Monitoring Atlantic salmon (*Salmo salar*) populations using imaging sonar technology in the Miramichi River

by

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Abstract

Atlantic salmon (*Salmo salar*) is an important species culturally and socially, and a target species of multiple fisheries globally. Primarily due to overfishing, water pollution, sedimentation, and damming, Atlantic salmon catches at sea are under a continuing decline; however, the state of different populations varies greatly, and it is important that each population is assessed accurately and independently. In this PhD research, non-invasive imaging SONAR technology was tested for collecting tributary-specific information about migrating fish in the Miramichi River, where the adult Atlantic salmon population is currently monitored using a traditional mark-recapture method.

The accuracy and precision of the length measurements using long-range (up to 30m) imaging sonar data was tested and deemed low; however, a Bayesian model was created with capacity to predict the size class of adult Atlantic salmon from the sonar measurements.

For efficient analysis of the sonar data, an automated data processing workflow was created. The automation counted the number of migrating fish similarly as different human-generated counts (with mean of differences between -39 % and 65 %).

The tail-beat frequencies of three-fish species (Atlantic salmon, striped bass (*Morone saxatilis*), and American shad (*Alosa sapidissima*)) were calculated from the sonar data and found significantly ($p<.05$) different from each other. An automated method was developed showing promising results that can be further developed into models distinguishing different species using sonar data.

Finally, underwater camera sampling was used for apportioning species in the sonar data in the Little Southwest Miramichi River. Hourly migration data indicated that both salmon and striped bass were rarely detected during daylight hours. When compared to downstream trap net catches that were adjusted for realistic values from literature (catchability 10 % and 40 % of fish moving to the same tributary), the counts were in close agreement for Atlantic salmon (sonar count 103-130 % of the adjusted trap net catch).

To combine all the information gathered throughout the project, a guide was produced for monitoring Atlantic salmon in rivers using imaging sonars. In conclusion, the imaging sonar method provides an efficient and non-invasive method for population assessment in the Miramichi River.

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List of Symbols, Nomenclature or Abbreviations

1SW	one-sea-winter or grilse; salmon <63 cm in fork length
2D, 3D, 4D	2,3,4 - dimensional
AC	Alternating Current
AIC	Akaike's Information Criterion
AICc	Akaike's Information Criterion, corrected for small sample sizes
Amp	ampere
ANOVA	ANalysis Of VAriance
ARIS	Adaptive Resolution Imaging Sonar
bps	beats per second
C°	Celsius degrees
Catchability	The proportion of the catch in the total returns (*i.e.*, fishing gear efficiency)
CI	Confidence Interval
cm	Centimeter
COM	Component Object Model
CRI	Canadian Rivers Institute
Cross-Range resolution	In multibeam sonar: all pixels at range R (from the transducer) across the multibeam array
CSOT	Contiguous Samples Over Threshold
dB	Decibel
df	Degrees of Freedom
DFO	Fisheries and Oceans Canada
DIDSON	Dual-frequency IDentification SONar
Downrange resolution	Detail; Sample period; the number of samples per beam; the number of pixels from the start to end range from the transducer in one beam.
Echogram	An image created using reflected soundwaves
Echosounder	"The echosounder is a particular kind of sonar, one whose acoustic beam is directed vertically downwards" (Simmonds and MacLennan, 2005)
EV1 - EV3	Echoview (dataset) 1-3
fps	Frames per Second
GB	gigabyte
ICC	Intraclass Correlation
kHz	kilohertz
LOA	(Bland-Altman) Limits of Agreement
log scale	logarithmic scale
LSW	Little Southwest Miramichi River (known by local Mi'kmaq as Tuadook)
m	meter
MAA	Major Axis Angle

MAD	Major Axis Distance
MCMC	Markov chain Monte Carlo
MHz	megahertz
min	minute
MSA	Miramichi Salmon Association
MSW	multi-sea-winter or large salmon; salmon ≥ 63 cm in fork length
n	Sample size
NAS	Network attached storage
NW	Northwest Miramichi River
OLS	Ordinary Least Squares Regression
P, p	probability
ping	Pulse of a sound (created electronically using a sonar)
r	Correlation coefficient
R^2	R-squared; proportion of the variance for a dependent variable explained by the independent variable (or variables).
RMSE	Root Mean Squared Error; the SD of prediction errors
SD	Standard Deviation
SONAR	SOund Navigation And Ranging; "general term for any device that uses sound for the remote detection or observation of objects in water" (Simmonds and MacLennan, 2005)
SW	Southwest Miramichi River
Target	A multibeam "target" in Echoview is a cluster of data points (*i.e.*, echoes) that meets specified value and size thresholds, and is assumed to represent a cross-section of an individual object (*e.g.*, a fish or other object with a density sufficiently different to that of the surrounding water) at a given point in space and time (Dunlop *et al.*, 2018).
TB	terabyte
TS	Target Strength
U1-U8	User 1 - 8
UPS	Uninterruptible Power Supply
V1-V3	Version 1 - 3
$\bar{x}$	Average value of x_i
σ	Standard deviation
Z-score	The standard score: number of SD's the observed value is above or below the mean value.

1. General introduction

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1.1 Fish stock monitoring

A fish stock is defined as an arbitrary group of fish that are large enough for self-reproducing and where members of each group have similar life-history characteristics (Begg and Waldman, 1999; Hilborn and Walters, 1992). Many other approaches to fish stock identification are used as well, but in principle, the management term 'stock' and the term 'population', as biologists commonly know it, are applied rather interchangeably (Begg and Waldman, 1999).

Understanding the stock structure and the distribution of fishing effort and mortality of a species is important for both fisheries and endangered species management (Begg and Waldman, 1999). As such, stock monitoring is a common practice in fish and fisheries biology. Monitoring provides information on the state of the stock (Lassen and Medley, 2001) and it may aim at maintaining or enhancing the distribution of fish species, or to provide recreation or harvest for fisheries (Pope *et al.*, 2010). Knowing the stock size is important so that changes in a population, and reasons behind them, can be assessed accordingly. As reviewed by Begg and Waldman (1999), there are many cases where high exploitation and ineffective fisheries management have resulted in depletion of fish stocks.

1.2 Atlantic salmon population characteristics and their monitoring

Salmonid (*i.e.*, *Oncorhynchus* and *Salmo*) species are economically important (Criddle and Shimizu, 2014; Gardner Pinfold, 2011), and thus, much effort is put into monitoring different salmonid stocks around the world. Throughout the North Atlantic Ocean, Atlantic salmon (*Salmo salar)* is an important species for multiple fisheries including indigenous fisheries for food, social, and ceremonial purposes, recreational, and commercial fishing. Moreover, it is also an important species in aquaculture (Gardner Pinfold, 2011) and culturally; its cultural value in northern Europe is so high it may exceed the value of commercial landings (Kulmala *et al.*, 2013). Primarily due to overfishing, water pollution, sedimentation and damming, Atlantic salmon catches at sea are under a continuing decline since 1987, and salmon was recently assessed Vulnerable by the International Union for Conservation of Nature (Nieto *et al.*, 2015). However, individual stocks differ clearly from each other; there are stocks that are not yet impacted, or are benefiting from successful conservation interventions, whilst some are in serious decline or are already extinct (Nieto *et al.*, 2015). It is therefore recommended that each stock are assessed independently (Chaput, 2012; Nieto *et al.*, 2015).

Atlantic salmon is an anadromous fish that spends its juvenile years in freshwater and migrate to the ocean to experience accelerated growth typically for 1-3 years (Figure 1), before returning to their natal rivers as a maiden or repeat spawner (Birnie-Gauvin *et al.*, 2019; Gross *et al.*, 1988).

Monitoring of Atlantic salmon populations in different rivers is conducted on both sides of the Atlantic Ocean by various governmental and non-governmental organizations (*e.g.*, Anonymous, 2019; DFO, 2010; Lilja *et al.*, 2010). Salmon populations can be monitored in different life stages (Figure 1) and using multiple different methods such as electrofishing, redd counts, fishing methods, snorkel surveys, and direct counts either physically or using technology (Johnson *et al.*, 2007). Integrating assessment of different life stages of the same population benefits stock assessment and can help identify potential issues (Massiot-Granier *et al.*, 2014).

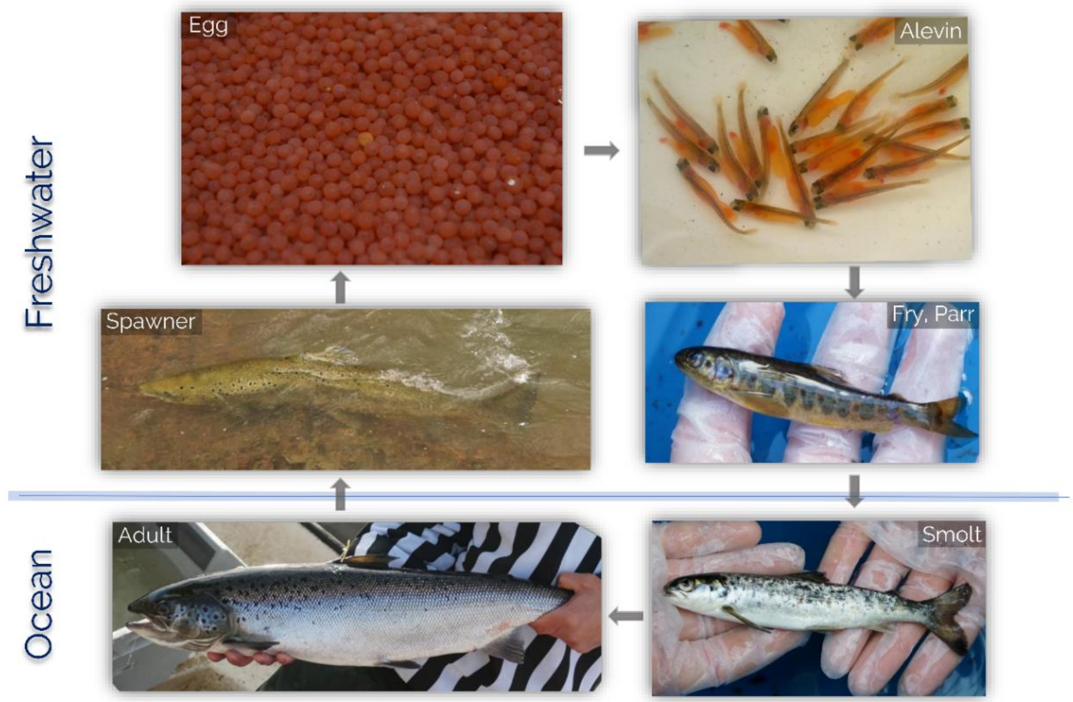

Figure 1. Generalized lifecycle of Atlantic salmon.

The adult stages of salmon are targeted by multiple fisheries (Skonhoft and Gong, 2014), and therefore information from monitoring the adults can directly be applied to management decisions. Furthermore, as the fish return to rivers all individuals will be concentrated to a small area such as the river mouth where it is technically possible to count all returning individuals with relative ease (Figure 2), at least as opposed to trying to establish the population size while distributed at sea.

Many different monitoring methods, such as test fishing programs (Faulkner and Maxwell, 2020), angling catches (Thorley *et al.*, 2005), mark-recapture methods (Chaput, 2010), and fish barriers (Figure 2) or weirs (Cameron *et al.*, 2009) are used for producing estimates of the numbers of returning adult salmon. Non-invasive methods are more desired in estimating the returning adult populations and they have replaced older trapping and mark-recapture programs in many rivers (Burwen and Bosch, 1998; Romakkaniemi *et al.*, 1997). Fish counting towers are used in rivers with high visibility, and they are considered one of the most trustworthy methods for estimating salmon abundance (Woody, 2007). The use of technology, such as video cameras (Anonymous, 2019)**,** resistivity (Beaumont, 2016) or infrared fish counters (Shardlow and Hyatt, 2004)**,** and sonar devices (Martignac *et al.*, 2014; Ransom *et al.*, 1998), has become common in recent years.

Figure 2. Jacquet River Salmon barrier, NB, Canada. Fish swimming from downriver (upper left corner) are caught in the trap located in the middle, counted, measured, and released on the upstream side of the barrier.

1.3 Use of sonar in fisheries management

Because sound penetrates water much better than electromagnetic waves (*e.g.*, visible light), sonars can produce an image in conditions (*e.g.*, turbid waters, night) where optical methods, such as underwater cameras, cannot be used (Simmonds and MacLennan, 2005). Sonars are generally divided to two groups depending on whether they transmit acoustic signals and detect the reflections (active sonars), or only detect sound or noise produced elsewhere (passive sonars) (Simmonds and MacLennan, 2005). In fisheries monitoring use, active sonars are typically used (Martignac *et al.*, 2014; Simmonds and MacLennan, 2005), but passive acoustics have recently been of interest as well (Luczkovich *et al.*, 2008).

Many types of active sonars are available for different uses. The most basic type, single-beam sonar, uses one beam to produce an image (Simmonds and MacLennan, 2005), and the technology is now found even in consumer-grade echosounders (Helminen *et al.*, 2019). Various other commonly used instruments are dual-beam echosounders, split-beam echosounders, sector scanners, and multibeam sonars, that all have their advantages in specific uses (Simmonds and MacLennan, 2005). Similarly, different sound frequencies are used depending on the needs, and the frequency is chosen to balance between the range and resolution (Simmonds and MacLennan, 2005): the higher frequencies make it easier to discriminate targets that are close together by allowing shorter pulses (*i.e.*, the duration of each sound pulse; a few cycles of a sine wave) and narrower beam patterns (*i.e.*, covering smaller area and thus increasing the resolution), but as the frequency increases, so does the absorption, limiting the maximum range of observations (Simmonds and MacLennan, 2005). Typical frequencies in the fisheries use are 38 kHz, 120 kHz, 200 kHz, and 420 kHz, but depending on the application, frequencies from 1 kHz to 5 MHz are used (Simmonds and MacLennan, 2005).

When used in rivers for monitoring, sonars are typically set in a fixed location and aimed across the river (Figure 3; Martignac et al., 2014; Ransom et al., 1998). Split-beam sonars have been used in several river systems in Alaska since the early 1970’s (Maxwell and Gove, 2004; Ransom *et al.*, 1998) and multibeam imaging sonars have become the standard of hydroacoustic monitoring of migrating fish populations in rivers in the last 10-20 years (Martignac *et al.*, 2014; Maxwell and Gove, 2004).

