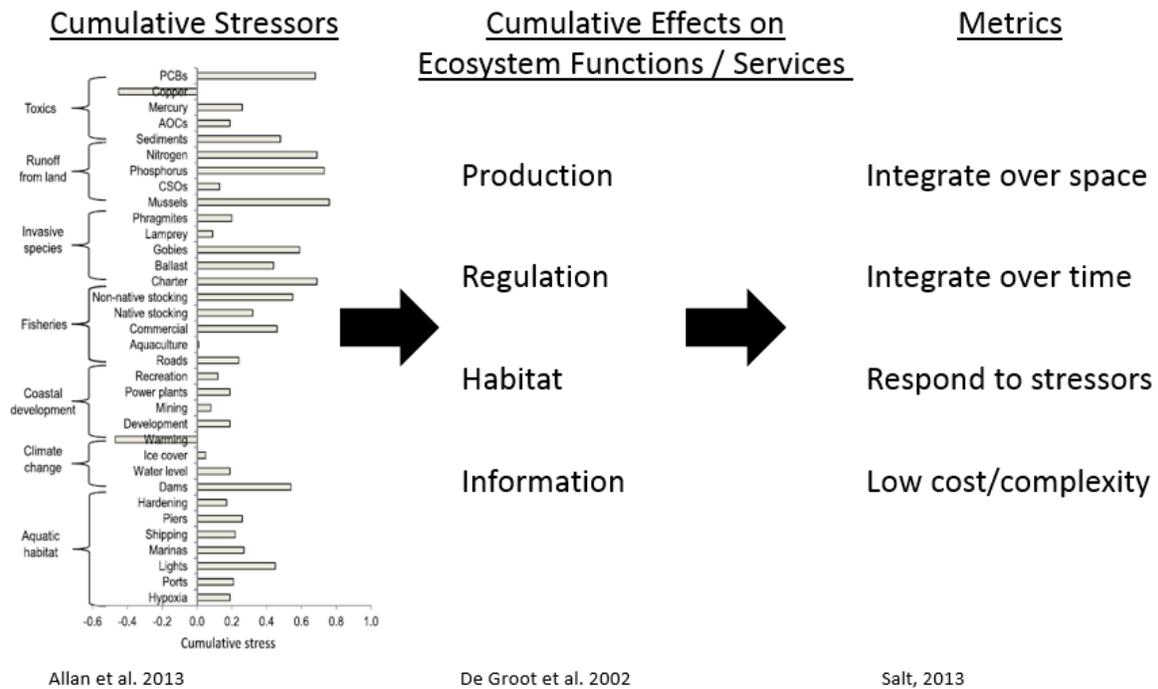
Figure 1: Conceptual Schematic of Cumulative Stress and Cumulative Effects

This schematic outlines the inter-related concepts of Cumulative Stress and Cumulative Effects and Metrics used to monitor them. Assuming a dose-response relationship, Cumulative Stressors interact with, and within, the ecosystem to drive changes in the Cumulative Effect receptors. In order to effectively monitor these Cumulative Effects, suitable Metrics must meet these criteria. Future studies should be prioritized using existing Cumulative Stress and Cumulative Effects Metrics data that meet these criteria in the pursuit of better quantitative Cumulative Effects management across all ecosystems. Large mobile consumers that are long-lived that have changed in their ecology (patterns of distribution and abundance) with existing stressor data from the same space and time make the best candidates.

CE management involves detecting effects as they occur to environmental receptors, which may reflect the manifestation of more than one interacting stressor (Figure 1). The environmental receptors in CE consist of both ecosystem structure and ecosystem function attributes. Examples of common ecosystem function attributes include production, regulation and habitat information (de Groot et al, 2002). Examples of common ecosystem structure attributes include diversity (May, 1973), top heaviness (Yodzis and Innis, 1992) and coupling (Vander

Zanden and Rasmussen, 1996) which collectively capture the path of energy flow within an ecosystem. These CE attributes of ecosystem structure and function have been both linked to stability of ecosystems (Rooney et al., 2006) and observed to change as a result of anthropogenic activity (GLRI, 2014), however quantitative understanding is poor from the perspective of their CS drivers (Tunney et al., 2012). In order to quantitatively assess and communicate CE for decision making, we rely on metrics and therefore must develop measurable and meaningful metrics of CE.

Desired Characteristics of CE metrics

In order to properly address the measurement of CE, we must address the issues of temporal and spatial scales of assessment. At present, CE assessments are carried out on a project-based scale (Noble 2010, CWA, 2006; CEAA, 2012). Advantages of this approach include relatively low costs and small spatial scales that facilitate application of widely-used protocols (Barbour et al., 1999). These small scale assessments have been found to have higher likelihood of detecting significant CE (MacDonald, 2000), likely due to the greater detail at finer-scale assessments (Abbruzzese and Leibowitz 1997). Such small-scale CE (e.g., changes in the invertebrate community), however, typically occur much lower in the food web than is often targeted in management objectives (e.g., fish stocks for fisheries). Noble (2010) and others argue that a region-based scale is needed to better reflect management objectives related to CEs.

Regional-scale CE assessments offer some advantages that project-based assessments do not. At a regional scale, mobile populations can be captured in their full range on a biologically meaningful scale (Long and Chapman, 1985). This expansion of scale to the regional level, however, can be expensive and is thus seldom done. Consequently there remain knowledge gaps

in knowing what specifically to measure at broader scales of CE assessments (McMeans et al., 2016). Though we have not identified the ideal CE metrics, there are common desired characteristics that apply across ecosystems (Salt, 2013).

As a first step towards the development of such a metric, Salt (2013) consolidated the management literature into the following three criteria for a suitable metric to quantify cumulative effects:

1) Integrate effects over regional spatial scales

2) Integrate over long temporal scales

3) Be responsive to variation in cumulative stress

While current methodologies for quantifying CE often meet the 3rd criterion (Barbour et al, 1993), the development of metrics that satisfy the first 2 criteria are either lacking or poorly developed. Salt (2013) suggests that a metric based on more mobile, longer lived organisms would be better suited for quantifying cumulative effects across both spatial and temporal scales, as long as large mobile consumers are potentially responsive to CS. For practical purposes it is also desirable for methods to be easy to measure and neither prohibitively expensive nor complex.

Large Mobile Consumers: Integrators of Their Environment

Large mobile consumers (LMC) can be thought of as natural ecosystem samplers because they depend on and integrate many parts of the ecosystem throughout their development (Vander Zanden and Vadeboncoeur, 2002). LMC are integrators of ecosystem processes, including those affected by anthropogenic stressors, because they are long lived, cover large spatial ranges and can be potent stabilizers for the food web through their feeding behaviour (Rooney et al., 2006).

Further, it has been shown that LMCs also respond to individual stressors. Iles and Rasmussen (2005) showed that growth of perch (*Perca flavenscens*) responded negatively to heavy metal contamination which is in line with the broader observation of CS being negatively associated with growth rates and age at maturation in fisheries (Pauly et al. 1998). This is because body size (individual-based metric) and trophic-level (community-based metric) are inter-related (Yodzis and Innes, 1992). Growth rates are easily measured and are abundantly available in fisheries reports. Thus, growth curves of LMC meet the first two criteria for a suitable metric for cumulative effects (Salt, 2013) and could feasibly meet the 3rd criterion as well (Figure 1).

Lake ecosystems tend to possess distinct but interconnected habitat types based on light and temperature conditions related to geomorphology and bathymetry. Large mobile consumers such as Lake Trout, Lake Whitefish and Walleye tend to prefer distinct habitat types; consequently, aspects of LMC biology can provide insights on conditions in lakes and their response to multiple anthropogenic stressors (Tunney et al. 2012).

A standard measurement of organismal growth is the Von Bertalanffy growth curve (Francis, 1988; e.g.). The Von Bertalanffy growth equation requires length and age measurements and consists of 2 parameters to describe growth, maximum length (L_{max}), and the growth rate, K. The maximum length parameter has implications for function as body size relates to predator-prey interactions (Yodzis and Innes 1992; McCann et al., 2005; Caskenette and McCann, 2017). Growth rate K is important for intermediate predators as they often have smaller maximum length (L_{max}) but reach larger sizes sooner than other organisms allowing them to feed on juvenile life stages within the fish community.

Hypothesis and Predictions

This study will investigate whether LMC growth curves meet the third criterion of a suitable CE metric (responsive to variation in cumulative stress). Using a previously published CS parameter (Allan et al., 2013), I tested the hypothesis that maximum length and/or growth rate in LMCs is consistent with CS as quantified by Allan et al. (2013) in Lake Huron. I predicted that CEs of LMCs, as estimated by the Von Bertalanffy growth equation (Francis, 1988), respond to changes in CS, as quantified by Allan (2013).

Methods

Study System

Part of the Laurentian Great Lakes, Lake Huron is a large, deep, oligotrophic lake. It is an important system to study as it supports commercial, recreational and First Nations sustenance fisheries (Allan et al., 2013; Southwick Associates, 2007). These fisheries are under threat from multiple stressors of anthropogenic origin within the watershed (GLRI, 2011). Previous studies have identified that Large Mobile Consumer (LMC) populations have historically fluctuated which could imply that CS have reached levels of biological relevance (Vander Zanden and Vadeboncoeur, 2002). Additionally, fisheries monitoring reports by the Lake Huron Management Unit have found that variation in fish growth rates within Lake Huron (Table 1) may be associated with stressors arising from anthropogenic activity (GLRI, 2014).