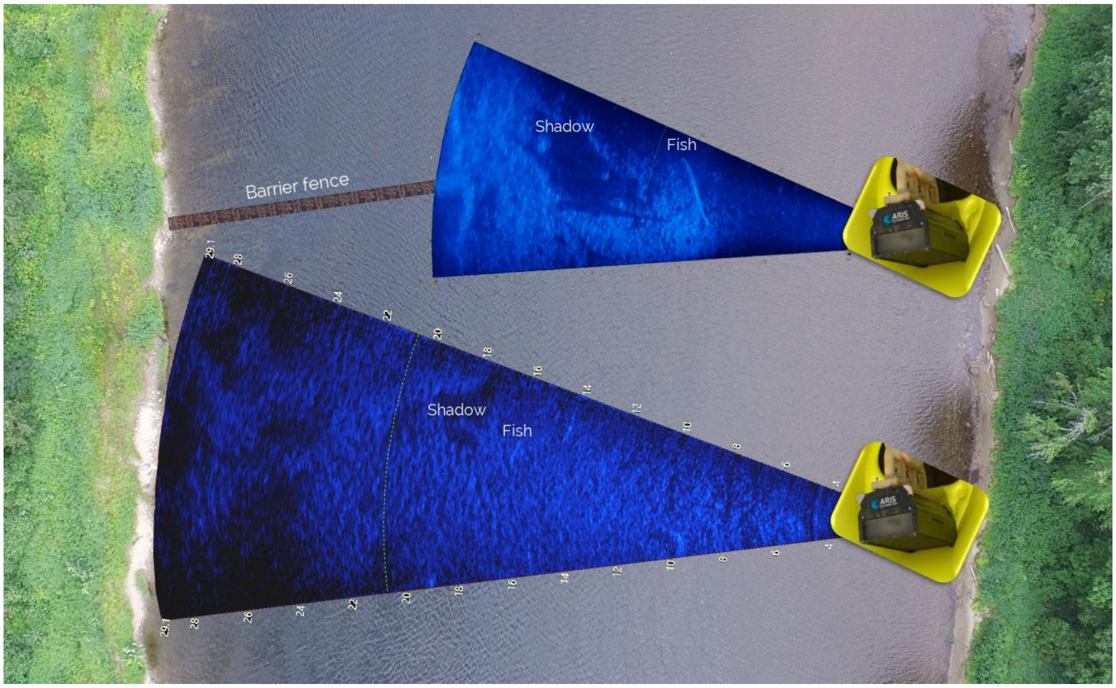

Figure 3. Two side-looking imaging sonar installations in a river. The whole river width is covered in the sonar field with a range of 29.1 m and using 1.1 MHz frequency (below) or with fencing or other structure that blocks the river partially and allows the use of a shorter sonar range and higher frequency (5.8 m and 1.8 MHz; above). The two sonar setups are not to scale.

The multibeam imaging sonars, or 'acoustic cameras' provide images of quality that approaches that of optical pictures (Figure 3). The concept of generating an array of visualized points (*i.e.*, pixels) using multiple beams and scanning or lenses has been around since the 1960s (Moursund *et al.*, 2003; Simmonds and MacLennan, 2005; Smyth, 1966). They operate in high (0.5-3 MHz) frequencies, and thus, produce high-resolution images (*e.g.*, 50 000 pixels formed from 96 beams; Moursund *et al.*, 2003) but have a limited (*e.g.*, up to 80 m; Lilja *et al.*, 2010) range (Belcher *et al.*, 2002; Simmonds and MacLennan, 2005). The two most common imaging sonars used in rivers in fisheries monitoring use are the Dual-frequency IDentification SONar (DIDSON; Sound Metrics Corp.; www.soundmetrics.com) and the newer version Adaptive Resolution Imaging Sonar (ARIS; Sound Metrics Corp.). The DIDSON was originally developed by the University of Washington Applied Physics lab as a compact device with low power consumption for identifying underwater intruders detected at a harbour surveillance system (Belcher *et al.*, 2002) but it is now commonly used in fisheries applications (Martignac *et al.*, 2014; Moursund *et al.*, 2003).

The DIDSON and ARIS sonars form the transmit and receive beams using acoustic lenses with rectangular apertures; the acoustic lenses have the advantage of using no power for beamforming and they can transmit and receive from the same beam (Belcher *et al.*, 2002). The images are formed using "line focused" beams that require the sonar beams be projected with a small grazing angle to the surface of interest, so that the image appears to be viewed from a direction perpendicular to the surface, with shadows identifying the sound source (Belcher *et al.*, 2002). The beams are very narrow (approximately 0.2° to 0.8°, depending on the model) and the lenses correct for the large nearfield of the small diameter beams (Belcher *et al.*, 2002; Faulkner and Maxwell, 2020) and thus, targets can be detected as near as 1 m away from the transducer (Faulkner and Maxwell, 2020; Martignac *et al.*, 2014).

Currently, different ARIS models are available with the frequencies ranging from 0.7 MHz to 3 MHz and the number of beams ranging from 48 to 128; the nominal effective range (*i.e.*, maximum end range) varies from 5 m with the highest frequency to 80 m with the lowest frequency (Sound Metrics Corp., 2019). In short ranges, a very detailed image can be produced with high frequencies, and much more detail of fish is recorded using 1.8

MHz frequency compared to 1.1 MHz (Figure 3; Moursund *et al.*, 2003). Additionally, the spreading effect of the acoustic beam makes the beams wider the farther they are from the transducer; thus, the pixels are wider at farther ranges (Burwen *et al.*, 2010). The field of view varies with the used model, lenses, and used settings, and with the current ARIS models the view is 28-30° horizontally and 14-15° vertically. The whole field of view is not ensonified at once; each frame (*i.e.*, image) is built using multiple (*e.g.*, six in 96 beam mode) sets of transmit/receive cycles (*i.e.*, pings per frame) that each use a different set of 16 channels (*i.e.*, beams) (Belcher *et al.*, 2002; Sound Metrics Corp., 2019). Therefore, while more beams increase the cross-range resolution, higher frame rates can be achieved with fewer beams. The pulse width is range-dependent and varies from 4 to 60 μs and frame rates can be set up to 15 frames per second (Sound Metrics Corp., 2019).

The data are collected and displayed in two dimensions: range and along the multibeam plane, but the angular position in the beam is not known (Belcher *et al.*, 2002; Martignac *et al.*, 2014). In a typical setting in a river the fish moving up- or downstream can be identified at different distances (ranges) from the transducer, but their depth is unknown (Figure 4C). For the same reason, the system cannot distinguish objects that are at the same range in the same beam but at different elevations (Belcher *et al.*, 2002), *i.e.*, at different depths in a typical river setting (Figure 4C). The best geometry to obtain images of fish is when the fish are ensonified simultaneously in multiple beams (Figure 4A, B), and the system is weak at identifying fish that are *e.g.*, moving parallel to the beams (Moursund *et al.*, 2003); the change in aspect angle reduces the amount of reflected energy causing the fish detected only intermittently. When aimed correctly, the system is capable of producing footage where both nearby structure and fish can be observed at the same time on the same transmitted pulse, and discrimination of fish within schools is also possible (Moursund *et al.*, 2003). Therefore, in highest frequencies, detail such as skin and fins are visible in the imaging sonar footage and more information can be collected about fish morphology and swimming behavior compared to more traditional types of sonars (Baumgartner *et al.*, 2006).

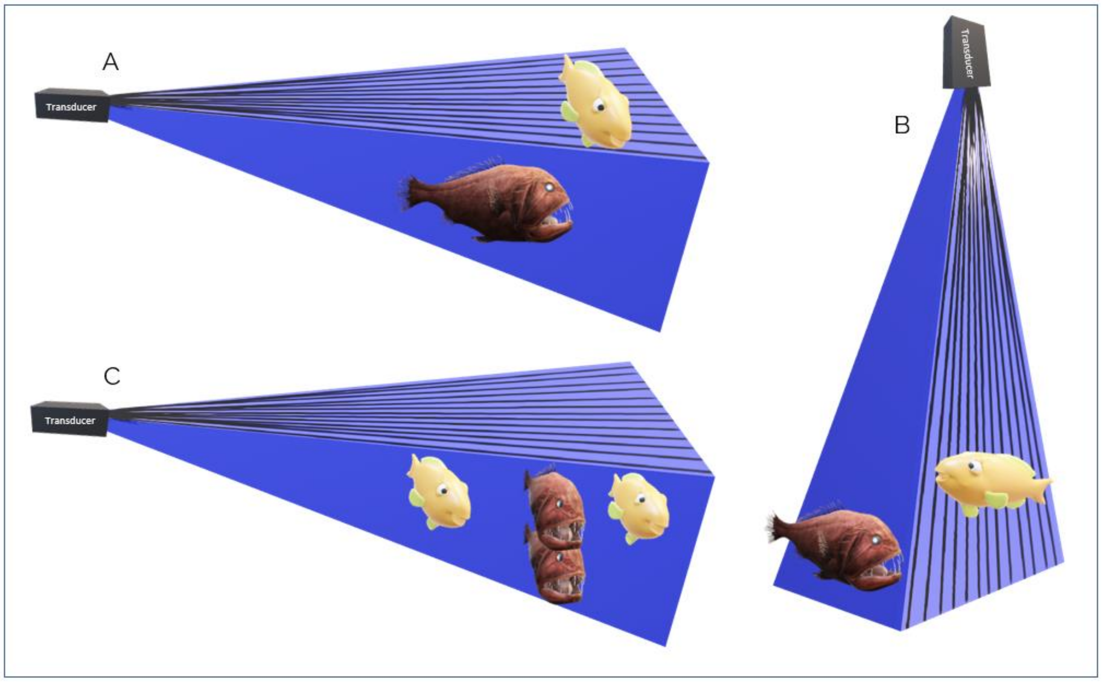

Figure 4. Identifying fish in the sonar field. The most detailed image of a fish is achieved when the fish is aligned so that it is ensonified in multiple beams at the same time; *i.e.*, the yellow fish in A) side-looking view (*e.g*., across a river) and B) down-looking view (*e.g.*, boat installation). The sonar image of the dark-red fish in A) and B) will not be as detailed because the amount of reflected energy is decreased (*i.e*., fish only in one or few beams). Because the fish's angular position in a beam is not known, the two dark-red fish in C) are not separated from each other in the image, but fish that are at different distances from the transducer at the same time can be counted; three fish would be counted in the example C).

Imaging sonars can provide accurate estimates of count and length of fish in rivers (Martignac *et al.*, 2014) and they can operate over a broad range of stream conditions such as high flows (Pipal *et al.*, 2012). In fisheries monitoring use, they can provide timely counts that can be used to *e.g.*, assess the run size every day. The main limitation of all hydroacoustic methods, the identification of fish species (Simmonds and MacLennan, 2005), limits the use of imaging sonars as well (Martignac *et al.*, 2014), although the detailed image of imaging sonars has allowed for species identification method development using *e.g.*, length and other morphometrics, behavioral characteristics such as the tail-beat frequency, and acoustic shadows (Burwen *et al.*, 2007; Langkau *et al.*, 2012; Martignac *et al.*, 2014; Mueller *et al.*, 2010, 2008). In addition to species identification, the other limitation concerns in the use of imaging sonars in monitoring migrating fish populations, as reviewed by Martignac *et al.* (2014), are 1) maximum range, 2) large file size (sampling strategy), 3) sonar maintenance 4) the lack and efficiency of automatic tracking, 5) minimum size of target detected, and 6) lack of calibration method for the sonar beams.

1.4 The Miramichi River

The Miramichi River, New Brunswick, Canada, has catchment of about 14,000 km^2 (Chaput *et al.*, 2016). The river and its estuary is a home to 47 fish species of which many have significant cultural value to First Nations communities and some of which are exploited commercially and/or recreationally (Hayward *et al.*, 2014). There are 11 diadromous fish species; the most common are Atlantic salmon, Striped bass (*Morone saxatilis*), American shad (*Alosa sapidissima*), American eel (*Anguilla rostrata*), blueback herring (*Alosa aestivalis*), and alewife (*Alosa pseudoharengus*). The Atlantic salmon run was historically the largest in eastern North America, with returns exceeding 100,000 salmon until early 1990’s (Chaput, 2010; Chaput *et al.*, 2016). Similarly to the majority of the salmon populations in continental North America, the salmon population in Miramichi declined in the late 1990's (Chaput, 2010; Chaput *et al.*, 2016). The trend is of serious concern for the conservation of the species and it has significant socio-economic influence in the province of New Brunswick where the annual value of recreational fishery alone is $54 million (Gardner Pinfold, 2011). The last full salmon population assessment for the Miramichi River was completed in 2014 (DFO, 2014), and updates have been published every year; the latest update is for the 2019 season (DFO, 2020a).

Adult Atlantic salmon return to the Miramichi River during the six-month period from May to late October (Chaput *et al.*, 2016). Currently, two index trap nets are used for catching, tagging, and releasing Atlantic salmon (Chaput, 2010) and the annual returns are assessed using a mark-recapture model that combines catches at estuary index nets, counts at inriver monitoring facilities, and inriver seining programs (Chaput, 2010). Many factors influence the accuracy of the mark-recapture model, and estimation or assumptions are needed for parameters such as the proportion of the catches on the total returns, tagging and handling mortality, and the variation in index net efficiency in the two branches and over time (Chaput, 2010). Equipment washouts and high water temperatures (due to potentially higher mortality) also prevent the use of index nets, especially in recent years (DFO, 2020a). A successful mark-recapture study requires a high proportion of the population tagged (Southwood and Henderson, 2000), which is often difficult to achieve in a natural river with migrating fish. Due to its regional importance, more information is needed on status of the Atlantic salmon population within various parts of the Miramichi River; the status of salmon populations in different tributaries relative to their conservation targets may vary largely (Chaput *et al.*, 2016; Vähä *et al.*, 2007). Additionally, the invasiveness associated with the current mark-recapture method is of concern; the model currently assumes a 10 % tagging and handling mortality (Chaput, 2010), and development of a reliable sonar-based method for monitoring would greatly alleviate incidental removals from the population.

1.5 Dissertation aim and objectives

In many rivers around the world, sonar methods have replaced other methods, such as mark-recapture programs in estimating the returning adult salmon populations (Burwen and Bosch, 1998; Romakkaniemi *et al.*, 1997). The main objective of this dissertation is to test and develop the ARIS method for monitoring the Atlantic salmon run in rivers in Atlantic Canada, using the Miramichi River as a method development case study, where the monitoring season is long and multiple species are present. Stemming from the introduction presented above, in order to make the sonar method feasible in Atlantic salmon monitoring in Atlantic Canadian rivers, there is a need to 1) find suitable study site and sonar setups (*e.g.*, frequency, end range, fencing or other structure); 2) test the accuracy of the fish counts and fish length measurements in such setup; 3) develop and test an efficient data analysis method; 4) develop and test a method for distinguishing between the different fish species in the sonar data; and 5) compare the sonar counts to current counting methods.

To address these knowledge gaps, five research chapters are presented in this dissertation. Each of these research chapters were designed with their specific objectives that allow addressing the overarching dissertation objective specified above. The research presented in this dissertation focuses especially on automating the data analysis, and the methods are applicable in any location where any type of imaging sonar is used for monitoring migrating fish. More specifically, the objectives in each of the research chapters were to:

1) **Compare the length measurements derived from a long-range (30m) ARIS sonar data to the true lengths of n=54 salmon and develop a model that predicts size classes of salmon.**

   Although the measurement accuracy is high in short-range (*i.e.*, <15 m) setups (*e.g.*, Daroux *et al.*, 2019; Hightower *et al.*, 2013; Tušer *et al.*, 2014), there is often desire or even need to use the sonar in long range setups. In the Miramichi River, this is the situation if the whole river width is covered with the sonar beam when additional structure (*e.g.*, fences) cannot be installed in the river channel. Such situation may be due to *e.g.*, retain the river channel open for boat traffic or if the installation of fence is delayed due to high floods. In Chapter 2 of this dissertation, I show that the length measurement accuracy in a long-range (~30 m) setup is low, but the size classes that are relevant for fisheries management of Atlantic salmon can be predicted using a model; the research has been published in the Journal of Fish Biology (Appendix A2. Permissions to Reprint from Journals).

2) **Develop an automated workflow that counts fish from the sonar data and compare the computer-generated counts to multiple human-generated counts in two 24-h datasets.**

   While a high accuracy fish count can be achieved using manual counting (Holmes *et al.*, 2006), manual analysis of the sonar footage for monitoring Atlantic salmon run over five to six months every year is a laborious task. Therefore, an automated data analysis workflow is developed and tested for datasets collected in the Miramichi River. I present this in Chapter 3 of this dissertation; the research has been published in Fisheries Research (Appendix A2. Permissions to Reprint from Journals).

3) **Measure and compare the tailbeat frequencies of three common migratory fish species (n=50 per species) directly from the sonar data in an experimental setup.**

Identifying fish species directly from the sonar data could increase the accuracy of the fish counts and decrease the cost of monitoring, especially if the process can be automated. In Chapter 4, I test a previously developed method (Mueller *et al.*, 2010) and compare the tail-beat frequencies of three fish species that are common in Atlantic Canada, have an overlapping migration timing, and have a similar length distribution: striped bass, Atlantic salmon, and American shad. Additionally, I develop an automated tailbeat counting method and compare the results to manual counts of tailbeats. The research has been published in the Transactions of the American Fisheries Society (Appendix A2. Permissions to Reprint from Journals).

4) **Collect sonar and underwater camera data for one month, adjust sonar fish count for species using underwater camera data, and compare the fish count to fish catches at a downstream index trap net.**

Long dataset (since early 1990's) of the Atlantic salmon run size exists using trap net catches and mark-recapture modelling for the two main branches of the Miramichi River: the Main Southwest Miramichi River and the Northwest Miramichi River. However, the current method cannot provide tributary-specific information. In Chapter 5, I test the sonar method combined with underwater camera data in one of the main tributaries, the Little Southwest Miramichi, compare the results to index trap net data, and show that the sonar method can be used to provide tributary-specific information of the adult Atlantic salmon run in the Miramichi River.

5) **Produce a guide that discusses the study site selection, sonar operation, data analysis, and costs, and is targeted to anyone considering or starting a salmon monitoring program using imaging sonars.**

While a large amount of experience was gained in the project, some of it was not easily quantifiable. The experience still represents extremely valuable information for sonar practitioners but there is a paucity of this hard-learned practical information in the current published literature. As an outcome, in Chapter 6 of the thesis, a guide was produced where the best practices from international literature and from the multiple practical "lessons-learned" throughout this dissertation research is presented.

Finally, I will answer the main objective in Chapter 7, where I synthesise the information learned in the dissertation, discuss the major considerations in applying the imaging sonar method in Atlantic Canada, and give recommendations for future work.

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2. Length measurement accuracy of Adaptive Resolution Imaging Sonar (ARIS) and a predictive model to assess adult Atlantic salmon (*Salmo salar*) into two size categories with long-range data in a river

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Abstract

Imaging sonars are used around the world for fish population monitoring. The accuracy of the length measurements has been reported in multiple studies for relatively short (<15 m) ranges and high image resolution. However, imaging sonars are often used at longer ranges (*i.e.*, > 15 m) where the images produced from sonar returns become less detailed. The accuracy of the length measurements from the Adaptive Resolution Imaging Sonar was tested by releasing n = 69 known-sized adult Atlantic salmon (*Salmo salar*) directly into the sonar field at ranges between 15 and 29 m, and measuring their echoes manually by four users and semi-automatically using a computer workflow in Echoview software. Overall, the length measurements were very variable: compared to true (fork) lengths, the mean of differences varied between −9.9 cm and 7.8 cm in the human-generated datasets, and between −42.8 cm and −20 cm in the computer-generated dataset. In addition, the length measurements in different datasets were only in poor or moderate agreement with each other (intraclass correlation <0.61). Contrary to our expectations, the distance from the transducer or the subjectively assessed echo quality did not have an effect on the measurement accuracy in most of the datasets and when it did, the effect was not systematic between the datasets. Therefore, a size class and length prediction model was implemented in a Bayesian framework to group salmon into two size categories: One-Sea-Winter (<63 cm) and Multi-Sea-Winter (≥63 cm) groups. The model correctly predicted the size category in 83% of the fish in the computer-generated dataset and ranged from 68% to 74% in the human-generated datasets. We conclude that fish length measurements derived from long-range imaging sonar data should be used with caution, but post-processing can

improve the usefulness of the data for specific purposes, such as adult Atlantic salmon population monitoring.

2.1 Introduction

Imaging sonar technology, such as the Adaptive Resolution Imaging Sonar (ARIS; Sound Metrics Corp.; www.soundmetrics.com) and the Dual-frequency IDentification SONar (DIDSON; Sound Metrics Corp.), has become a popular fish population assessment tool for various fish species in rivers across the world (Atkinson *et al.*, 2016; Buck *et al.*, 2012; Lilja *et al.*, 2011; Martignac *et al.*, 2014; Pipal *et al.*, 2012). Because imaging sonars use sound energy to produce the image underwater, they can be used in low-visibility conditions such as high turbidity and night-time (Moursund *et al.*, 2003; Simmonds and MacLennan, 2005). Sound can penetrate water over a long distance (Simmonds and MacLennan, 2005) which makes imaging sonar monitoring non-invasive and less dependant on additional infrastructure needed in the river channel (*e.g.*, fences or fishing gear). Often called "acoustic cameras", imaging sonars produce high-quality sonar video material that allow measurements (*e.g.*, length, width, speed, count) of objects entering the sonar field (Martignac *et al.*, 2014). In addition to population assessment, these measurements may be used to determine species or age-groups within a species and they can be an important factor when assessing population metrics such as the total egg deposition of the run (Barneche *et al.*, 2018; Burwen *et al.*, 2007; Grote *et al.*, 2014; Gurney *et al.*, 2014; Lilja *et al.*, 2010).

The sonar image is produced using sound waves and therefore, the resolution is defined by the used frequency: higher frequencies make it easier to discriminate targets that are close to each other but increasing frequency limits the maximum range due to increased absorption (Simmonds and MacLennan, 2005). Therefore, imaging sonars use high frequencies to produce high resolution images at a rather short range (Belcher *et al.*, 2002; Burwen *et al.*, 2010; Martignac *et al.*, 2014). As an example, the DIDSON at 1.8 MHz is used to produce very high resolution images at ranges up to 18 m, and up to 40 m ranges can be reached with 1.1 MHz, although with lower resolution (Belcher *et al.*, 2002). The range can be exacerbated in certain environmental conditions such as rivers with high glacial silt load where the detectability of a fish is significantly lower at 20 m in comparison to 10 m (Burwen *et al.*, 2007). Consequently, a common practice in fisheries use is to deploy one sonar with a range of less than 15 m (Grote *et al.*, 2014; Holmes *et al.*, 2006; Moursund *et al.*, 2003).

The accuracy of fish length measurements derived from imaging sonars has been tested in multiple studies using different sonars and experimental designs. Within ranges < 15 m and using a 1.8 MHz frequency, DIDSON- or ARIS-derived lengths and true lengths of fish have been found to be similar (Burwen *et al.*, 2007; Cook *et al.*, 2019; Daroux *et al.*, 2019; Grote *et al.*, 2014; Gurney *et al.*, 2014; Han *et al.*, 2009; Hightower *et al.*, 2013; Tušer *et al.*, 2014). As the frequency decreases, the length measurements are less accurate; using a 1.2 MHz frequency in a short-range setup (< 13 m), Zhang *et al.* (2014) found that the measurements from DIDSON were 35.6% shorter than in-hand measurements of fish lengths. In spite of the limitations in resolution, longer range setups are needed, and used, when the whole river width needs to be covered (due to the prohibitive costs of the sonar units, often exceeding $US 100,000) or when the site location is best accessible from farther away (*e.g.*, dams and fishways; Hakkola, 2011; Lilja *et al.*, 2011; Lin *et al.*, 2016;

Valjus *et al.*, 2017). The measurement accuracy of the imaging sonars in these setups is not as well tested, but the measurements have been compared between low-frequency DIDSON and other methods. Lin *et al.* (2016) used ranges up to 30 m and found that the average DIDSON-measured fish size was similar to the average length of fish in a drift gill net survey. Lilja *et al.* (2010) compared the size distributions produced from long range (up to 80 m) DIDSON and angling catch size distribution, and concluded that the DIDSON lengths were approximately 5 – 10 cm shorter than the true lengths of the fish. In order to produce higher resolution images at longer ranges, Burwen *et al.* (2010) tested the DIDSON with a high-resolution lens with 1.2 MHz frequency and concluded that relatively accurate and precise fish length estimates are possible at up to 21 m. The DIDSON estimates were highly correlated with fork lengths of tethered fish, but there was a negative bias in the length estimates ($R^2 = 0.90$, RMSE = 5.76 cm) (Burwen *et al.*, 2010).

Different factors have been shown to affect the accuracy of length measurements. Species (Hightower *et al.*, 2013), fish length (Burwen *et al.*, 2007; Hightower *et al.*, 2013; Tušer *et al.*, 2014), and swimming pattern (Zhang *et al.*, 2014) have all been reported to have a strong influence on the accuracy of length estimation. There is also a high variability in length measurements during a single tail-beat cycle (Burwen *et al.*, 2010). The off-axis angle (left-right position in the beam array) did not affect the measurement accuracy when tested with 31 – 110 cm fish (Gurney *et al.*, 2014), but the lengths were underestimated at the edges of the array when tested using fish between 10 cm and 60 cm in length, (Tušer *et al.*, 2014). Off-axis angle also influenced the measurement accuracy when the fish was automatically measured from each frame (Hightower *et al.*, 2013).

In the last 5 to 10 years, the use of automatic fish detection and measuring techniques has increased (Jing *et al.*, 2017; Tušer *et al.*, 2014; Zhang *et al.*, 2014), but manual or semi-automatic counting and measuring is still the most common analysis method when using imaging sonar technology for monitoring fish populations (Atkinson *et al.*, 2016; Lilja *et al.*, 2011, 2010). However, in manual measurements, the consistency of human-generated lengths remains an issue contributing to a measurement bias, and inter-observer error has been reported in many instances (Daroux *et al.*, 2019; Hakkola, 2011; Keefer *et al.*, 2017). Daroux *et al.* (2019) also highlight a high intra-individual error and suggest that 3 – 5 measurements per fish on the best quality frames will improve the length measurement accuracy.

Due to its socio-economical value, Atlantic salmon (*Salmo salar* L.) is often monitored with imaging sonars to provide in-river adult return counts (Gurney *et al.*, 2014; Lilja *et al.*, 2011, 2010). Atlantic salmon has a complex life-history strategy: juveniles typically spend one to several years in rivers before migrating to sea where they spend one or several years (Birnie-Gauvin *et al.*, 2019). When returning to rivers, the adult Atlantic salmon are often classified in two categories for management purposes: One-Sea-Winter (1SW or grilse) are salmon that spent one year in the ocean and Multi-Sea-Winter salmon (MSW) are larger salmon that have spent multiple winters in the ocean and return to their natal river either first time or as returning spawners (DFO, 2014; Locke *et al.*, 1998). This classification is used in population assessment as larger fish have higher fecundity and may possess higher quality eggs (DFO, 2014; Fleming, 1996; Reid and Chaput, 2012). In some rivers, the population size estimates are focused on MSW salmon (Lilja *et al.*, 2010) and in others, particularly in Atlantic Canada, the two groups are divided using their lengths as a proxy for their size category (*i.e.*, a 1SW is < 63 cm and an MSW is any salmon ≥ 63cm (DFO, 2014; Locke *et al.*, 1998)).

Despite the research conducted on DIDSON and ARIS length measurement accuracy to date, a better understanding of the length measurement accuracy is needed when imaging sonars are used in low-frequency (1.1 MHz) mode and longer ranges (> 15 m). To this end, this study had three objectives. The first objective was to assess the accuracy and consistency of length measurements of adult Atlantic salmon at far range (> 15 m) using human-generated and computer-generated measurements. Related to this, the second objective was to assess the degree to which the range (*i.e.*, distance of measurement from the sonar unit) and subjective sonar image quality assessment may influence or improve the measurement accuracy. Finally, the third objective was to assess how reliably adult Atlantic salmon can be categorized as either small (1SW, < 63cm) or large (MSW, ≥ 63cm) based on the information derived from sonar using human-generated or computer-generated data. We hypothesized that there would be a high intraclass correlation between the different human-generated and computer-generated lengths. We further hypothesized that subjectively assessed high-quality echoes would produce higher accuracy length measurements compared to lower quality echoes and that the ARIS measurement accuracy would decrease as a function of distance from the transducer, and as such, the length determination would become unreliable after some (currently unknown) distance irrespective of data being generated by human-observer or computer-assisted algorithms. However, we hypothesized that the sonar data can be reliably used to distinguish between 1SW and MSW salmon.

2.2 Materials and methods

The study was conducted on October 1st, 2018 at an Atlantic salmon protection barrier (47°36'40.30"N, 66°48'45.47"W) in the Upsalquitch River, a tributary of the Restigouche River in northern New Brunswick, Canada. The purpose of the protection barrier is to prevent illegal capture of salmon, and the salmon are held at the barrier enclosure until they are released to continue their migration upriver in the autumn after the fishing season (Locke *et al.*, 1998). As such, the location allowed relatively easy capture, measurement, and release of adult Atlantic salmon in a short time frame (*i.e.*, every three minutes). The care and use of experimental animals complied with Canadian animal welfare laws, guidelines, and policies.

At the study site, located 250 m downstream of the barrier fence, an imaging sonar (ARIS Explorer 1800, Sound Metrics Corp.; www.soundmetrics.com) was deployed aiming across the river (Figure 5a). The transducer was set 10 cm below the surface and tilted down 3° using Sound Metrics AR_2 rotator. Low-frequency mode (1.1 MHz) was used and the range was set to reach from 1.44 m to 29.12 m (Figure 5d). Sound Metrics ARIScope 2.6 software was used for recording. To represent typical fisheries monitoring studies, the settings were set either automatically by the software or to the maximum possible value: automatic settings were used for detail (downrange resolution, *i.e.*, the resolution across the river, was 1189/23.2 mm) and focus (*i.e.*, the range where the image is sharpest, was between 19.92 m and 22.26 m throughout the experiment), and maximum frames-per-second was used (4.0 fps). The water temperature varied between 12°C and

13°C and therefore, the software-set sound velocities were between 1456 m^1s^{-1} and 1457 m^1s^{-1}.