Table 1: Summary of Age, Length and CS index
Table 1 is a summary of the lake-wide data obtained from the Lake Huron Management Unit, A Division of Ontario's Ministry of Natural Resource and Forestry for Lake Trout, Lake Whitefish and Walleye from 2010-2013. As shown in Figure 4, these species tend to differ across the lake in several sub-regions however even at the lake wide scale there were observed differences in age, length and Cumulative Stress (CS) across species. More Lake Whitefish were sampled than either Lake Trout or Walleye. Lake Trout tended to be the largest on average followed by Walleye and then Lake Whitefish. This is consistent with their characteristic trophic positions with Lake Trout as the apex predator, Walleye as an intermediate predator and Lake Whitefish as an opportunistic forager. Lake Whitefish tended to be older than either Lake Trout or Walleye. All species were found to occupy similar ranges of CS though Walleye were found at more stressed sites on average.

Species	# of Fish	# of Sites	Min Age	Mean Age	Max Age	Min Length	Mean Length	Max Length	Min CS	Mean CS	Max CS
Lake Trout	6551	852	1	6.40	23	171	545.05	890	0.093	0.49	0.99
Lake Whitefish	19915	508	1	7.43	24	154	485.71	730	0.091	0.49	0.99
Walleye	6507	441	1	5.79	24	136	482.12	760	0.012	0.71	0.99

Study Species

In accordance with Salt (2013) and McCann et al. (2005), emphasis was placed on selecting fish

species that are mobile and long-lived as such species are most likely to provide the strongest

integration of stressors over space and time per the first two assumptions of a good biological

integrator within the food web. Three species, Lake Trout, Lake Whitefish and Walleye were

selected as ideal integrators of CS in Lake Huron.

Lake Trout (*Salvelinus namaycush*) live predominantly in the pelagic zone of large

temperate lakes. These open water systems draw their energy primarily from phytoplankton

growth in the water column (Vander Zanden and Vadeboncoeur, 2002). Usually associated with

short lived forage species such as cisco (*Coregonus artedi*), this highly palatable high energy

channel (*sensu* Yodzis and Innes, 1992) with cannibalistic Lake Trout at its top may be

particularly vulnerable to bioaccumulating contaminants with some studies reporting increased rates of bioaccumulation from high rates of turnover within the foodweb (Watras et al., 1998).

Lake Whitefish (*Coregonus clupeiformis*) live in the profundal zone of the lake. These deep sections of the lake occur beyond the reach of sunlight and consequently rely on detrital deposits from adjacent areas of the lake. Though not as palatable of a basal resource as the phytoproduction of the Littoral and Pelagic zones (Yodzis and Innes, 1992), the detrital energy channel consists of slowly decomposing carbon sources such as lignin, which means that the food supply can be very consistent with intermittent supplies of more nutritious organic matter. This zone of the lake is an important repository for hydrophobic contaminants which settle out of the water column and are stored in the sediment (Johnson et al, 1992).

Walleye (*Sander vitreus*) live in the littoral zone of the lake. These are the shallow, nearshore habitats in which energy is predominantly derived from macrophytes and benthic algae, although some energy also comes from water column primary production and riparian inputs (Wetzel, 1992). These systems consist of many inputs that tend to be less palatable than pelagic phytoplankton sources but more palatable than the lignin rich deposits of the profundal zone (Yodzis and Innes, 1992). The greater productivity and therefore broader array of food sources and structural refugia of littoral habitats make them important habitat for juvenile life stages of many fish species (Middlebach, 1988). Immediately adjacent to shore, this zone is often directly exposed to CS and is often the most degraded habitat type throughout the Great Lakes (Allan et al., 2013).

OMNRF Lake Huron Management Unit Fisheries Monitoring Data

I used age and length data from the Lake Huron management unit monitoring fishery between 2010 and 2013. This unit is managed by the Ontario Ministry of Natural Resources and Forestry (OMNRF). Monitoring within the management unit is done using gill netting. Fish are identified, fork length measured, and age determined by counting annual growth rings on otoliths.

Cumulative Effects Scores

Once data were sorted by species and location, they were then used to calculate Von Bertalanffy L_{max} and K growth parameters (von Bertalanffy, 1938). The von Bertalanffy model was fit to length-at-age data using a sum of squares based method for quantifying growth parameters in Wolfram's Mathematica version 9 "NonLinearModelFit" (Wolfram Research inc., 2012). Francis's (1988) method was specifically developed for fish growth parameter estimation from length at age fisheries data. The equation is $L_t = L_{max} \times e^{(-Kt)}$ where L_t is the observed fish length at age t. L_{max} is the maximum value of L_t where t is the maximum age observed and represents the maximum predicted size of a species sampled from the fish population. K is the growth rate of the fish population; it is a unitless metric with possible values ranging from 0-1 with higher values representing faster growth rates. Only sites from which greater than ten fish were collected and that had a statistically significant Von Bertalanffy growth curve fit to the data ($\alpha = 0.05$) were used in the analysis (Figure 2).
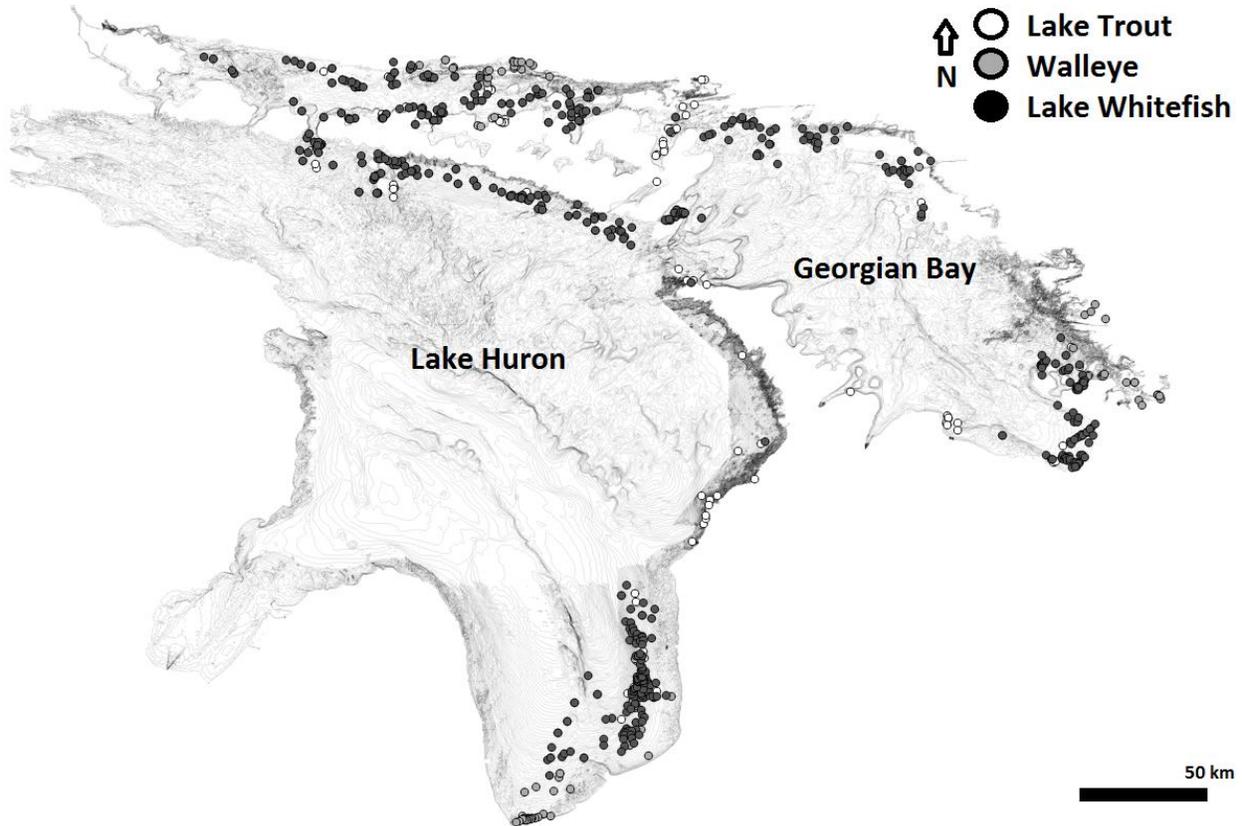
Figure 2: Map of Sites for Lake Trout, Walleye and Lake Whitefish Used in this Study

This map shows the distribution of length-at-age data obtained from the Ontario Ministry of Natural Resources Lake Huron Management Unit. Each dot represents a site at which at least 10 fish were terminally sampled using gill nets between 2010 and 2013 as part of fisheries management protocol. The underlying bathymetry data was obtained from the National Geophysical Data Center as a shapefile and combined in ArcGIS with spatial bound box coordinates (N:46.50 S: 43.00 E: -79.68 W: -84.50) LWD: 176m (NGDC, 1999).

Cumulative Stress Scores

The CS scores from Allan et al. (2013) were recorded at the co-ordinates where fish were sampled using ArcGIS to overlay the OMNRF sampling sites on Allan et al.'s (2013) GIS shapefile. The Von Bertalanffy L_{max} and K growth parameters were then regressed against Allan et al's (2013) CS scores to test their relationship with CS. I used a simple sum of squares linear regression as an initial test for spatial consistency of the CE-CS relationship using Wolfram Mathematica version 9 "LinearModelFit" (Wolfram Research inc., 2012). Though more complex

functional responses (e.g. thresholds) have been discussed (e.g. Metz and Diekmann, 2014), their extension to CS and CE on large spatial scales (e.g. Lake Huron) is poorly understood and they were not considered before the simpler tests used in this study. This was done for Lake Trout, Walleye and Lake Whitefish individually and in pooled datasets to test if guild and or habitat affect how CS is reflected in CEs.