The ARIS Explorer 1800 produces an image using 96 acoustic beams that together form a wide field of view of 28° (horizontal) and 14° (vertical). The width of the sonar field was tested visually by walking across the field, and the downstream end of the field was marked with metal rebar that were vertically driven into the riverbed at 10, 15, 20, 25, and 29 m distance from the transducer (Figure 5b). The riverbed substrate was mainly gravel, devoid of large objects obstructing the field of view, and mainly uniform, with the exception of some areas within the 24 – 29 m range where small deeper areas were present (Figure 5d). The water clarity was excellent with the Secchi depth reaching from surface to the bottom throughout all the depths along the measurement transect, and there was no noticeable inference from bubbles (*i.e.*, turbulence) in the sonar footage. The whole river width was approximately 40 m, and the transducer was placed in the river so that the sonar field would cover the deeper sections of the river and avoiding the very shallow areas near shoreline; the depth was 0.6 m at the transducer and gradually increased to a maximum of 1.3 m at 25 m from the transducer.

A total of 69 Atlantic salmon (31 1SW and 38 MSW) were seine-netted from the barrier enclosure pool and held within a small staging area at the side of the river (Figure 5c). All salmon were measured for fork length, total length, and girth, and were subsequently released one at a time at 15, 20, 25 and 29 m alternatively (Figure 5b); closer than 15 m ranges were not of interest due to the previous studies on the subject (*e.g.*, Daroux *et al.*, 2019; Hightower *et al.*, 2013; Tušer *et al.*, 2014). The fish behaviour was recorded by a person standing on the shore as either turning downriver, swimming straight upstream, or turning to left or right. This helped to confirm the behaviour in the sonar recordings and to confirm if a fish turned downriver and was therefore not expected to be seen in the sonar image. The salmon captured for this experiment were divided to two size groups using the length proxy of 63 cm that is used in Atlantic Canadian rivers (DFO, 2014; Locke *et al.*, 1998). The fork length ranged from 49 to 99 cm, and the average fork length was 53.0 ±SD 3.0 cm for 1SW and 77.5 ±SD 6.42 cm for MSW (Appendix A4), which was similar to lengths encountered throughout the catchment (Locke *et al.*, 1998; O'Connell *et al.*, 2006).

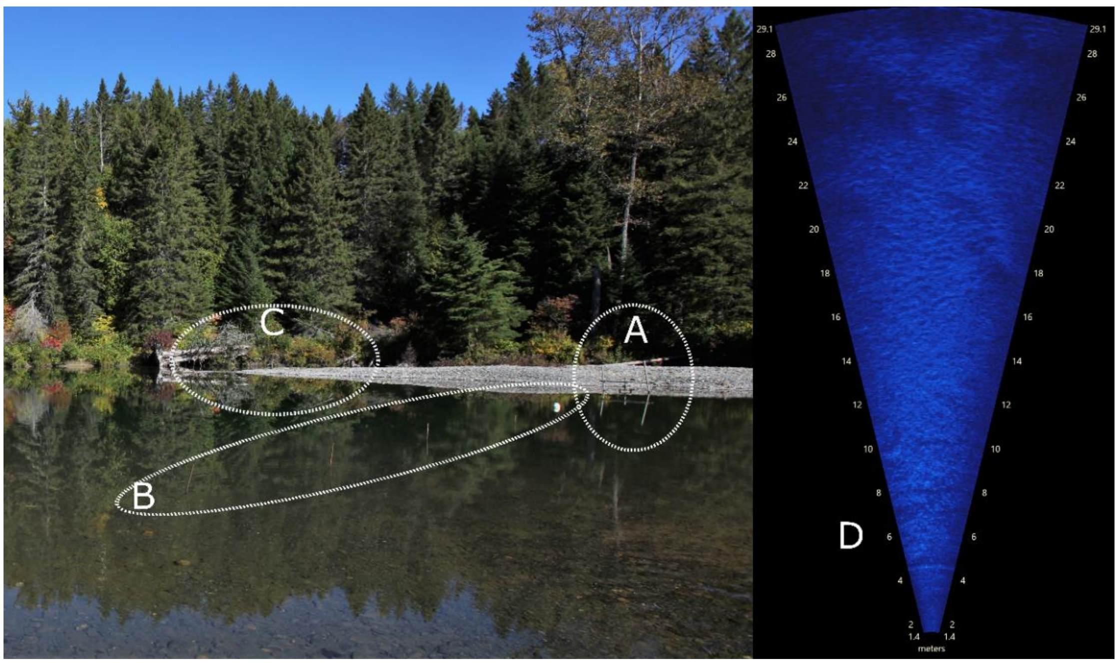

Figure 5. The study site on the Upsalquitch River, New Brunswick, Canada, where the transducer was deployed aiming across the river (a) and the sonar field was marked with metal rebars every 5 m (b). Fish were caught and held close by (c) before measuring and releasing them into the sonar field. The sonar image (d) shows no large objects within the field but some deeper (darker) areas were present at far ranges from 24 to 29.1 m.

Data Processing

Protocol for human-generated length readings

The sonar data were analysed using ARISfish software (Sound Metrics Corp.; www.soundmetrics.com) version 2.6.2. Data entries of all individual salmon were isolated and time of entry of the salmon in the sonar field was marked. The formatted data were then distributed to four users (Users 1 – 4). User 1 was an experienced sonar analyst; Users 2, 3, and 4 all had previous experience in analysing ARIS data in an Atlantic salmon monitoring project but had less experience than User 1. Each user was instructed to find at least one, and ideally up to four frames deemed sufficient to measure the length of each salmon (*i.e.*, 1-4 length measurements were generated for each fish / user). After identifying suitable frames, the users measured the fish echo in those frames and subjectively commented on the quality of the fish echo in the frame as Very good, Good, Fair, Poor, or Very poor. All users were instructed to measure the fish like they normally would as part of their routine monitoring work but to take as much time as needed. This was done in an effort to make the data from this study relevant for the monitoring work in practice, rather than creating "ideal" conditions only relevant for an academic study. There were some differences in measuring methods between the users. Three users measured the fish without background subtraction, while the feature was on during measurements by User 2. Two users (2 and 3) measured the fish mainly using a straight line while the other two (1 and 4) typically used multiple clicks to more accurately match the shape of the fish.

Protocol for computer-generated length readings

The original sonar files (Figure 6a) were first processed for background subtraction (Figure 6b) using Sound Metrics ARISfish 2.6.2 software. This process removes the echoes that are not in motion (Sound Metrics Corp., 2019). The background subtracted files were then processed in Echoview software (Echoview Software Pty Ltd; www.echoview.com, Version 9.0.333.35479) using a similar workflow as Kang (2011) and Boswell *et al.* (2008). The workflow consists of operators in the following order: Cluster detection operator (Figure 6c, Figure 7), Target property threshold operator (Figure 6d), Target conversion (Figure 6e), and TS (target strength) substitution operator (Figure 6e).

The Cluster detection operator was used to generate multibeam targets from groups of adjoining datapoints in multibeam data (Echoview, 2018), *i.e.*, fish targets are generated from echoes at each frame (Figure 6c). Next, all the targets with a length < 10.00 cm were removed using the Target Property Threshold Operator (Figure 6d). The threshold was chosen by visually inspecting the echogram in order to remove reverberation and noise that occurred especially at farther ranges, and to facilitate the detection of true fish echoes in later steps of the workflow. The Target Conversion Operator was then used to generate single target data from multibeam targets (Figure 6e) allowing the use of the Echoview fish tracking feature (Echoview, 2018). The fish tracks were created manually by simultaneously viewing the original sonar video and the view from the TS substitution operator that displays target range in Y-axis and time on X-axis, and indicates the length (Figure 6e) or angle (position in the sonar field) in different colours. The fish tracks were created manually to ensure that all the correct targets were included as opposed to the use of automatic fish track detection which could have led to more variation in the targets (and false objects) selected. Only the targets that could be confidently assigned to a fish were accepted for the fish track to avoid measurements from other objects, although this limited the number of targets in some of the tracks. As a last step, all fish tracks were exported as .csv tables.

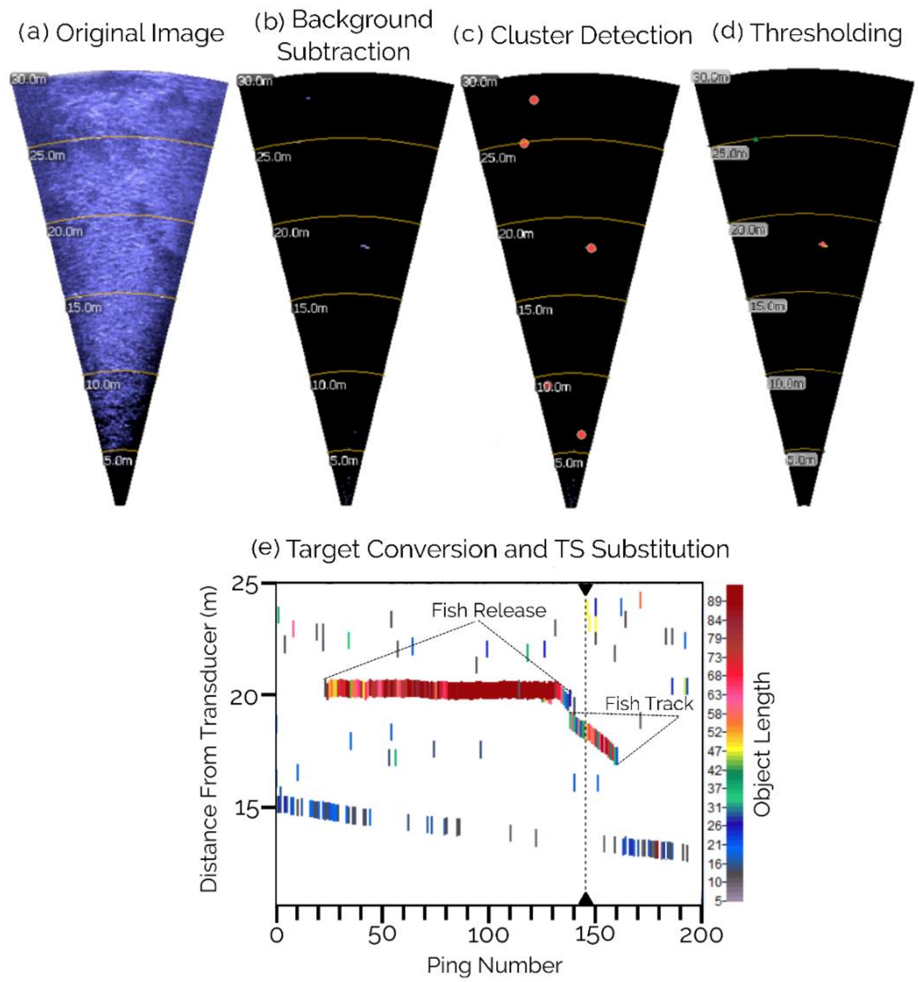

Figure 6. An example of the workflow for measuring fish lengths in Arisfish/Echoview. The process starts in Arisfish with original image (a) where the background is subtracted (b). Workflow then continues in Echoview where clusters are detected to generate multibeam targets (c) and thresholding (d) is used to remove smallest (<10 cm length) targets. Fish tracks are created in an echogram (e) where each target is displayed with their distance from the transducer and time (frame/ping number, four frames-per-second). The colour in (e) indicates the length of the target and the dashed line between the two arrows in (e) indicates the frame that is displayed in (a)–(d).

Depending on the settings used in the Cluster Detection Operator the length of the object can vary largely (Table 1, Figure 7). In principle, the user defines the distances and sizes of clusters (i.e., echoes) that will be included in one target. Therefore, three dataset versions were created using different cluster detection operator settings (Table 1, Figure 7). Version 1 (V1) included satellite targets farthest away from the seed target and was therefore likely to create largest targets to represent the fish echoes in each frame. The possible downside of using these settings was that more noise was likely to be included in the objects and that multiple fish swimming close to each other could be grouped to one object. Versions 2 (V2) and (V3) were therefore tested as they did not allow linking from far distances. In addition, V3 had the smallest seed threshold, meaning that it created multiple small targets, if present. In some fish tracks, V2 and V3 resulted in multiple targets measured within one frame. Additional datasets (V2B and V3B) were created where these frames were removed before analysis. The data from all five datasets were exported as tables where each row represented a measurement at each measured frame.

Table 1. Settings used in the Cluster Detection Operator to create three different datasets (V1, V2, and V3) for adult Atlantic salmon length data.

Dataset	Echoview setting					
	Link Target Clusters	**Seed Threshold (cm^2)**	**Satellite Threshold (cm^2)**	**Link Distance (m)**	**Link Satellite Clusters**	**Retain Unlinked Satellites**
Setting explanation (Echoview, 2018)	Allow linking of Seed and Satellite targets.	Detected multibeam target with target area greater than or equal to the threshold.	Detected multibeam target with target area less than seed threshold but greater than or equal to the satellite threshold.	The potential targets to link are found at distances less than linking distance.	Satellite clusters can link to each other	Retain unlinked satellites as detected targets
Version 1	Enabled	400	10	0.5	Enabled	Disabled
Version 2	Enabled	400	20	0.2	Enabled	Disabled
Version 3	Enabled	30	10	0.2	Enabled	Disabled

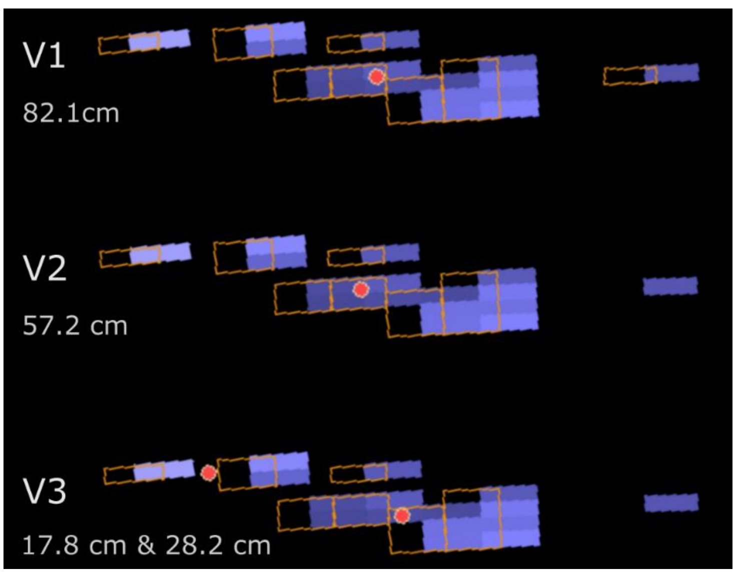

Figure 7. Example of a fish echo (total true length 79.5 cm) at 17.8 m range from the transducer and resulting length measurements using three different cluster detection settings (V1–V3; Table 1). Blue pixels represent background subtracted echoes (*i.e.*, echo of fish), orange lines are the predicted edges of the fish (shifted by one pixel for clarity), and orange dots show the centre of each target. In the example, Cluster Detection Operator in V3 predicts the echo as two separate fish.

Measurement accuracy and the influence of measurer and distance

Statistical tests were run using R software (version 3.6.0; R Core Team, 2019). The agreement between the true fork length and the ARIS (estimated) length was calculated for all datasets following Bland-Altman method for repeated measurements that defines the mean difference (mean of individual differences) and the 95% limits of agreement (LOA; mean difference ± 1.96 x SD) (Bland and Altman, 2007). However, due to large differences between the true length and ARIS length, the plot was modified to use only the true length as a reference method instead of the average of the two methods (Krouwer, 2008) and a one-sample test of major axis differences was used to test if the slope of an Ordinary Least-Squares regression (OLS) deviated significantly from 0 (flat line). Repeated measures correlation (Bakdash and Marusich, 2017) was calculated using *Rmcorr* package (Bakdash and Marusich, 2018) for all datasets to test if there was a significant association between the distance at which the measurement was made and the measurement error ($ARIS\ length - True\ length$). To assess the agreement between the datasets, three length-summary tables (Average, Minimum, and Maximum length for each fish separately) were calculated for each dataset, and the Intraclass correlation (ICC) was computed using the summary tables. The ICC was calculated using all the datasets together, for human-generated datasets only, and for computer datasets only using the R package *psych* (Revelle, 2018). The two-way random effects ICC model was used because all measurers used the same dataset and because the measurers (raters) were randomly selected; the results from this model can be generalised to any similar measurers (Koo and Li, 2016). Additionally, the model was based on "single rater" (*i.e.*, single measurer rather than a mean of *k* measurers) and "consistency" (*i.e.*, correlation of the measurements rather than the same measurement) (Koo and Li, 2016). The ICC value was interpreted using Koo and Li (2016) suggestions: poor (<0.5), moderate (0.5–0.75), good (0.75–0.90), and excellent (>0.9). Finally, for the human-generated datasets only, the influence of the subjectively assessed quality on the measurement error was tested using a Kruskal-Wallis test for each user separately.

Predictive Size-Category Model Description

For human-generated data, the number of variables available was limited to the measurements taken in the field, distance of the fish to the transducer, and angular position of the fish in the sonar field. More variables were available in the computer-generated dataset, in particular in relation to the size/shape of the target. However, most of the variables were correlated and/or did not segregate the two size categories of adult salmon (Appendix A4).

While the Echoview workflow typically generated numerous short measurements for all salmon, the number of longer measurements appeared higher for larger fish. That information was used in the model to categorize salmon in either 1SW or MSW category.

Following the approach described by Craigmile *et al.* (2009), that is, successively testing various hypotheses and only retaining the ones that were consistent with the data, an initial version of the model only used a multivariate linear regression to predict true length of the fish. However, this model provided an overall poor fit to the data which hinted that predicting true length would be challenging and led to the development of a model that predicts a size category for each salmon (either 1SW or an MSW) in addition to predicting its fork length. Henceforth, the notation $a|b \sim f(b)$ means the random variable a (whether observed or unobserved) is distributed according to the probability distribution function f conditionally on b. Unobserved quantities are necessarily unknown, but observable quantities may be unknown in the case of missing data. For clarity, the variables used, the main parameters of the model, and their descriptions are listed in Table 2. Two indices are used: n refers to a unique fish and i refers to a human-generated or a computer-generated reading on a sonar recording. Note that each salmon did not necessarily have the same number of readings.

Table 2. Main variables and parameters used in the size-prediction model with their descriptions and prior distributions.

Variable	Description	Prior distribution
$R_{n,i}$	The i th ARIS measurement associated with fish n	
σ^R	The standard deviation associated with the ARIS readings	$Uniform(0,100)$
L_n	The observed/true total length of fish n	
$D_{n,i}$	The distance from the transducer at which the i th ARIS measurement of fish n was obtained	
$\theta_{n,i}$	The major axis position in the sonar field (0 is center)	
$\bar{L}^{1\mathrm{SW}}$	The average size of a 1SW (Mean length: O'Connell *et al.*, 2006)	$Normal(50,10)$
$\bar{L}^{MSW}$	The average size of multi-sea-winter salmon (Mean length: O'Connell *et al.*, 2006)	$Normal(80,10)$
σ^L	The standard deviation associated with the average 1SW and MSW salmon length	$Uniform(0,100)$
$I_n^{1\mathrm{SW}}$	The index indicating if fish n is a 1SW or not (if I_n^{1SW}=1 the fish is a 1SW)	
$p_n^{1\mathrm{SW}}$	The probability of fish n being a 1SW or not	
C_n^{MSW}	The number of times fish n was measured with a size ≥63cm	
$\bar{D}_n$	The average distance at which fish n was measured (average distance of all readings of fish n)	
$\alpha_{0:3}$	Slope and various effect of the logistic regression to predict size group	$Normal(0,10)$
$\beta_{0:3}$	Slope and various effect of the multivariate regression to predict length	$Normal(0,10)$

There were two main components in the model. First, it is assumed that $R_{n,i}$ (log scale) is drawn from a Normal distribution with mean $\mu_{n,i}^R$ and associated standard deviation σ^R (Eq. 1):

Eq.1 $$Log(R_{n,i})|\mu^R_{n,i},\sigma^R \sim Normal(\mu^R_{n,i},\sigma^R)$$

Eq. 2 $$\mu^R_{n,i} = \beta_0 + \beta_1 \cdot Log(L_n) + \beta_2 \cdot D_{n,i} + \beta_3 \cdot \theta_{n,i}$$

Where $\mu^R_{n,i}$ is the predicted ARIS measurement written as a hierarchical multivariate linear regression using the observed length of the fish L_n (in log scale), the distance from the transducer at which the fish is measured $D_{n,i}$, and the angular position in the sonar field $\theta_{n,i}$.

The second component of the model attempts to classify the fish in either 1SW (<63cm) or MSW (≥63cm) category. To do so, a logistic regression was implemented (Eq. 3, Eq. 4), where the 1SW indicator variable $I_n^{1\mathrm{SW}}$ (1 = 1SW, 0 = MSW) was drawn from a Bernoulli distribution with a probability of fish *n* being a 1SW p_n^{1SW}. This probability was a function of the number of times fish *n* was measured as an MSW fish C_n^{MSW} (≥63cm), the average distance at which it was measured $\overline{D}_n$ as well as the interaction between these two variables.

Eq. 3 $$I_n^{1\mathrm{SW}}|p_n^{1\mathrm{SW}} \sim Bernoulli(p_n^{1\mathrm{SW}})$$

Eq. 4 $$logit(p_n^{1\mathrm{SW}}) = \alpha_0 + \alpha_1 \cdot C_n^{MSW} + \alpha_2 \cdot \overline{D}_n + \alpha_3 \cdot C_n^{MSW} \cdot \overline{D}_n$$

The two components of the model were linked together through the observed (true) length L_n (in log scale) which was drawn from a normal distribution (Eq. 5, Eq. 6). The mean of the normal distribution was determined by the 1SW indicator variable $I_n^{1\mathrm{SW}}$. The associated standard deviation σ^L was assumed to be the same for 1SW and MSW as the fish size category is not known before prediction.

Eq. 5 $$Log(L_n)\,|\mu_n^L,\sigma_k^L \sim Normal(\mu_n^L,\sigma^L)$$

Eq. 6 $$\mu_n^L = Log(I_n^{1\mathrm{SW}} \cdot \overline{L}^{1\mathrm{SW}} + (1 - I_n^{1\mathrm{SW}}) \cdot \overline{L}^{MSW})$$

Data preparation and Bayesian inference

ARIS measurement $R_{n,i}$ and the observed length L_n were log-transformed to reduce skewness. In order to deal with multi-collinearity, the data associated with the logistic regression (*i.e.*, the average measurement distance $\overline{D}$ and the number of counts ≥ 63cm C^{MSW}) were centered on the mean.

Statistical inference was conducted in the Bayesian framework allowing for the estimation of all model parameters and their uncertainties in a single coherent framework. Weakly informative and independent prior probability distributions were assigned to model parameters (Table 2) to make sure the posterior inferences primarily reflect the information brought by the experiment and the observations. The joint posterior distributions of all the model unknowns (*i.e.*, unobservable quantities and observables in case of missing data) were approximated using Markov chain Monte Carlo (MCMC) sampling (Gelman *et al.*, 2003). All computations were carried out with the JAGS (Plummer, 2003) and R software (R Core Team, 2019). To test the convergence of the MCMC sampling on the model parameters, three MCMC chains with contrasted starting points were run in parallel. The Gelman-Rubin diagnostic (Brooks and Gelman, 1998), which evaluates MCMC convergence by comparing between-chain and within-chain variances, indicated that good mixing of the MCMC chains was obtained after 5×10^5 iterations. One in every 50 iterations was retained to obtain a sample of 20 000 values. The first 10 000 were discarded to remove the influence of the MCMC starting values. The remaining 10 000 values were then used to approximate the posterior distributions of all the model unknowns. All human- and computer-generated datasets were used for statistical inference independently. Fork length and size category were predicted for each individual salmon using only the ARIS readings and associated covariates and the parameters estimated from the full dataset.

The performance of the model with the various datasets was assessed as the ability to assign fish in the right size category, as the proportion of the predicted fish lengths (median of the length posterior distribution) within 5 cm and 10 cm of the true length, and through inspection of the length prediction's Studentized residuals $\left(\mathrm{X}^{obs} - mean(X^{pred})\right)/sd(X^{pred})$, where X^{obs} is an observed variable and X^{pred} the posterior distribution of the predicted variable. The ability of the model to categorise fish in the two size categories was summarised using a separation plot (Greenhill *et al.*, 2011). Finally, the predictive model outputs (number of correctly assigned fish size categories) for each human and computer-generated dataset were compared to the mean, median, minimum, and maximum values (henceforth "baseline data models") derived from the ARIS data analysis (*i.e.*, length estimates extracted by the four users or by the semi-automated Echoview workflow without any modelling), and the resulting classification as 1SW or MSW (if the output was <63 cm or ≥63cm, respectively) using this baseline (raw) data alone.

2.3 Results

Out of the 69 salmon released, 12 fish turned downstream and therefore were not recorded. In addition, three fish were observed moving upstream in the field but could not be identified from the sonar footage (a 1SW released at 20m, a 1SW at 29 m, and an MSW at 29 m); two of them were very difficult to identify from the footage and one fish was impossible to uniquely identify because of another salmon that moved in from downstream at the time of release. Therefore, the final dataset (DFO, 2018) used for this analysis consisted of 54 salmon, of which 22 and 32 were 1SW and MSW, respectively (Table 3). Furthermore, one 1SW-sized fish was recorded manually (released at 15 m) but could not be measured using Echoview as it was not visible in background-subtracted data (Table 3). The fish tracks for the computer-generated lengths were easier to define at distances <20 m. At longer ranges, reverberation combined with weak echoes of the fish made defining the fish tracks more difficult.

Table 3. Summary of number of unique 1SW and MSW Atlantic salmon observed in the four human-generated datasets and in the five computer-generated datasets, and number of length measurements for each dataset. Also shown is the subjective quality assignment of measurements for human-generated datasets (Very Good, Good, Fair, Poor, and Very Poor).

Data set	n of 1SW salmon	n of MSW salmon	Total n of unique measurements	Average n of readings per fish	Very Good	Good	Fair	Poor	Very Poor
User 1	22	32	207	3.8	1%	11%	49%	29%	10%
User 2	22	32	98	1.8	-	14%	59%	22%	5%
User 3	22	32	100	1.8	-	1%	43%	44%	12%
User 4	22	32	119	2.2	-	9%	51%	29%	11%
EV1	21	32	829	15.6					
EV2	21	32	722	13.6					
EV2b	21	32	638	12.0					
EV3	21	32	818	15.4					
EV3b	21	32	602	11.4					

Measurement accuracy, consistency, and influence of measurer and distance

Overall, the human-generated length measurements were variable, *i.e.*, a fish of a given length produced a wide range of measurements and the smallest difference between the upper and lower Limits of Agreement (LOA) was 67.5 cm (User 1) and the largest was

94.5 cm (User 3; Figure 8). The Bland-Altman mean of differences was negative in three users and positive in User 4 dataset (Figure 8), and the mean of differences closest to zero was in the User 1 dataset (-0.9 cm; Figure 8). The slope of an OLS fitted through the datapoints differed significantly from zero (One-sample test of major axis slope, $p<.001$), revealing a proportional bias in all the datasets. The repeated measures correlation test revealed no correlation between measurement error and range (distance from the transducer) in two human-generated datasets (User 1; $r(152)=-0.01$, $p=.85$ and User 3; $r(45)=-0.19$, $p=.21$), but there was a moderate positive (User 2: $r(43)=0.62$, $p<.001$) correlation in the User 2 dataset and a weak negative relationship in the User 4 dataset ($r(64)=-0.29$, $p=.02$).

Of all the human-generated measurements, 50% were classified as fair, 41% of the measurements were Poor or Very Poor, and only 9% of the measurements were classified as good or very good (Table 3). For two users (1 and 4), the quality of the frame did not influence the difference between the true length and the length estimated from ARIS (Kruskal-Wallis, $H=8.73$, $df=4$, $p=.07$ and $H=5.54$, $df=3$, $p=.14$ for Users 1 and 4, respectively). The two other users showed differences in length measurement accuracy in frames of different quality, however, these differences were not systematic (*i.e.*, accuracy was not necessarily better with a higher quality ranking and the differences were not the same for both users). This heterogeneity, as well as the overall low number of length measurements across all quality-ranking classes translated to omission of this information from the subsequent predictive model.

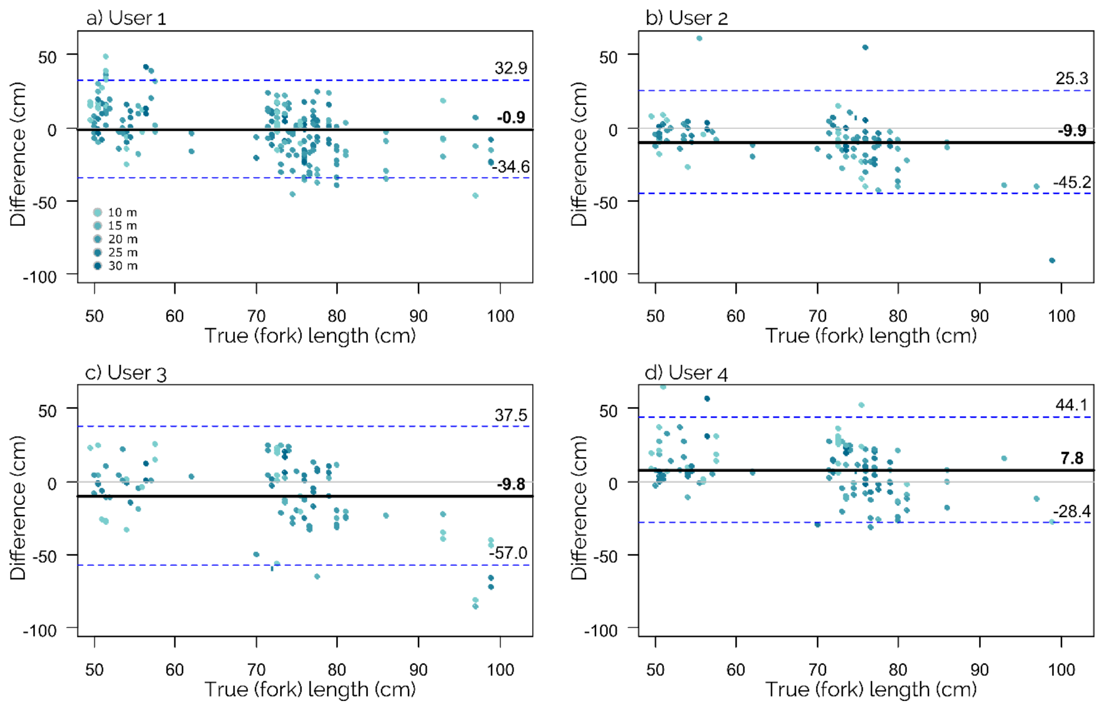

Figure 8. Bland–Altman difference plots for repeated measurements for human-generated data for User 1 (a), User 2 (b), User 3 (c) and User 4 (d). The y-axis represents the measurement difference (ARIS (estimated) length − observed (true) length) and the x-axis is the observed (true) length of adult Atlantic salmon. Colours indicate the distance of the observation from the ARIS transducer. The black line is the mean of differences, dashed lines show the limits of agreement and the grey line shows the no-bias (0) line for reference.