RESULTS

Descriptive Statistics

Length-at-age data were obtained from 1801 sites in Lake Huron from the OMNRF including 852 sites for lake trout, 508 sites for lake whitefish and 441 for walleye (Table 1). Of these 1801 sites, 948 sites contained at least 10 fish and fit a statistically significant Von Bertalanffy growth curve ($\alpha = 0.05$) including 333 sites for lake trout, 486 sites for lake whitefish and 129 sites for walleye (Table 2; Figure 2). Fish ranged in age from one to 24 years old. Data summarized in Table 1 suggests that lake trout were the largest fish species examined with a longest length of 890 mm while lake whitefish and walleye had an observed longest length of 730 mm and 760 mm, respectively. Lake trout (545.5 mm) were larger on average than lake whitefish (485.7 mm) or walleye (482.1 mm). All species were present at the highest (0.99) ends of CS scores (Table 1), however, lake trout and lake whitefish tended, on average, to be found at less stressed sites than walleye which is consistent with the higher near-shore distribution of CS reported by Allan et al. (2013).

Table 2: Summary of Von Bertalanffy Parameters Lmax and K for 3 Species

Table 2 is proof of concept. More ecologically insightful than the static age and size parameters from Table 1, by fitting the length and age data to the Von Bertalanffy growth equation, we were able to identify evidence of differential life strategies across species. At face value, we have 3 species of large bodied, highly mobile and long lived species. When we consider the differential growth rates of these fish we can infer their role in the food web. Lake Trout tend to exhibit Apex predator growth patterns with a slower rate but largest overall size. Walleye exhibit typical intermediate predator growth with highest K to allow feeding on juveniles of other species but a smaller eventual size than apex predators like Lake Trout. Lake Whitefish exhibit typical lower trophic level growth with fast growth rate but a small maximum size.

Species	# of Sites	Min Lmax	Mean Lmax	Max Lmax	Min k	Mean k	Max k
Lake Trout	333	387.97	690.02	1156.38	0.09	0.32	0.99
Lake Whitefish	486	281.04	532.56	791.91	0.14	0.39	0.99
Walleye	129	336.65	572.39	1027.85	0.12	0.41	0.99

Von Bertalanffy Parameters

Lake Trout exhibited typical top predator growth with relatively low K (0.32) and a high L max

(690.02 mm) on average (Figure 3; Table 2). Walleye exhibited growth more consistent with

intermediate predators with a smaller Lmax (572.39 mm) but higher growth rate K (0.41) than

other species (Table 2). Lake Whitefish had the smallest Lmax (532.56 mm) with intermediate

growth rate (0.39) which is consistent with lower trophic level position of Lake Whitefish in lake

food webs (Figure 3) (McCann et al. 2005).

Mean Von Bertalanffy Growth Curve by Species
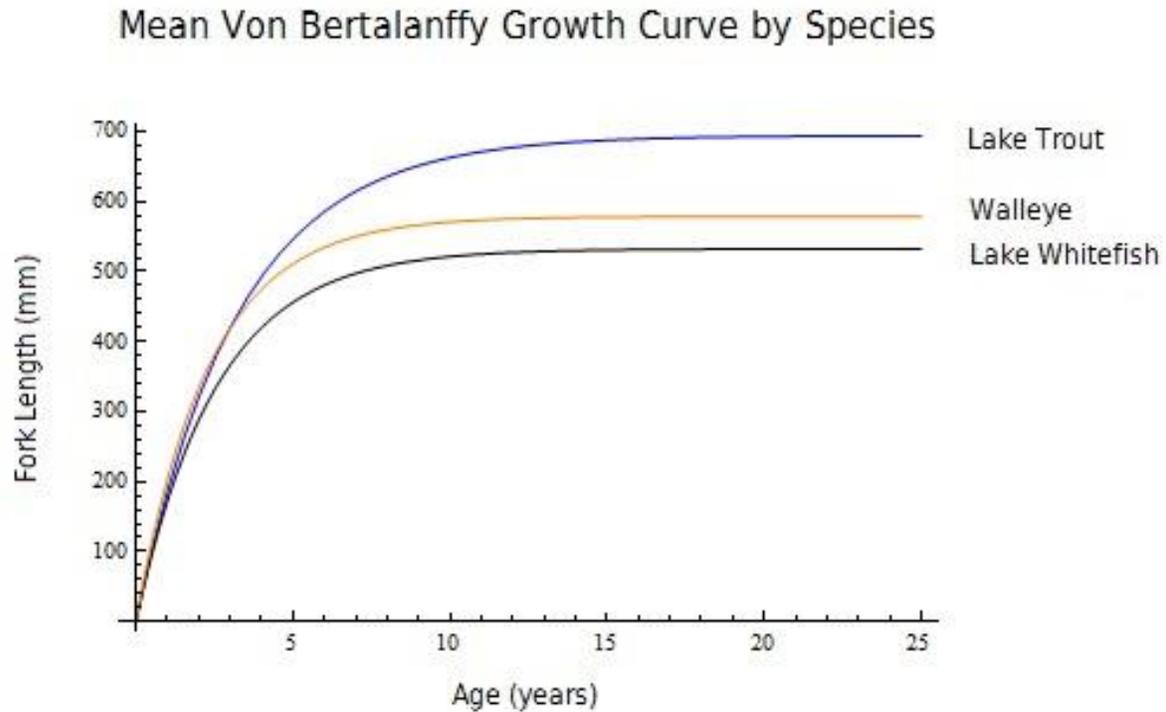
Figure 3: Mean Von Bertalanffy Growth Curves by Species
Though there is unknown quantitative connection between ecosystem function measurements such as growth rates, body size and food web structure, simple predictions (ie Gape limitation), supported by longstanding correlational evidence, can be used to predict trophic position from body size of these fish in Lake Huron. Lake Trout and Lake Whitefish exhibit slower growth rates than Walleye and consequently we can predict that the larger-bodied Walleye have a higher trophic position than Lake Trout and Lake Whitefish of the same age during juvenile life stages. Lake Trout reach the largest body size at maturation and consequently we predict them to have the highest trophic position at mature life stages. The smallest-bodied and slowest growing Lake Whitefish are predicted to be lowest trophic position of the 3 species of the same age however the eldest life stage is larger than Lake Trout and Walleye under 4 years of age and likely not a convenient food source for them. Further, adult Lake Trout body size may be driven by size of Lake Whitefish and Walleye- body size prey in order to capitalize on resources not available to other species. These curves are consistent with the life histories of the 3 species providing supporting evidence to their plausible validity as a Cumulative Effects Metric in spite of misalignment with CS. Further information on the above regressions is provided in an appendix of **Tables.**
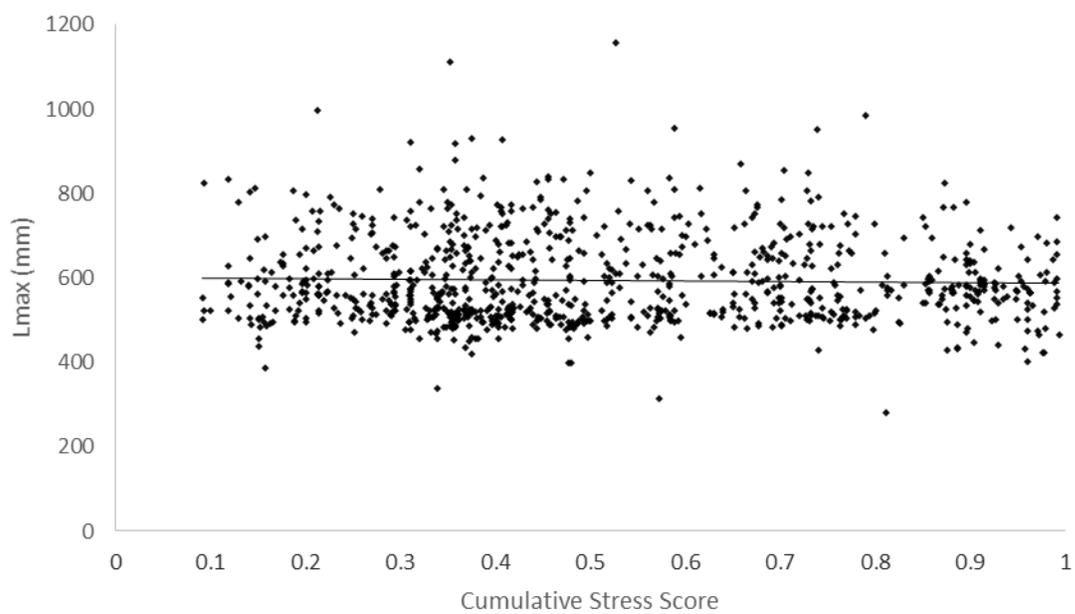
Relationship between Von Bertalanffy Parameters and CS

When the species data were pooled, there was a slight decrease in Lmax that was not found to be statistically significant (slope: -12.57mm +/- 104.18mm; p: >0.05; R^2: 8.1 x 10^{-4}; Figure 4a; Table 3) and a slight but significant increase in K with increasing CS scores (slope: 5.6 x 10^{-2} +/- 0.13; p: <0.05; R^2: 1.1 x 10^{-2}; Figure 4b; Table 3). When examined individually, the fish species exhibited variable trends, increasing in some cases and decreasing in others with common directional trends observed in the predator guild LMCs Lake Trout and Walleye decreasing in Lmax and increasing K with increasing CS while the profundal scavenger guild Lake Whitefish increased in Lmax and decreased in K with increasing CS. However, the only statistically significant regression in individual species was an increase in Lmax in Lake Whitefish with increasing CS (Table 3). All slopes were negligibly different than zero and R^2 values were very low which, biologically speaking, suggest that little of the variation in growth (both Lmax and K) observed in this study could be explained by the CS index (Table 3). Dividing samples by geographic regions from the lake-wide scale down to smaller sized regions did not increase the explanatory power of the CS estimates (Appendix I).

**Table 3: Relationship between CS index and von Bertalanffy Growth Parameters Lmax and K for 3 species**

Table 3 shows the differential relationships between growth rates and Cumulative Stress across species. This demonstrates the importance of differentiating between species when examining anthropogenic stress as they respond differentially. Consider the Lake Whitefish that tend to grow larger but slower in more stressed environments. This can be attributed to factors such as increased carrion from high mortality of other species or the absence of large enough predators as both Lake Trout and Walleye decrease in size in response to stress. Another interesting phenomenon is that although Walleye were found in more stressed sites on average than Lake Trout in Table 1, they decreased in maximum length more than twice as much as Lake Trout (-41.5mm for Walleye vs. -15.5mm for Lake Trout). This may be an indication of an opportunistic shift towards an even more intermediate predator life strategy in order to take advantage of the struggling Lake Trout. Evidence to support this hypothesis can be seen as the higher growth rate of Walleye.

	R^2	Slope	SE	p value
Pooled Species				
Lmax	8.1×10^{-4}	-12.57	104.18	>0.05
K	1.1×10^{-2}	5.6×10^{-2}	0.13	<0.05
Lake Trout				
Lmax	1.2×10^{-3}	-15.52	96.93	>0.05
K	3.5×10^{-3}	3.6×10^{-2}	0.13	>0.05
Lake Whitefish				
Lmax	1.9×10^{-2}	30.5	49.41	<0.05
K	3.0×10^{-3}	-2.8×10^{-2}	0.11	>0.05
Walleye				
Lmax	1.46×10^{-2}	-41.50	94.57	>0.05
K	6.55×10^{-5}	4.70×10^{-3}	0.16	>0.05

a)

b)
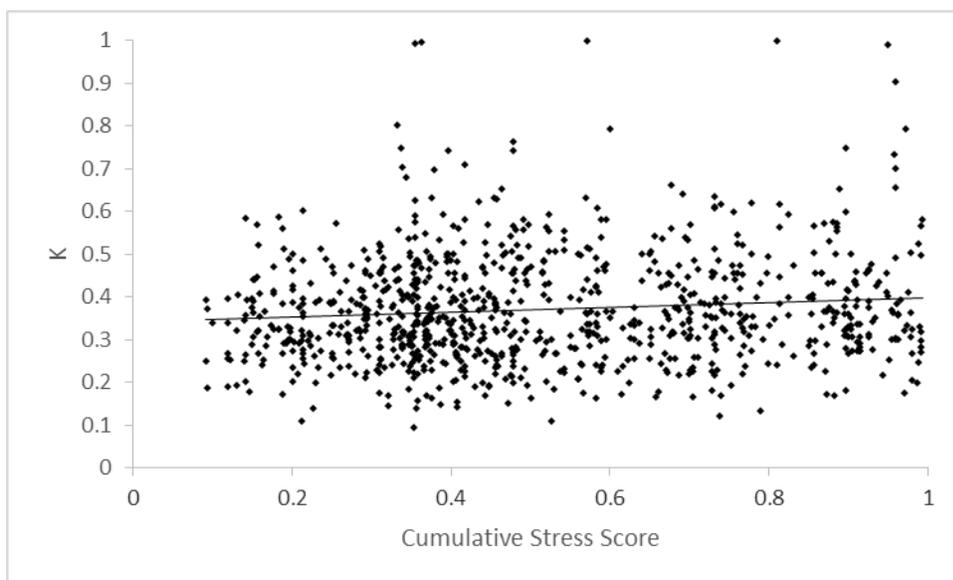
c)
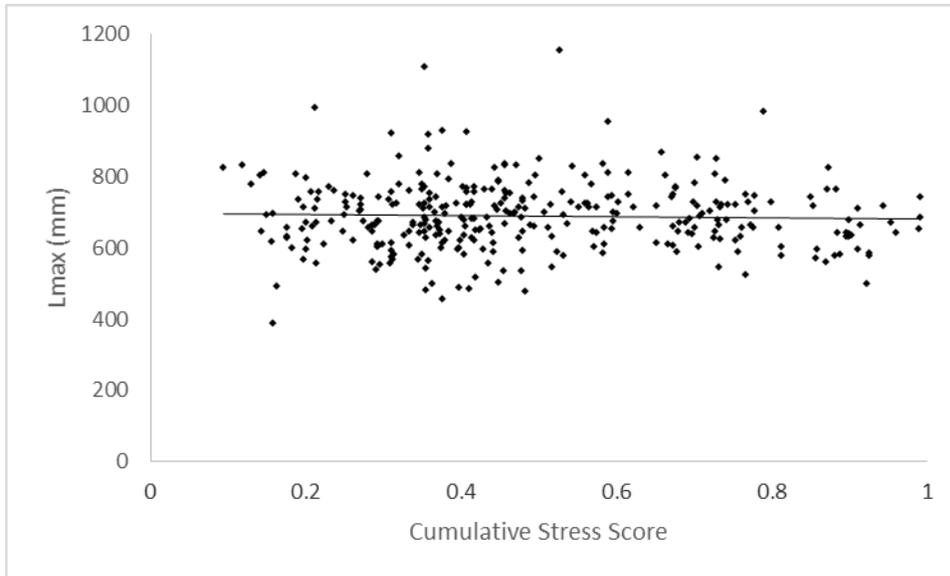
d)
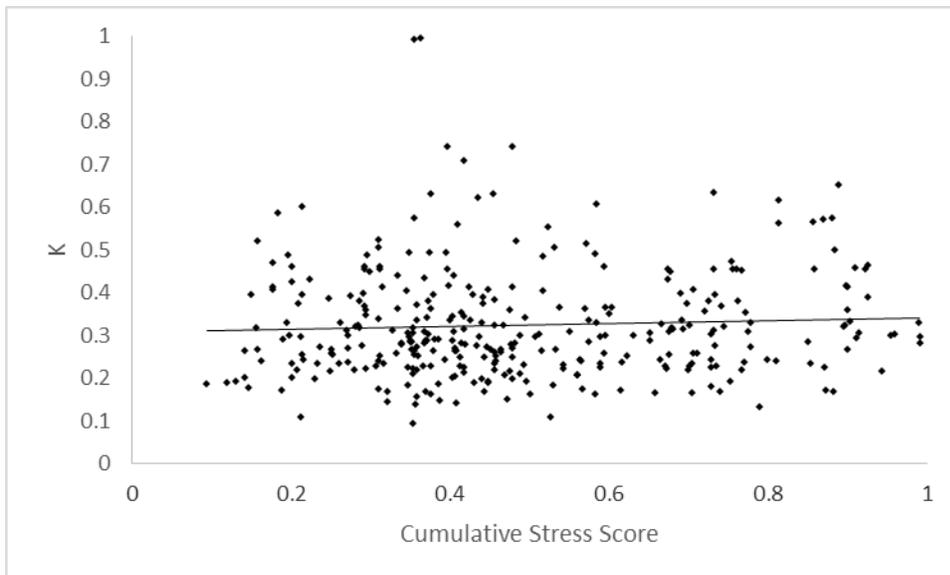
e)

f)
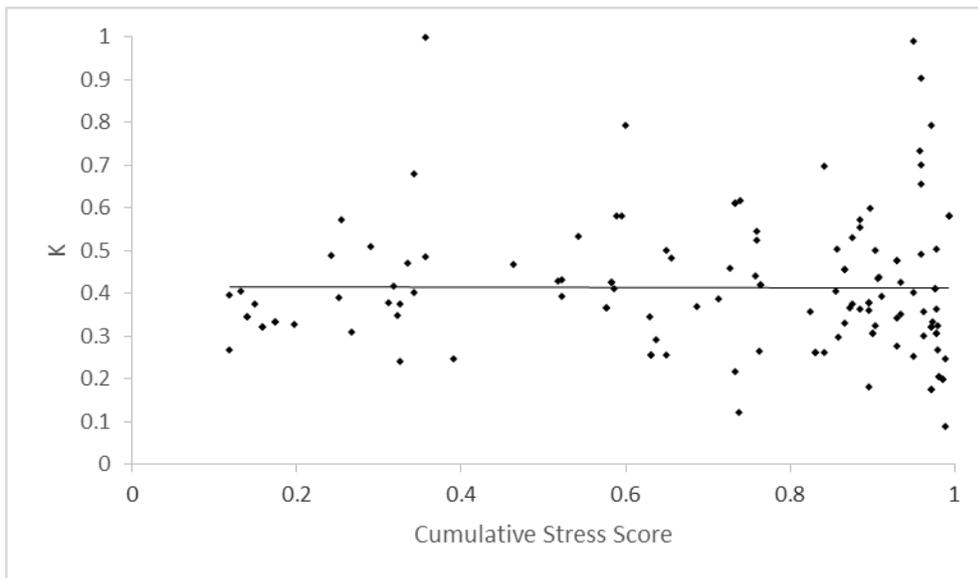
g)
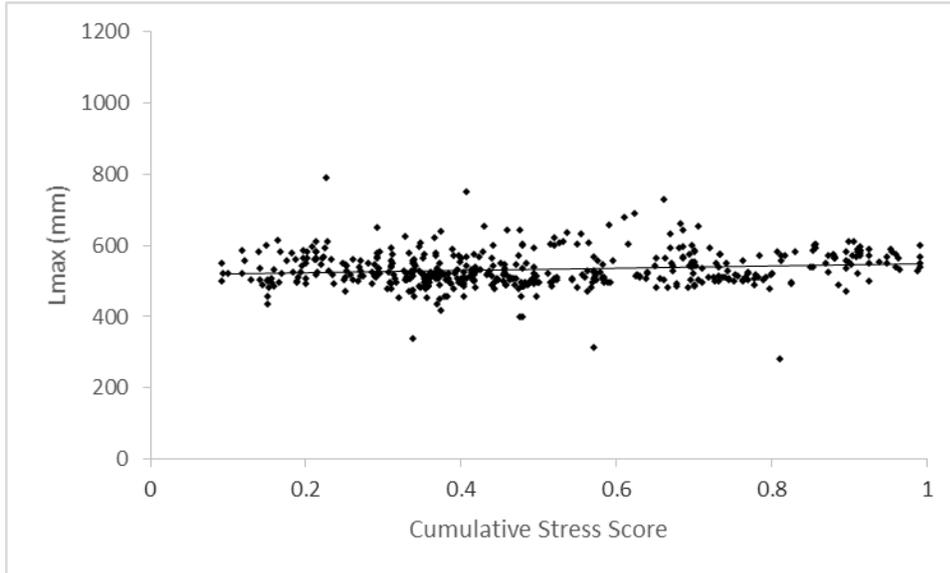
h)
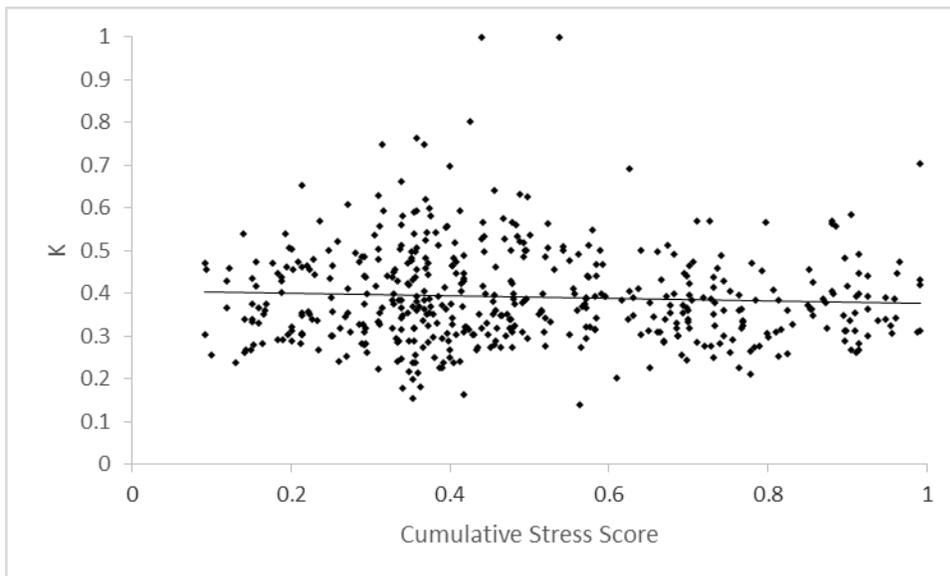
Figure 4: A Comparison of Von Bertalanffy Growth and Allan's Cumulative Stress Score