Similar to the human-generated measurements, the computer-generated measurements were variable, and the smallest difference between LOAs was 78.7 (EV3) cm and the largest was 119.0 cm (EV1) (Figure 9, Appendix A4). The Bland-Altman mean of differences was negative in all the datasets as most of the measurements were underestimations of the true length (Figure 9, Appendix A4). The mean of differences closest to zero was in the EV1 dataset (-20 cm; Figure 9, Appendix A4). The slope of an OLS fitted through the datapoints differed significantly from zero (One-sample test of major axis slope, *p*<.001), revealing a proportional bias in all the datasets. The repeated measures correlation test revealed no linear relationship (r<0.1) between measurement error and range (distance from the transducer) in four computer-generated datasets and a very weak positive relationship in the EV2 dataset (r(668)=0.11, p=.005).

The Intraclass correlation coefficient (ICC) indicated poor agreement in all the tests except computer-generated average and maximum lengths, where there was a moderate agreement. The ICC (and 95% CI) for all the datasets (53 subjects, 9 measurers, p<.001) was 0.36 (0.26-0.48) for the dataset with average fish lengths, 0.13 (0.06 – 0.23) for the dataset with minimum fish lengths, and 0.41 (0.3-0.53) for the dataset with maximum fish lengths. Between the human-generated datasets (53 subjects, 4 measurers, p<.001) the ICC was 0.34 (0.2-0.5) for average, 0.23 (0.10-0.39) for minimum, and 0.36 (0.22-0.51) for maximum fish lengths and between the computer-generated datasets (53 subjects, 5 measurers, p<.001) the ICC was 0.61 (0.50-0.73) for average, 0.39 (0.27-0.53) for minimum, and 0.59 (0.47-0.70) for maximum fish lengths.

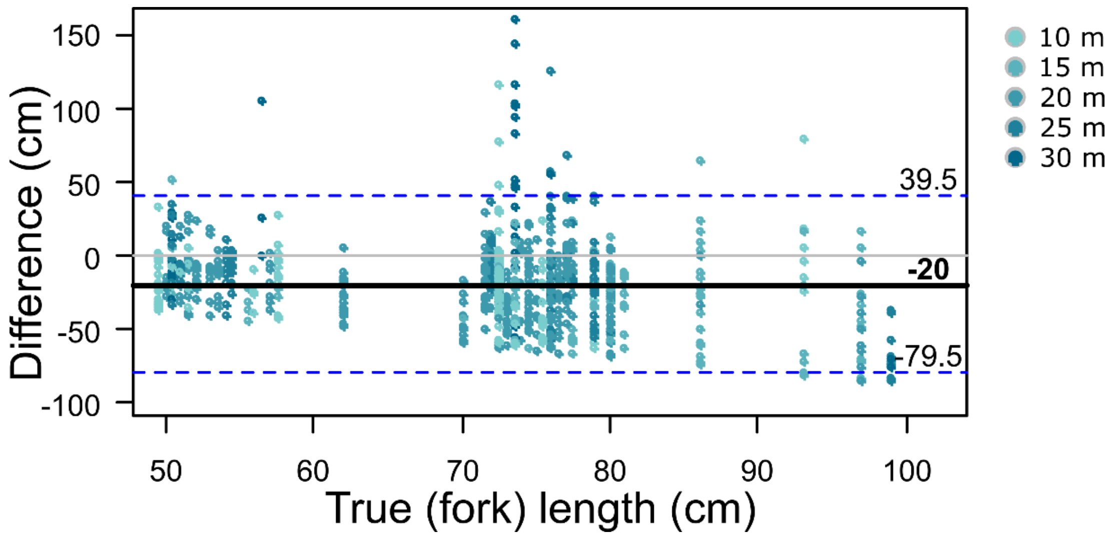

Figure 9. Bland–Altman difference plots for repeated measurements for the computer-generated EV1 dataset. The y-axis represents the measurement difference (ARIS (estimated) length − observed (true) length) and the x-axis is the observed (true) length of adult Atlantic salmon. Colours indicate the distance of the observation from the ARIS transducer. The black line is the mean of differences, dashed lines show the limits of agreement, and the grey line shows the no-bias (0) line for reference.

Size category attribution and length prediction model in Bayesian framework

In total, nine datasets (four human-generated and five computer-generated sets) were available for the modelling exercise. Of the five computer-generated datasets, the mean of differences closest to zero was in the EV1 dataset (Figure 9); it was therefore chosen for further analysis and only the EV1 outputs are presented (Table 4). All human-generated dataset outputs were retained in modelling exercise, however, outputs for only the best-performing dataset (User 4, Table 5) are presented to retain readability (Table 4); the modelling outputs for the other human-generated datasets are presented in Appendix A4.

Table 4. Summary statistics of the posterior distributions of the main parameters of the models obtained with the EV1 and User 4 datasets. See Table 2 for parameter descriptions.

Dataset	Parameter	mean	SD	2.5th	25th	Median	75th	97.5th
EV1	$\bar{L}^{1SW}$	52.54	0.93	50.7	51.92	52.55	53.17	54.36
	$\bar{L}^{MSW}$	78.41	1.11	76.3	77.64	78.38	79.14	80.66
	σ^L	0.08	0.01	0.07	0.08	0.08	0.09	0.11
	σ^R	0.55	0.01	0.53	0.54	0.55	0.56	0.57
	α_0	-2.49	0.88	-4.38	-3.06	-2.43	-1.87	-0.94
	α_1	-1.18	0.3	-1.83	-1.37	-1.16	-0.97	-0.66
	α_2	-0.27	0.14	-0.55	-0.36	-0.27	-0.18	-0.01
	α_3	-0.05	0.04	-0.12	-0.08	-0.05	-0.03	0.04
	β_0	1.09	0.32	0.45	0.88	1.1	1.31	1.69
	β_1	0.76	0.07	0.62	0.71	0.76	0.81	0.91
	β_2	-0.03	0	-0.03	-0.03	-0.03	-0.03	-0.02
	β_3	0.01	0	0	0	0.01	0.01	0.01
User 4	$\bar{L}^{1SW}$	52.73	0.84	51.08	52.18	52.73	53.29	54.36
	$\bar{L}^{MSW}$	77.94	1.02	75.98	77.25	77.92	78.6	79.99
	σ^L	0.08	0.01	0.06	0.07	0.08	0.08	0.09
	σ^R	0.2	0.01	0.18	0.2	0.2	0.21	0.22
	α_0	-0.59	0.34	-1.28	-0.81	-0.58	-0.36	0.06
	α_1	-1.77	0.38	-2.56	-2.01	-1.75	-1.51	-1.1
	α_2	-0.03	0.07	-0.16	-0.07	-0.03	0.02	0.11
	α_3	0.09	0.07	-0.04	0.04	0.09	0.14	0.24
	β_0	1.55	0.32	0.92	1.34	1.55	1.76	2.18
	β_1	0.62	0.08	0.47	0.57	0.63	0.67	0.77
	β_2	0.01	0	0	0	0.01	0.01	0.01
	β_3	0	0	0	0	0	0	0

There was a positive relationship between the observed ARIS measurements of fish length and the true length of the salmon used in this experiment ($\beta_1 > 0$) for both the EV1 and User 4 datasets. For the EV1 dataset, distance and the angular position in the sonar field had a negative effect on the ARIS length measurements; the fish were measured shorter at higher angles and longer ranges. For the User 4 dataset, distance from the ARIS had a significant but small (positive) effect on the ARIS length measurements.

For the EV1 dataset, the number of times a salmon was read as MSW (length ≥ 63cm) and the average distance at which the length measurements were made had a significant (95% of the posterior probability distribution < 0) negative effect on the probability of being a 1SW (Figure 10, Figure 11). While not significant at the 95% threshold, the interaction between the average distance and the number of times counted as an MSW was also negatively correlated with the probability of being a 1SW.

For the User 4 dataset, only the number of times a fish was measured as an MSW had a significant negative effect on the probability of being a 1SW; the distance from the transducer was not significant (Figure 10, Figure 11). However, the interaction between the number of times a fish was measured as an MSW and the distance had a negative effect, albeit not significant at the 95% threshold.

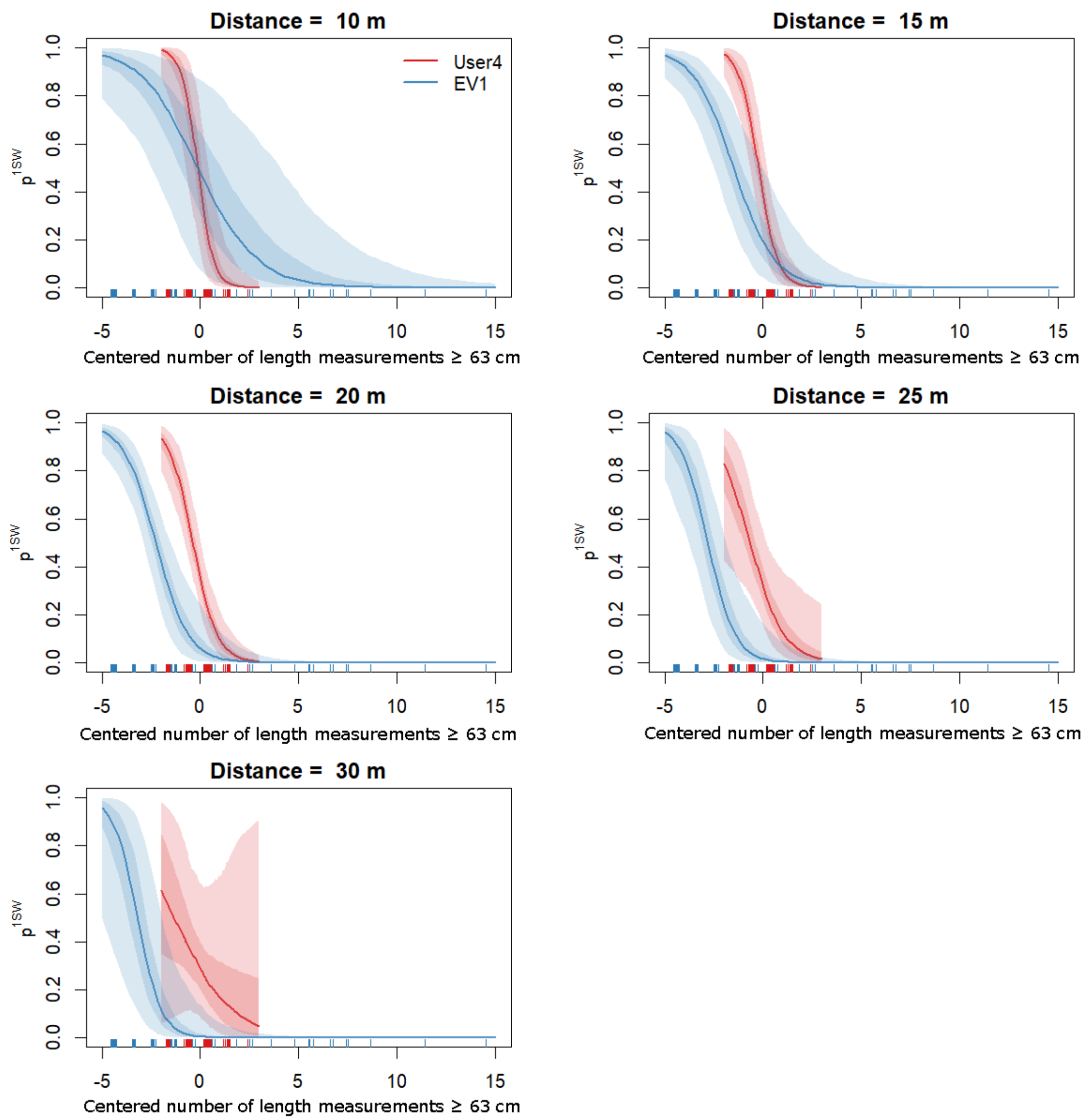

Figure 10. Probability of being a 1SW salmon (p^{1SW}) as a function of the (centred) number of MSW salmon length measurements (≥63 cm) at a fixed distance (10, 15, 20, 25 and 30 m) from the ARIS transducer. The red and blue solid lines correspond to the average relationships obtained with the User 4 and EV1 datasets, respectively, with the dark and light envelopes indicating the 25th–75th and 2.5th–97.5th credibility intervals in each dataset. The tick marks above the x-axis indicate the observed data in each dataset. Note: The human-generated dataset had significantly fewer observations than the computer-generated EV1 dataset. The best-performing datasets User 4 and EV1 were selected for graphical representation.