Figure 4 shows the observed relationships between Von Bertalanffy Parameters and Cumulative Stress (CS) scores. Only graphs 4b and 4g represent statistically significant relationships (Table 3) though none of these relationships were found to be biologically significant. Low coefficients of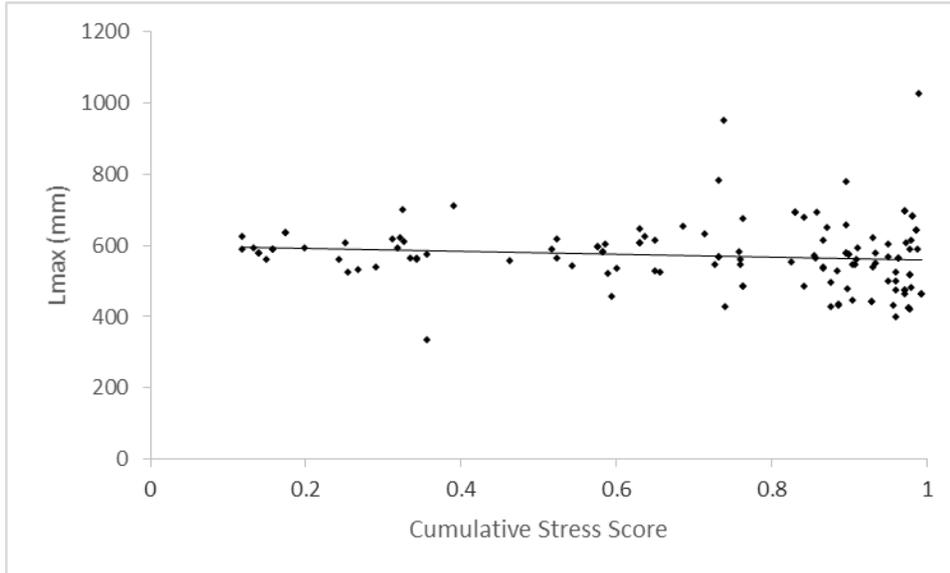 determination in all instances suggest that little of the variation in growth observed in this study could be explained by Allan et al.'s (2013) CS index. Growth rates do however meet the

criteria for a suitable Cumulative Effects Metric and consequently they are representative of these sites. The observed differential responses to the same CS between similarly long-lived large mobile consumers suggests that the exposure varies by habitat and/or guild. The common trends observed in predatory guild Lake Trout and Walleye of decreasing Lmax and increasing K with CS which was found to be opposite in the profundal opportunist Lake Whitefish which may be because of increased mortality fueling the primarily detrital profundal energy channel of the lake. Further information on the above regressions is provided in an appendix of **Tables.**

Discussion

Growth Rates and Cumulative Stress: an Issue of Scale

Growth Rates, an otherwise robust diagnostic tool in fisheries management to assess ecosystem stress, aligned poorly with previously quantified Cumulative Stress (CS) scores (Allan et al., 2013) at the lake-wide scale (Figure 4; Table 3). This is in contrast to the findings that LMCs respond to individual stressors and integrate over long timescales and large spaces (Iles and Rasmussen, 2005; Salt, 2013). Table 3 shows that most of the regressions in this study were not significant statistically and none were biologically significant showing a size change of only a few millimeters over the full range of CS occurring in the great lakes according to (Allan et al. 2013). Large sample sizes of LMCs used in this study (Tables 1 &2) suggest the weak statistical relationships were not due to insufficient replication. Three hypothesized drivers for this observation are; i) Allan et al.'s projected CS values may be miss-calibrated but may be adjusted to align better with CE, ii) Uncertainties associated with the growth-based metrics, notably that they may be responding to variation in factors other than the anthropogenic stressors indicated by the CS scores, or iii) The system may be too complicated to predict without first decomposing it into functional units based on spatial, ecological or toxicological compartmentalization of Cumulative Stressors and Cumulative Effects in Lake Huron.

Allan et al.'s (2013) work was an important contribution to this discussion as it projected what had previously been done on small spatial scales with CS measurements to a system wide

scale consistent with management objectives (GLRI, 2011). However, it is plausible that the viability of projected metrics that do not align with observed biological measurements is suspect (Long and Chapman 1985). What Allan et al.'s metric essentially provides is a first approximation of cumulative stress in the Great Lakes system. Allan et al. (2013) projects measurements from small scales onto the large area of Lake Huron where there remains physical uncertainty in the spatial distribution of the stressors themselves within the three-dimensional space of the lake (de Zwart and Posthuma, 2005). In this space, biological uncertainties exist in the nature of the relationships between CE and CS (Fleeger et al. 2003). For example, some CS results in threshold CEs, whereas others may exhibit linear relationships. Further, Allan's metric was calculated under the assumption that the stressors interact additively, meaning that while he acknowledges that there were both positive and negative impacts of CS on CE that can work antagonistically, he failed to address other ways in which CS interact in space and time (Crain et al., 2008, Schindler 2001). This study suggests that there are remaining challenges to applying Allan's (2013) CS metric to the management of CEs. However, a careful consideration of how the individual stressors are grouped and quantified could move us towards a viable management tool. There are contrasting ways in which invasive species, nutrients and/or toxins might be correlated in distribution, such as at the mouths of large rivers (Allan, 2013), but not necessarily in the nature of their effects (Fleeger et al., 2003). I propose that what we need is a calibration of the CS metric, and the only way to do that is to develop and test it alongside metrics of CE. By using growth rates of LMC to functionally sample Lake Huron's CS, these blunt growth rate based diagnostic tools are coarse scale and represent an inexpensive and parsimonious first step toward a refined approach. Addressing the complexity of the system may require expansion to broader community level metrics (McMeans et al., 2016). The range of cost,

complexity and resolution, however, of the techniques to quantify CE are consequential with respect to their feasible application in management. Thus, we should consider less expensive and simpler metrics, if proven sufficiently robust and sensitive, (e.g., growth rates) before moving to more expensive and complex metrics (e.g., stable isotopes).

Quantitative understanding of restoration efforts using CS-based methods involves two levels of understanding: First, all individual CS components must be measured, then must be numerically translated from their CS value to their related CEs and associated ecosystem services in order to compare to management objectives (e.g. Regulation of CS or CE: Figure 1). The most meaningful contribution of the present study is that the observed disconnect between our projections of CS, management efforts (US EPA, 2012; GLRI 2014) and the CE on growth suggest that our spatial and/or quantitative understanding is inconsistent across these approaches in Lake Huron. This means that we are presently unable to predict how changes to inputs through management actions, for example, reduced run-off via development of improved BMPs for agricultural or urban run-off, will be reflected at the coarse ecosystem levels of CE, around which management objectives are based. This is problematic as projections that quantify CS such as Allan et al.'s (2013) index are extrapolated from smaller scale findings to inform interpolation of observations in the environment in ecological risk assessment. If the projections do not align with the observations of ecosystem structure and function then they are simply extrapolated projections (Long and Chapman, 1985). In other words, we remain functionally stuck in Canter's (1999) description of CEs where the effects are not foreseeable by the viewpoint of individual inputs but we remain bound to CS methods that emphasize individual stressor assessment by precedence in both policy (CEAA, 2012) and restoration efforts (USEPA, 2012). Consequently,

there is limited certainty on the influence that a given management action might have on CEs. Current management literature (CEAA, 2012) implies that we have a scientific understanding of the quantitative relationship between CS and CE sufficient to regulate CS. In contrast, this study demonstrated that even with simple measurements of CE (McMeans, 2016), we were unable to identify strong correlations between CS and CE, a necessary prerequisite for validating projected spatially restricted indices of CS (Long and Chapman, 1985).

Given that the underlying mechanisms relating CSs to CEs are unknown, this study suggests that they might differentiate along guild and/or habitat space based on the differential responses to CS observed in Walleye, Lake Trout and Lake Whitefish. This study suggests that these differences are based on differential exposure to CS because of physical habitat differences in the distribution of CS and/or feeding behavior across these species (Figures 3+4). This uncertainty related to the vectors along which these stressors are culminating suggest that although precise, we aren't at a level of understanding where such detailed measurements of CS can be taken with a frame of reference for understanding at an ecosystem level. The distribution of stressors in the Great Lakes shows that high CS usually occurs as a combination of many stressors as opposed to any particular one (Allan et al., 2013). Applied toxicology methods such as vulnerability analysis used to advise restoration efforts in these multiple stressor scenarios require knowledge about the relative sensitivity of all specific exposure pathways, but these remain uncertain in Lake Huron (Adger, 2006).

There may be more stressors than the 34 measured by Allan et al. (2013) and the spatial and temporal scale of these stressors may be different than the one square kilometer scale used (McMeans et al. 2016; Araujo and Guisan, 2006). However, if differing stressors are experienced differentially between species in the lake (Figure 4), the exercise of compiling a meaningful,

integrative CS-based index across explicit space and time will be daunting. This suggests that future analyses should avoid the use of projected stress values favouring generalized interpolated measurements of stressor levels in place of extrapolated/modeled stress values that consider littoral, pelagic and profundal lake substructures as differentially responsive to CS. These stressors should then be grouped into functional groups based on predicted outcomes to address the complexity of stressor interactions. This approach should not be explored without validation from CE metrics as the responses are the most parsimonious way to ensure accuracy given the uncertainties of both exposure and cumulative hazard (Long and Chapman, 1985).

Growth Rate Based CE Metrics

Growth rate indicators of ecosystem function have been used widely as they are very simple to measure and were shown to have predictive power (Francis, 1988). Figure 4 shows the observed relationships between Von Bertalanffy Parameters and Cumulative Stress (CS). As seen in graphs a and b, when fish species were pooled together, as is common practice with the Ontario Clean Water Act (CWA, 2006), there was a slight but significant observed decrease in maximum length (Lmax) with increasing CS. When examined individually to account for differing habitat, only Lake Whitefish increased in maximal size with increased CS. Low coefficients of determination in most instances (Table 3) suggest that little of the variation in growth observed in this study could be explained by Allan et al.'s (2013) CS index. Growth rates do, however, meet the criteria for a suitable Cumulative Effects Metric and consequently they are representative of the sites from which they were sampled (Figure 2). The observed differential responses to the same CS between similarly long-lived large mobile consumers suggests that the exposure of each to stressors varies by habitat (littoral, pelagic, profundal) and/or guild (Walleye, Lake Trout, Lake

Whitefish).

A fish's energy resources (Figure 1), however, can be expended towards a number of outlets including growth, reproduction, energy stores, and behaviour (Simpson et al. 2010). This means that a fish may experience increased resource intake but decreased growth because of increased reproduction or behavioral energetic expenditure. Evidence of this being a potential confounding factor includes observed discrepancies in LMC reproductive output across Lake Huron (Mac and Edsall, 1991). For example, Lake Trout are reproducing in places such as Parry Sound, but not in other places such as Owen Sound (Johnson, 2017). Parry Sound may exhibit lower growth but an overall assessment of ecosystem function (Figure 2) for these 2 sites would reveal that Parry Sound fish have a higher ecological function if reproduction and growth are considered together. If this is the case, we would need to measure multiple proxies of ecosystem function and not just growth to capture effects of CS on ecosystem function such as reproduction or behavior. Additionally, it is not known that there will be a singular direction of effect on ecosystem function with anthropogenic stress intensity. Consider for instance the case of destabilizing enrichment (e.g. algal blooms) where entire foodwebs can have increased ecosystem function with anthropogenic eutrophication (Carpenter, 2005). In such cases, eventual habitat destruction results not from impaired food web function but from compromised food web structure which has been found to change along the eutrophication stress gradient with thresholds (Jeppensen et al., 2000). Fisheries management (Ontario Clean Water Act) acknowledges that both increased and decreased growth of fish may result from anthropogenic contamination and incorporates equal preventative measures towards both possibilities (CWA, 2006). If algal bloom dynamics seen in Lake Erie is the pattern we're trying to diagnose, where the system is enriched until

destabilized, then a measure of ecosystem structure may be favoured over measurements of ecosystem function. In these instances, because of the threshold response to nutrient enrichment, growth trends would show increases right up until the hypoxia sets in and collapses the aquatic ecosystem. Stable isotope analysis on the other hand would provide early warning signs by showing density dependent shifts in feeding towards planktonic fish guilds leading up to blooms.

The application of Von Bertalanffy growth rates to assess and quantify cumulative effects was based on assumptions of unknown viability in the unknown quantitative relationship between size and function (Figure 3), or between spatial scale and structure of the Lake Huron fish communities. These are, however, known issues with these diagnostic tools and an inherent flaw in all work under Ontario's Clean Water Act (CWA, 2006) which uses it. Specifically, the quantitative relationship between size and function and which sizes correspond to what feeding stages remains unknown. Additionally, it remains unknown on what spatial and temporal scales this functional relationship of size and trophic level from McCann et al. (2005) translates into the binary scenario of gape limited feeding events and the stunting they can drive (Iles and Rasmussen, 2005, Figure 3). The unknown spatial scale of the CE-related structures within the community is particularly problematic as the associated CS values need to be considered on the same scales (McMeans et al., 2016). Consider for instance the Parry Sound area, if the 1 square km scale from Allan et al. (2013) is used, it indicates lower stress than the Wiarton area. However, if the fish are affected over a greater area, for instance a 10 km^2 area, then averaging CS measurements makes Parry Sound appear more stressed because of higher stress levels in the surrounding area. In order to objectively discern which is higher or lower, the size and directional effect must be compared from the perspective of CE receptors for context. This is because, just like the values themselves, the spatial scale of CSs is only made relevant by their

associated CE (Long and Chapman, 1985; McMean et al., 2016).

Multiple Scales of Cumulative Effects

This study used a growth rate based model taken from policy (CWA, 2006). There remain many other methods for capturing the state of nature from individuals to ecosystems (McMeans et al., 2016). These methods are of varying spatial and temporal scale but we don't know which work best for quantifying cumulative effects (e.g., a better diagnostic tool for management applications). Community level methods tend to be more expensive and complex however they are more closely linked to the CS mechanism by better connecting large mobile consumers to their basal resources. Expansion to regional management would be more consistent with emerging trends in the academic literature including population or community level monitoring (e.g., Tunney et al. (2012) observed correlation between stable isotopes and temperature). Community based metrics for food web structure have been tied to stability but cost more to undertake than abundance and individual-based methods (Rooney et al., 2006). There has been a shift towards even more expensive but more parsimonious and higher resolution fatty acids analysis (Olsen, 1999). All could feasibly be used as metrics for quantifying CE in the lower Great Lakes for fisheries management. The range in cost and strengths of monitoring methods means they should be applied with preference given to the most efficacious and to cost and feasibility until they are practical, cheap and easy (i.e. data already available) (Bottril et al., 2008).

Conclusions

Regardless of which CE metric is found to align best in capturing the state of nature relevant to quantifying cumulative effects, the fact remains that a metric is needed for management. CE have been noted since 1748, discussed conceptually since Penek (1979), and though written into legislature in 1992 (CEAA, 2012), without the development of a suitable metric or metrics to quantify cumulative stress, a CE-based approach can't be put into practice. Advancement of understanding in this area and development of diagnostic tools for management is the only way to address a fundamental flaw in cumulative effects management and restoration today. We must acknowledge and address the uncertainties that lacking a CE metric implies for management of the Great Lakes. We must not forget that management actions taken with weak quantitative understanding of the system can result in adverse effects (Fryxell et al., 2010).

Allan et al.'s work in investigating and quantifying CS at a system-wide scale was well received and attempted to bridge a very relevant knowledge gap, but I have shown that it is disconnected from the natural ecosystem integrators, LMC, and the uncertainty of the vector mechanisms as CS is scaled up to CE. Therefore, the CS or CE parameters need to be re-evaluated (Long and Chapman, 1985). Without further development of a quantitative understanding of CS and CE, restoration efforts will remain no better informed than Kalm's (1748) blame of species loss on over-fishing. Quantitative diagnostic tools are needed; although two (Lmax and K) were evaluated in the present study, they proved to be unsuitable, at least in their application to the CS metric developed by Allan et al. (2013). We still need a metric for Cumulative Effects. Decisions are being made beyond the current level of understanding and widespread environmental degradation could result from these decisions.

Final Thoughts and Future Directions

On the subject of cumulative stress and cumulative effects management in the Great Lakes, the

topic is advancing and needs to continue to advance on 3 fronts: increasing resolution of

cumulative stress; quantifying cumulative effects; and incorporating ecological knowledge into

the framework.

Resolutions of Cumulative Stress

The Great Lakes Environmental Assessment and Mapping team (GLEAM, 2017) has

continued producing the mapping necessary for the inexpensive comparative approach used in

this study. Recent advances in the GLEAM mapping includes greater inclusion of watershed and

landscape characteristics to provide needed context to advance from regional observations (e.g.

eutrophication) to the anthropogenic origin (e.g. unbuffered agricultural/industrial development)

(Walker, 2017). There still needs to be ecological context to capture the asynchronous response

across habitat and/or guild to the CS observed in the similar body sized and aged fish species in

this study (Figure 4). However this is a much needed improvement to existing non-point source

contamination management such as the 48 million dollar investment to remediate only 0.03% of

the nutrient problem in Owen Sound with their Wastewater Treatment Plant filtration upgrade

(Kraska, 2015).