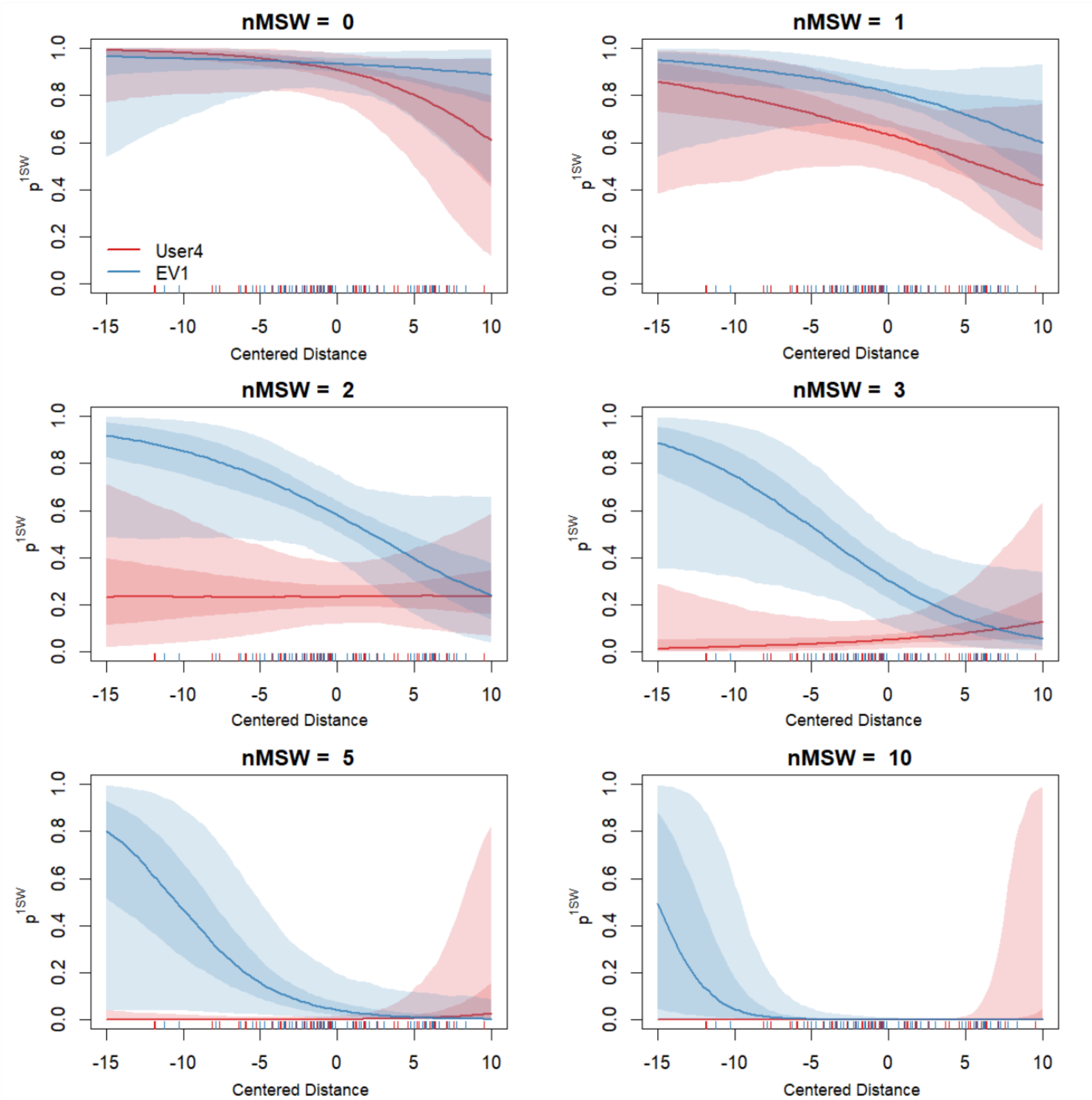

Figure 11. Probability of being a 1SW salmon (p^{1SW}) as a function of distance and a fixed number of MSW salmon measurements (n^{MSW} = 0, 1, 2, 3, 5, 10). The red and blue lines correspond to the average relationships obtained with the User 4 and EV1 datasets, respectively. The solid lines indicate the average relationship, the dark and light envelopes indicate the 25th–75th and 2.5th–97.5th credibility intervals. The tick marks above the x-axis indicate the observed data in each dataset. Note: The human-generated dataset had significantly fewer observations than the computer-generated EV1 dataset. The best-performing datasets User 4 and EV1 were selected for graphical representation.

Overall, the studentized residuals associated with the model's length prediction for User 4 and EV1 datasets were centred on zero (Appendix A4). However, in both datasets, 1SW and MSW lengths were consistently slightly over- and under-estimated, respectively (Appendix A4). This was likely a consequence of the mixture model: the probability of being a 1SW was rarely 0 or 1 and therefore the length predictions were often bimodal.

The mean of the predicted length was within ±5 cm of the true length in 21 (40%) and within ±10 cm of the true length in 35 (66%) fish in the EV1 dataset (Figure 12). The probability of being a 1SW (p^{1SW}) was > 0.50 in 90% of the 1SW fish, however, 21% of the MSW fish also had a > 0.50 probability of being a 1SW (Figure 12). In the User 4 dataset the predicted length was within ±5 cm of the true length in 23 (43%) and within ±10 cm of the true length in 38 (70%) fish (Figure 13). The probability of being a 1SW (p^{1SW}) was > 0.50 in 64% of the 1SW fish and 19% of the MSW fish (Figure 13).

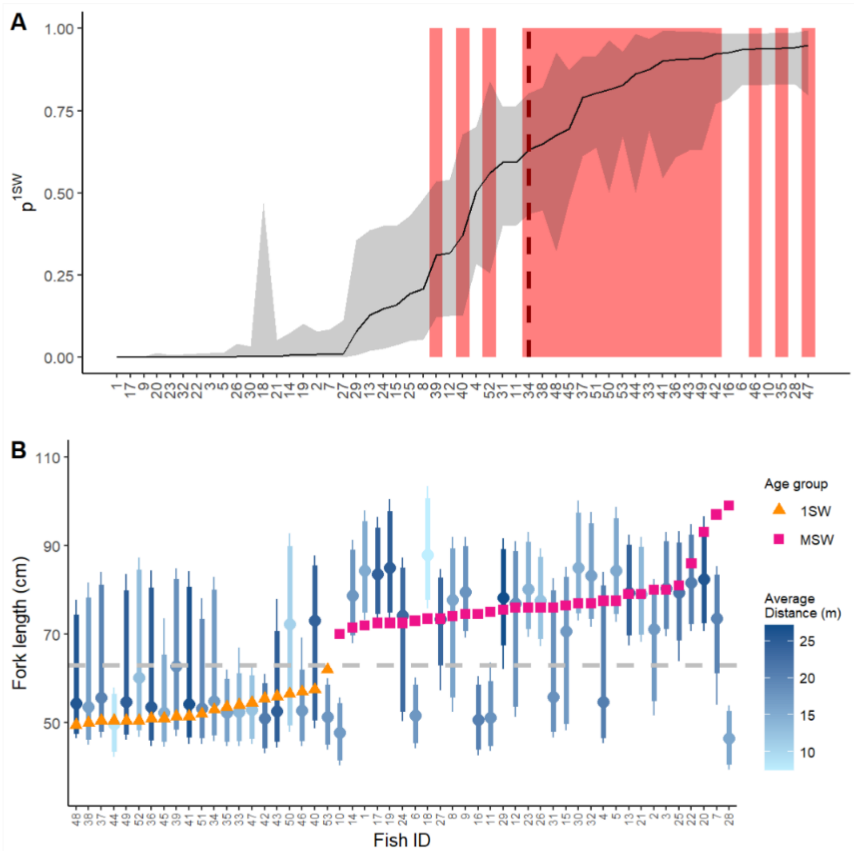

Figure 12. (a) Separation plot of the probability of being a 1SW salmon (p^{1SW}) based on the Bayesian predictive model in the computer-generated (EV1) length measurement datasets. The red polygons indicate known (true) 1SW salmon. The dashed vertical line indicates the total number of 1SW (on the right side of the line) and MSW (left side of the line) based on observed data, that is, if the model perfectly predicted size categories the area on the right of the line would be fully red. Salmon are arranged in ascending order based on the median of the posterior distribution of being a 1SW (black line; dark grey area represents the 2.5th–97.5th interquantile range). (b) Total length prediction (cm) for each fish based on the Bayesian model in the computer-generated EV1 length measurement dataset. Each box indicates the 2.5th–97.5th (thin line) and 25th–75th (thick line) interquantile ranges. The median value predicted by the Bayesian model is indicated by the circles while the triangles and squares indicate the true size of 1SW and MSW salmon, respectively. The shade of blue in each box plot indicates the average range (distance from the transducer), with darker shades representing increasing distance. The dashed horizontal line indicates the threshold size used to separate 1SW from MSW size categories (*i.e.*, 63 cm). Salmon are arranged in an ascending order based on the true fork length of the fish.

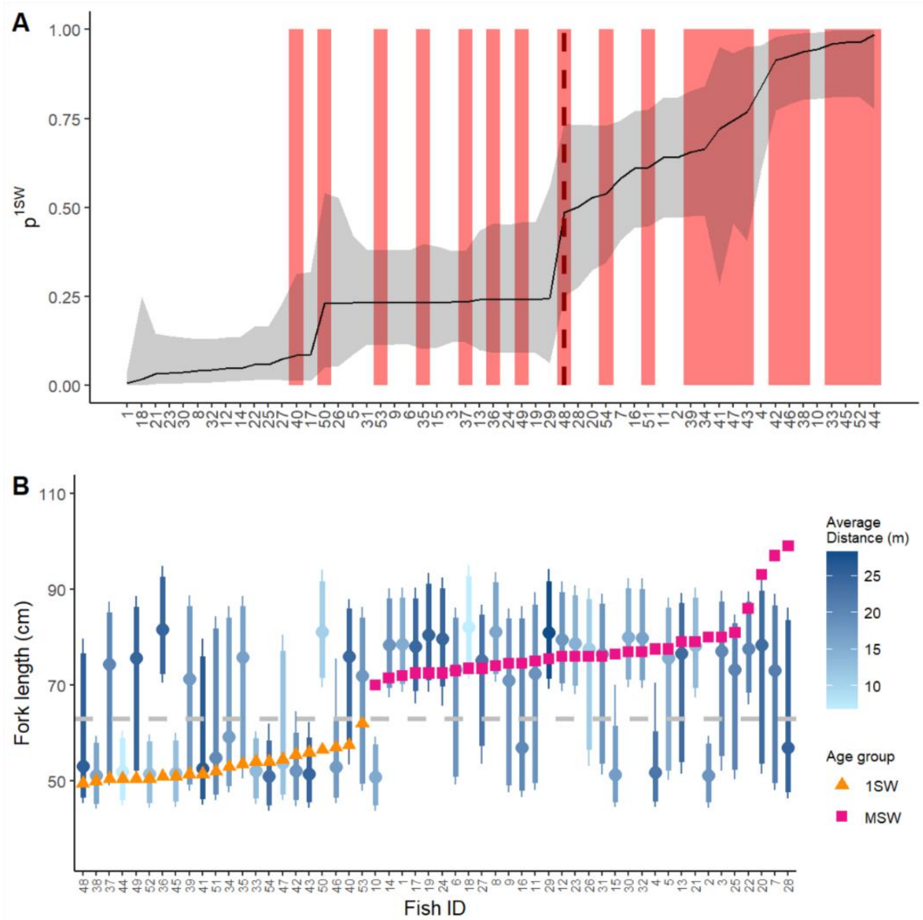

Figure 13. (a) Separation plot of the probability of being a 1SW salmon (p^{1SW}) based on the Bayesian predictive model in the human-generated (User 4) length measurement datasets. The red polygons indicate known (true) 1SW salmon. The dashed vertical line indicates the total number of 1SW (on the right side of the line) and MSW (left side of the line) based on observed data, that is, if the model perfectly predicted size categories the area on the right of the line would be fully red. Salmon are arranged in an ascending order based on the median of the posterior distribution of being a 1SW (black line; dark grey are represents the 2.5th–97.5th interquantile range). (b) Total length prediction (cm) for each fish based on the Bayesian model in the human-generated (User 4) length measurement dataset. Each box indicates the 2.5th–97.5th (thin line) and 25th–75th (thick line) interquantile ranges. The median value predicted by the Bayesian model is indicated by the circles while the triangles and squares indicate the true size of 1SW and MSW salmon, respectively. The shade of blue in each box plot indicates the average range (distance from the transducer), with darker shades representing increasing distance. The dashed horizontal line indicates the threshold size used to separate 1SW from MSW size categories (*i.e.*, 63 cm). Salmon are arranged in an ascending order based on the true fork length of the fish.

The final model categorized 83% of the salmon in the right size category in the computer-generated EV 1 dataset (19/21 of 1SW and 25/32 of MSW, Table 5). The human-generated datasets had classifying accuracy ranging from 68% to 74%. The highest accuracy was in User 2 (21/22 of 1SW and 19/32 of MSW, Table 5) and User 4 datasets (14/22 of 1SW and 26/32 of MSW, Table 5). When compared to baseline models where the size category was predicted by using only the mean, median, minimum, and maximum values derived from raw data without any modelling, the selected model consistently provided better (or equal) categorization capability than any of the baseline models (Table 5). For three of the human-generated datasets (Users 1–3), one of the baseline models produced similarly good prediction result as the predictive model (Table 5), while the predictive model produced more accurate categorization capability than any baseline model for the dataset generated by User 4 (Table 5).

Table 5. Absolute number and percentage of correct assignments of salmon as either 1SW (<63 cm) or MSW (≥ 63cm) using the Bayesian model and four different baseline metrics (*i.e.*, length measurement data extracted by users or Echoview algorithm from raw ARIS footage). The metrics were separately calculated for the computer-generated Echoview 1 (EV1) dataset (n=53) and human-generated datasets (User 1-4; n=54). The model with best capability to correctly assign size category are highlighted with grey colour for each dataset.

	Predictive Model	**Mean length**	**Median length**	**Minimum length**	**Maximum length**
Echoview 1 (EV1)	***44 (83 %)***	29 (55 %)	28 (53 %)	21 (40 %)	36 (68 %)
User 1	***38 (70 %)***	***38 (70 %)***	37 (68 %)	28 (52 %)	35 (65 %)
User 2	***40 (74 %)***	38 (70 %)	37 (68 %)	32 (59 %)	***40 (74 %)***
User 3	***37 (68 %)***	34 (63 %)	34 (63 %)	30 (55 %)	***37 (68 %)***
User 4	***40 (74 %)***	39 (72 %)	39 (72 %)	38 (70 %)	39 (72 %)

2.4 Discussion

Measurement accuracy and consistency of measurers

Although many studies have been previously conducted testing the measurement accuracy of imaging sonar using short ranges (Burwen *et al.*, 2007; Cook *et al.*, 2019; Daroux *et al.*, 2019; Grote *et al.*, 2014; Gurney *et al.*, 2014; Hightower *et al.*, 2013; Tušer *et al.*, 2014), there is often a need to use ARIS in longer (> 15 m) ranges in fisheries management (Hakkola, 2011; Lilja *et al.*, 2011; Lin *et al.*, 2016; Valjus *et al.*, 2017). To our knowledge, this study is the first to investigate the length measurement accuracy of an ARIS imaging sonar using 1.1 MHz frequency at ranges up to 29 m with free-swimming fish.

Overall, direct length measurements either by various users or by semi-automated computer algorithm were variable and resulted in deviations from the true length of the salmon. The means of differences varied between -9.9 cm and 7.8 cm in the human-generated datasets, and between -42.8 cm (EV3) and -20 cm (EV1) in the computer-generated dataset. The smallest difference in the estimated LOAs was 67.5 cm in the human-generated datasets and 78.7 cm in the computer-generated datasets. In all datasets except the User 4 data, the measurements extracted from the sonar imagery were generally underestimating the true fish lengths. This was especially evident in the computer-generated data where the majority of the measurements for individual salmon were underestimations, as the computer mechanically, and without observer-bias, takes length measurements from every recorded frame irrespective of fish's position in the frame. The difference in the accuracy found in this study and in results found in a previous study (Lilja *et al.*, 2010) that compared the length distributions produced from long range (up to 80 m) DIDSON and angling catch size distribution is notable; they concluded that the DIDSON lengths were approximately 5 – 10 cm shorter than the true lengths of the fish. This indicates that although the error is large in individual measurement, a fish length distribution can be produced using a large sample size and potentially used in population estimates.