Quantifying Cumulative Effects

Quantifying cumulative effects remains challenging as there are many metrics used in

different applications of management and each has trade-offs that differ depending on the

specific ecosystem services in management objectives. There is not one human "impact" on the

environment as Walker (2017) suggests, rather a myriad of cumulative effects and even within a

common cumulative effect such as fish growth rates, the same human impact is expressed

differentially across habitat and trophic level (Figure 4). McMeans et al. (2016) makes it clear

that the range of metrics used in monitoring can be complementary. Existing monitoring and

collaborations such as this study using GLEAM and the Ontario Ministry of Natural Resources

Lake Huron Management Unit can provide context to better consider the complex dose of CS on

an ecosystem with spatial and temporal complexity. For all metrics, from the cheap and coarse

scale (e.g. growth rates) to the expensive and precise next generation tools (e.g. quantitative fatty

acids, stress hormones and DNA), exploratory comparison of existing data is useful for context

of the increasing resolution of cumulative stress (McMeans et al, 2016; Long and Chapman,

1985). Further, quantitative methods such as AIC can be used to consider many competing

hypothesized metrics simultaneously improving the ecological understanding (Fryxell et al,

2010) by that action alone (Betini et al, 2017) without needing to identify a single metric (Salt,

2013).

Incorporating Ecological Knowledge into the Framework

Different species have different life strategies (Figure 3), consequently, not only can the

same CS affect two CEs differently but different CS can affect the same CEs the same way.

Large complex lake systems such as in the Great Lakes can exhibit the gradual decline in size

and age-at-maturation of fish (e.g. Figure 4; Pauly et al, 1998) while the same reduction in size

and age-at-maturation could plausibly result in the stunting in a smaller simpler lake (e.g. Iles

and Rasmussen 2005, Tunney et al. 2012). These complex dose-response relationships have

complex responses (Schindler, 2001) and complex dynamical system feedback interactions in

space and time within the foodwebs responding to these CS perturbations (McCann, 2000;

Yodzis and Innes 1992).

There are different responses to stressors (McMeans et al, 2016) collectively contributing to the tyranny of small decisions (Noble, 2010) that need to be accounted for on regional spatial scales in the diagnostic metrics for CS and CE management. There is extensive ecological characterization of the complexity of these ecosystem responses that needs to be better incorporated into the interpretation of CS and CE (e.g. top-down vs. bottom-up feedbacks (McCann, 2000), humans increasing extinction risk with management (Fryxell et al, 2010), resistance vs. resilience, R* and community assembly, Grime's Triangle, weak interactions and omnivory, stage-structure, Regimes and Regime Shifts etc).

Future study related to CS and CE should use measured data for stressors over modelled projections to reduce a major source of uncertainty in this study. Across many ecosystems, the comparison of measurements of CS and CE with mapping, as was done in this study, has the potential to contribute to advancing management diagnostic tools.

Most of all what is needed for all cumulative effects management, cancer and climate change included, is better objective communication and quantitative understanding of monitoring and cause and effect. In the case of anthropogenic cumulative stress and cumulative effects, that means Malthus' principle of population as well. Per-capita reduction of CS is progress but CE is the product of per-capita CS and the population and consequently population management is a major component of the management of CS and CE.

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Appendix I: Regional Comparison of CS and Growth Rates of Lake Trout, Lake Whitefish and Walleye in Lake Huron

Localized sub-populations appear to better align with CS within the three fish populations. This finding is consistent with longstanding knowledge of the great lakes that the far corners of the large lakes are distinct populations though the scale on which this aggregation was found is smaller than previous discussion suggests. More formal techniques would need to validate these "borders" between regions and consequently no polygons were delineated to draw these regions beyond the individual sites. The concept of lakes-within-lakes with meta-community dynamics is perhaps the most parsimonious explanation for the anomalous stability of these large freshwater systems.
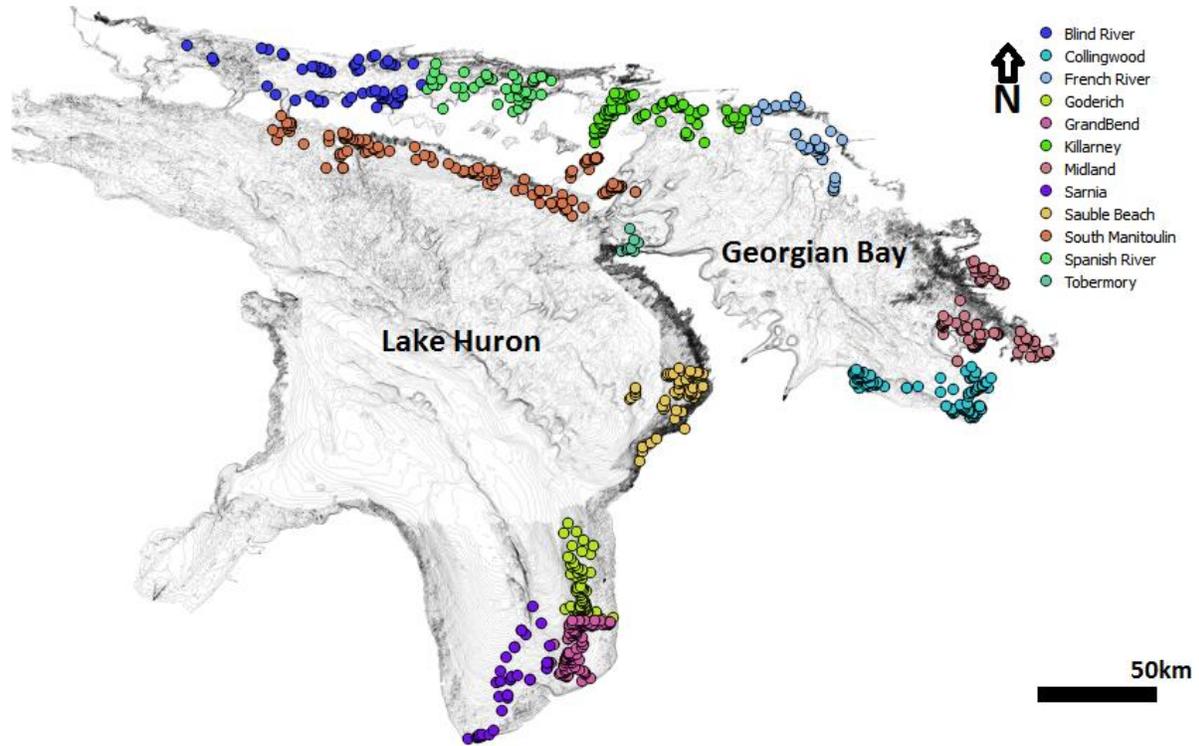
Figure 5 Lakes-within-Lakes of Lake Huron

These lakes within lakes could be used as an estimate of regions for advancement from Project-Based management to the coarser scale Regional management frameworks. Similarly, community-based metrics such as Stable Isotopes and Fatty Acids could strive to characterize foodwebs within these lakes-within-lakes. The underlying bathymetry data was obtained from the National Geophysical Data Center as a shapefile and combined in ArcGIS with spatial bound box coordinates (N:46.50 S: 43.00 E: -79.68 W: -84.50) LWD: 176m (NGDC, 1999).
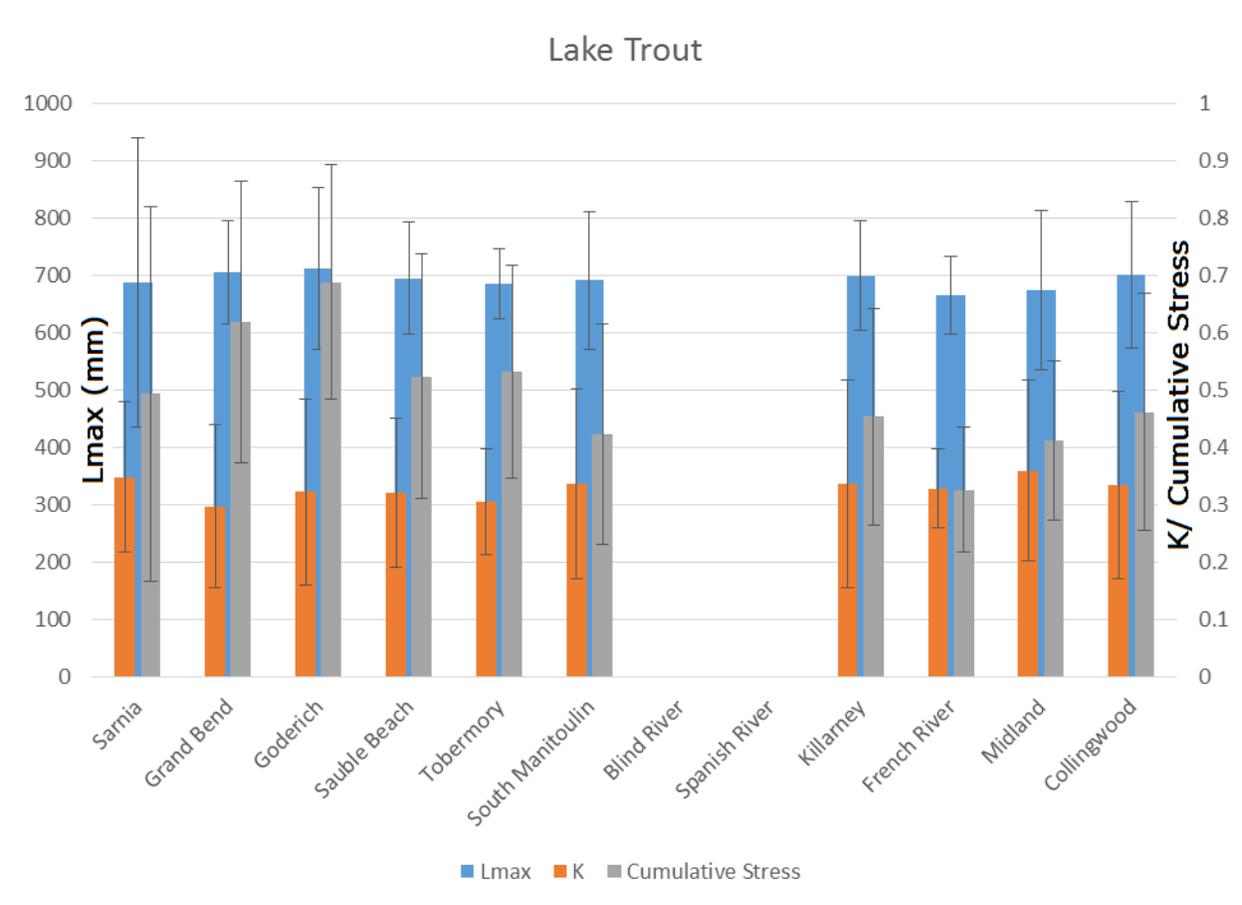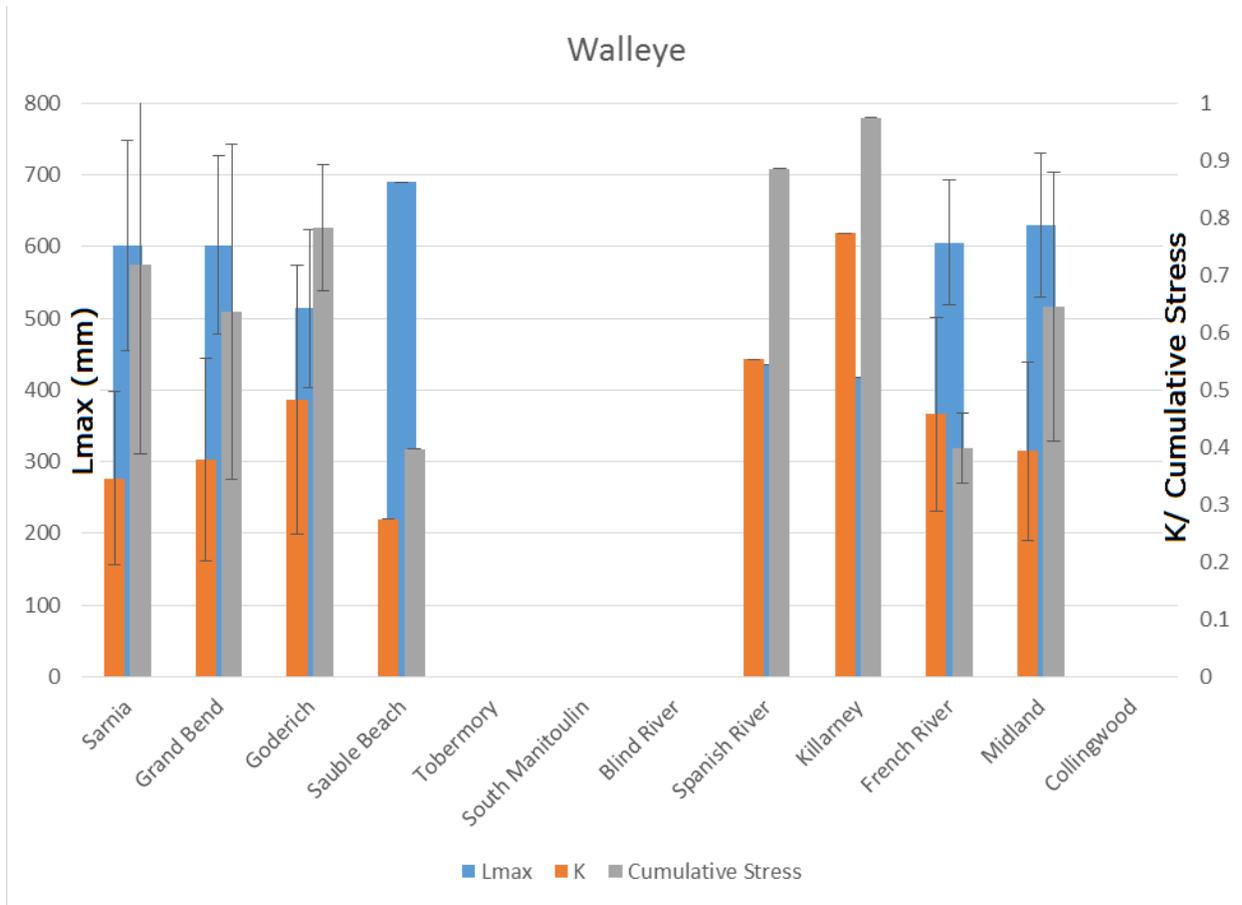
Figure 6 Regional Trends in Lmax, K and Cumulative Stress for Lake Trout

When I compared mean Lmax, K and Cumulative Stress across the 12 regions for Lake Trout, there appears to be inconsistent relative values but consistent growth rates (Lmax and K). This suggests that Lake Trout growth does not appear to be responding to CS as defined by Allan and others.
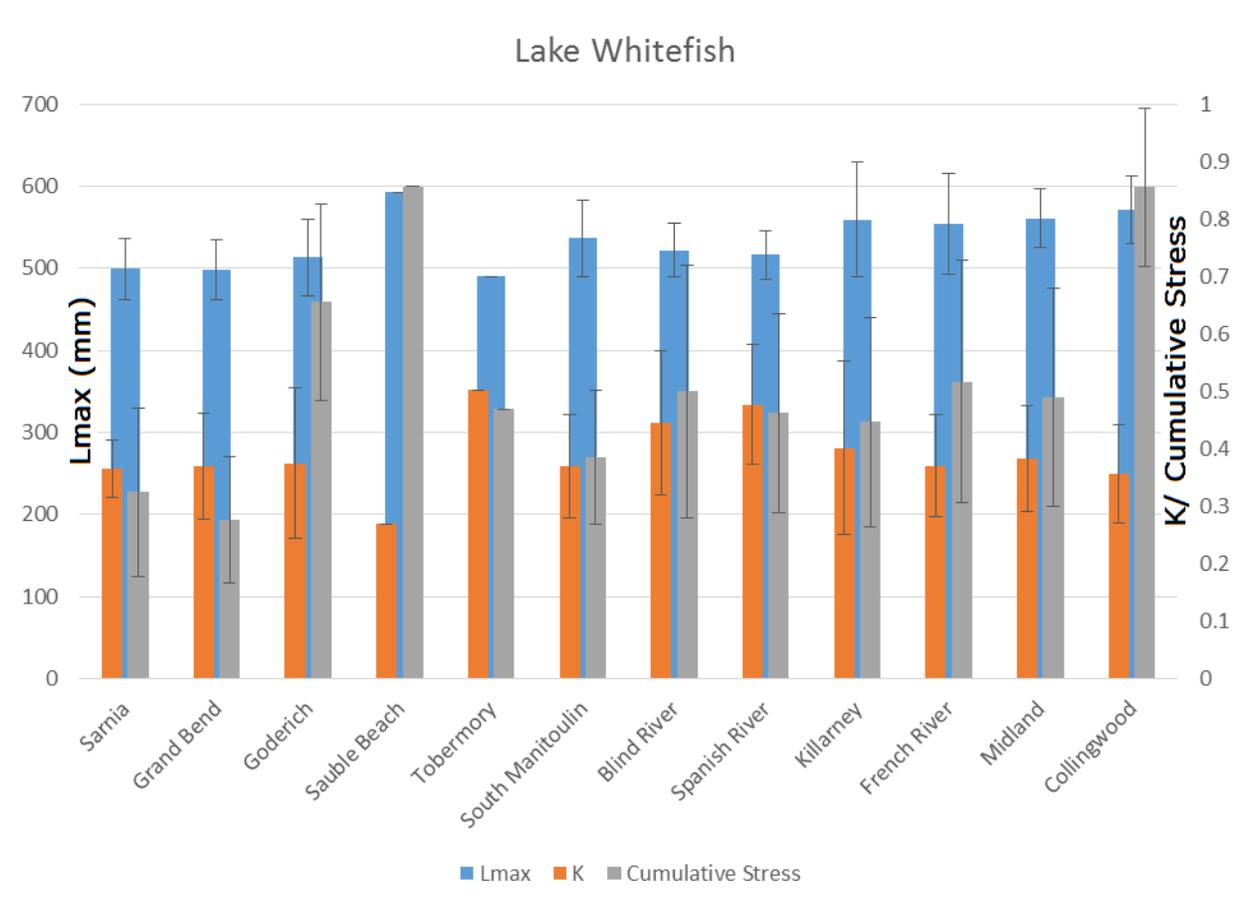
Figure 7 Regional Trends in Lmax, K and Cumulative Stress for Lake Whitefish

When I compared mean Lmax, K and Cumulative Stress across the 12 regions for Lake Whitefish, there appears to be inconsistent relative values and fluctuating growth rates (Lmax and K). This suggests both that Lake Whitefish growth does not appear to be responding to CS as defined by Allan and others and that growth rates are fluctuating, presumably attributable to some unidentified CS.

Figure 8 Regional Trends in Lmax, K and Cumulative Stress for Walleye

When I compared mean Lmax, K and Cumulative Stress across the 12 regions for Walleye, there appears to be inconsistent relative values and fluctuating growth rates (Lmax and K). This suggests both that Walleye growth does not appear to be responding to CS as defined by Allan and others and that growth rates are fluctuating, presumably attributable to some unidentified CS.