Similarly to a previous study (Burwen *et al.*, 2010), proportional bias was found in all datasets, indicating that the measurement error increased as the length of the fish increased. However, as shown previously, plotting the difference against a "gold-standard" may show a relationship between difference and magnitude even when there is none (Bland and Altman, 1995). We chose to use the true length as x-axis (Krouwer, 2008) because 1) the difference in the individual measurements was large; 2) because the true length used herein (*i.e.*, fish length physically measured by manual means) can be considered a "gold standard"; and 3) a "gold standard" made comparison between datasets possible.

The intraclass correlation coefficient indicated a generally poor agreement among the datasets. This was the case for all the human-generated datasets, and the correlation was moderate in two of the computer-generated tables that were calculated using average and maximum fish lengths. Thus, contrary to our hypothesis, the length measurements of different fish by different users and automation methods were not in a high agreement. A clear inter- and intra-observer error has also been reported previously (Daroux *et al.*, 2019; Hakkola, 2011; Keefer *et al.*, 2017). Therefore, it is recommended that the measurement errors for different methods are tested at the beginning of each monitoring program to ensure the comparability of the length results. Also, it is currently unknown if the measurement error changes over time as the users develop their analysing skills. The importance of quality control assessment has also been highlighted in previous studies (Keefer *et al.*, 2017; Tušer *et al.*, 2014).

Although the workflows used for producing computer-generated datasets were similar, they still produced different length readings and were either in a poor or at best moderate agreement with each other. This finding is of relevance in monitoring studies where changing environmental conditions may prompt practitioners to change workflows within a monitoring season. However, based on the findings herein, it is recommended to retain the same workflow throughout the monitoring season to keep the measurement error constant throughout the study. Changes in *e.g.*, fish density or flow conditions has been shown to result in variable measurements in other studies (Helminen *et al.*, 2021; Helminen and Linnansaari, 2021), but changes in the protocol can also introduce new errors in the study. Therefore, if possible, the measurement accuracy should be assessed in different conditions and applied into the monitoring dataset.

Data quality assessment and influence of range on the measurement accuracy

The quality of most of the fish echoes was deemed low and only 10% of the measurements were classified as good or very good by the users. There was no significant difference between the accuracy of the length measurements irrespective of the quality-rating of echoes in two of the four users, and where a difference was found it was not systematic or consistent as a function of improving the length measurement accuracy. The quality-rating did not provide useful information in this dataset to improve length prediction on long-range ARIS footage and therefore, it was not used in our predictive model.

In the raw sonar footage, the sonar image was clear throughout the whole range, and although some deeper areas were unavoidable in the ranges >24 m, length measurements were made throughout all ranges and no "blind-spot" was identified. Therefore, it was somewhat unexpected that two fish in human-generated data and three fish in computer-generated data (representing 4-5% of all upstream moving salmon in this study) could not be seen in the footage although they were seen (by a human observer) going upriver during data recording. The overall low quality of the echoes and number of fish not seen in the image warrants further research on the accuracy of fish counts produced using imaging sonars using similar ranges (between 15 and 29 m) in field studies.

We hypothesized that the length measurement accuracy would decline as the distance from the transducer increased, but there was no or only a weak correlation between the measurement accuracy and range in eight of the nine datasets. However, the distance of the ARIS measurement from the transducer was still used in the Bayesian model as it improved the prediction capability (a positive effect on the length measurement in the User 4 dataset; a negative effect on the length measurement and on the probability of being a 1SW in the EV1 dataset). Many previous studies have reported that there is no range dependency in the accuracy of the length estimates using high frequency mode and a shorter range (Burwen *et al.*, 2010; Daroux *et al.*, 2019; Gurney *et al.*, 2014; Hightower *et al.*, 2013). Burwen *et al.* (2007) found no range-dependent bias on free-swimming fish but found it on tethered fish, and had a lower measurement accuracy on tethered fish. Similarly, Tušer *et al.* (2014) reported range-dependency on the measurement accuracy of stationary anesthetised fish. Based on the previous studies and our finding, the distance can have an effect on the measurement but other factors, such as noise and fish movement, are likely causing more variation in the measurements, therefore decreasing the effect.

Bayesian model outputs

Since the length measurement accuracy was generally variable, a model was built to predict if a salmon was a 1SW (< 63 cm) or MSW (≥ 63 cm) based on the sonar data. The model correctly categorized 83% of the salmon in the best-performing Echoview dataset, and 68% to 74% of the salmon in the human-generated datasets. Compared to the baseline models that used either mean, median, minimum, or maximum lengths to determine if a fish was 1SW or MSW, the Bayesian model provided consistently the best size category discrimination. For the Echoview dataset, the model correctly predicted the size category of eight more salmon (83% of all salmon) than the best baseline model (using maximum length; 68% of all salmon), and therefore improved the computer-generated dataset. For the human-generated data, the benefit of using the model was not as straightforward. On the User 4 dataset, the most accurate predictions were made with the Bayesian predictive model (74% for Bayesian model *vs*. up to 72% for baselines models). For the three other users (1, 2, and 3), one of the baseline metrics predicted accurately the size category of a similar number of salmon as the Bayesian model. However, the baseline metric that resulted in a similar categorization result as the Bayesian model was not consistently the same between users, and in practice (*i.e.*, when no validation dataset is available to compare true lengths vs measured lengths from sonar data), there is no way to know which baseline metric would yield the best result for the given user. Therefore, use of the Bayesian model is recommended despite apparently similar performance in some baseline models in the human-generated data.

Lengths that were predicted for each fish using only the ARIS readings were overall centred on zero. However, the MSW lengths were consistently slightly overestimated and 1SW lengths underestimated. This is likely a result of the underlying mixture model. The mean of the predicted length was within ±5 cm of the true length in 40% of the fish in the computer-generated dataset (EV1) and in 43% of the fish in the human-generated dataset (User 4).

For the computer-generated dataset, the probability of being a 1SW was smaller the more times a fish was measured as an MSW fish and the farther it was measured. The interaction of these two variables also had an effect, although it was not significant on 95%

threshold. For the human-generated dataset, only the number of times the fish was measured as an MSW had significant effect in the probability of being a 1SW. For both human and automated datasets, the probability of being a 1SW was very high when there were zero or only one ≥ 63cm measurements; as the number of ≥ 63cm measurements increased, the probability of being an MSW fish also increased. For the human-generated dataset the relationship became less clear at distances > 20m, and the probabilities became more uncertain. On the contrary for the computer-generated dataset, the relationship between the probability of being a 1SW fish and the number of measurements ≥ 63cm was more uncertain at shorter distances (< 15m). This result probably stems from the fact that several 1SW salmon were measured at length ≥ 63cm and only few MSW salmon were not measured at length ≥63cm from the ARIS footage in our datasets.

Although the length measurements derived directly from long-range imaging sonar data should be used with caution, the Bayesian modelling approach reported herein can improve the efficiency in specific cases such as Atlantic salmon monitoring programs. The modelling approach improved the size categorization most in the computer-generated data where the fish was measured in each frame and thus multiple measurements were created rapidly. Therefore, it is practical to use the number of measurements as a predictor for size class. Manual measurements are more laborious and recording multiple measurements for each fish is time-consuming and thus, impractical in larger monitoring studies.

Future considerations and research

The current study used only the basic ARIS Explorer 1800 with a rotator and utilized the automatic software recording settings. Data collection may be improved in other study sites with additional equipment such as variety of lenses and by adjusting settings (*e.g.*, focus, detail, frame rate) manually. As an example, a high-resolution lens may provide higher resolution at longer distances, but will also decrease the width of the beam, making detection at short distances more difficult (Burwen *et al.*, 2010). Naturally, the sonar image can be processed using different methods than presented here. Improvements to measurement accuracy may be achieved, for example, by using different background subtraction method or by adding other operators in Echoview, such as 3x3 median that has been used previously (Kang, 2011). Although other image processing methods can be considered to change the measurements, the measurement accuracy presented here is ultimately based on the recorded sonar feedback and therefore, provides a good baseline for any study that uses automated length measurements with similar sonar data.

While it was not the focus of this study, there were differences in the measuring techniques in human-generated datasets, which may have introduced differences in the measurement accuracy. The mean of differences was lowest in the two datasets (Users 1 and 4) where the fish were measured using multiple clicks rather than a straight line. Additionally, the mean of differences was farthest from zero in the dataset where the measurements were made using the background subtraction (User 2).

The computer-generated dataset that linked objects from 0.5 m distance produced average measurement error closer to zero than other versions that linked the objects from only 0.2 m away and probably did not correctly include the whole fish echo in the target. However, increasing the linking distance is only possible in cases where the acoustic noise is minimal and when fish do not swim close to each other. While this may the case in many Atlantic salmon rivers where the absolute density (frequency) of fish is generally low, other fish species, such as Pacific salmonids (*Oncorhynchus spp.*) can return to river in large numbers over a short time period (Cronkite *et al.*, 2006; Lilja *et al.*, 2008) thus limiting the use of linking distance.

2.5 Conclusions

Overall, the computer-generated and human-generated measurements were variable, *i.e.*, sonar measurements of a fish of a given length resulted in a wide range of measurements that were poorly-moderately repeatable within and between readers. Contrary to our expectations, the distance from the transducer or subjectively assessed echo quality did not have a significant effect on the measurement accuracy. Overall, we conclude that fish length measurements derived from long-range imaging sonar data should be used with caution, especially if little post-processing is done. Post-processing can improve the accuracy of interpretation for specific questions. In this particular case, a model was successfully created for Atlantic salmon population management purposes to predict the status of migrating salmon as either One-Sea-Winter or Multi-Sea-Winter size category, which is of significant management utility. The model correctly predicted the size category in 83% of the fish in the computer-generated dataset and 68% to 74% in the human-generated datasets. While the combined imaging sonar and modelling approach can improve population management, the prediction accuracy will need to be considered in management decisions; are the accuracies (whether the length measurements or the size class prediction) presented here enough considering the population-specific statistics and management needs?

2.6 Authors’ contributions

Conceptualization: J.H., G.J.R.D, and T.L, Formal analysis: J.H and G.J.R.D, Methodology: J.H. and G.J.R.D, Supervision and funding acquisition: G.J.R.D and T.L., Writing, original draft: J.H and G.J.R.D, Writing - review and editing: J.H, G.J.R.D, and T.L.

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3. Object and behavior differentiation for improved automated counts of migrating river fish using imaging sonar data

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Abstract

Imaging sonars, such as the Adaptive Resolution Imaging Sonar (ARIS; Sound Metrics Corp.) produce continuous stream of sonar video footage, and they are commonly used for counting and sizing migrating fish in rivers. Although automated methods have been developed for processing imaging sonar data, manual analysis of the data is still common in fish population monitoring projects. In this study, we used Echoview software to automatically produce fish counts from long-range (up to 30 m) imaging sonar data in a prominent Atlantic salmon (*Salmo salar*) river; the Little Southwest Miramichi River, New Brunswick, Canada. We added postprocessing steps to address sources of error that have been reported in previous studies: 1) Major Axis Distance was used to filter out erroneous fish tracks (89 % of dynamic noise and 67 % of milling fish in the test-set) and to calculate the swimming direction (96 % correct), and 2) a logistic regression (target length, average speed, and absolute fish track change in range) was used to predict downstream moving fish from other objects with a test-set accuracy of 84 %. When 15-min tally counts were compared between computer-generated data and multiple human-generated counts, the mean of differences varied between -39 % and 65 % in the upstream counts in different datasets, and different analysing methods were in a good agreement between each other (ICC=0.79). There were larger differences in the downstream counts where the mean of differences varied between 14 % and 115 % and there was no agreement between the datasets (ICC=0.03). With a double-tracking method where the fish are tracked twice, the computer analysed the 24-hour datasets in 500 to 600 minutes and was slower than human-generated counts that required 200 to 600 minutes, however, computer generated-counts

can be derived in the background without the presence of a technician and may produce significant savings in personnel cost.

3.1 Introduction

Multibeam imaging sonars, such as the Adaptive Resolution Imaging Sonar (ARIS, Sound Metrics Corp.; www.soundmetrics.com) and the Dual-frequency IDentification SONar (DIDSON; Sound Metrics Corp.), are commonly used for monitoring migrating fish in rivers (Baumgartner *et al.*, 2006; Lagasse *et al.*, 2017; Martignac *et al.*, 2014). They produce high-resolution underwater sonar video footage without source of light (*i.e.,* work overnight and in turbid waters), and the fish can be counted and measured from the footage (Martignac *et al.*, 2014; Moursund *et al.*, 2003).

While sonars allow for rapid monitoring of migrating fish populations in rivers, analysing the sonar footage is still a laborious task (Boswell *et al.*, 2008; Martignac *et al.*, 2014). The footage is typically analysed manually by users, either by using tally counters while watching the video (Faulkner and Maxwell, 2015; Hateley and Gregory, 2006), or by using a software to count and measure by drawing a line along the body of each identified fish (Cronkite *et al.*, 2006; Lilja *et al.*, 2010; Martignac *et al.*, 2014). Different data sampling methods are also used to reduce the amount of data analysed (Lilja *et al.*, 2008; Petreman *et al.*, 2014).

Automated and semi-automated data processing tools have been used to process the sonar files, and they have the potential to reduce costs by generating fish counts with significantly fewer user interactions than manual counting (Boswell *et al.*, 2008; Eggleston *et al.*, 2020; Han *et al.*, 2009; Handegard and Williams, 2008; Kang, 2011; Kupilik and

Petersen, 2014a; Petreman *et al.*, 2014). Kang (2011) presented a template for semiautomated analysis using Echoview software that can be applied to new research, and cautions that parameter settings must be tailored to the characteristics of the data and research aim. The basic outline of the process is subtraction of the stationary background, tracking moving objects, filtering, and calculation of properties from the echoes (Boswell *et al.*, 2008; Kang, 2011). Building the basic workflow in Echoview is possible without programming experience, but the same operations can be implemented in other software (Boswell *et al.*, 2008). Similar algorithms have been used in other studies, but different approaches are used in some of the necessary steps due to differences in research aims and software (Han *et al.*, 2009; Handegard and Williams, 2008; Kang, 2011). As an example, Handegard and Williams (2008) used MatLab (The MathWorks Inc.; www.mathworks.com) to track fish in trawls and Han *et al.* (2009) developed their software for counting and sizing farmed Yellowtail (*Seriola quinqueradiata*). The same methodology can be applied to other imaging sonars as well (Kang, 2011).

The Echoview approach has since been utilized and tested in fish migration studies (Faulkner and Maxwell, 2015; Jones and Petreman, 2015; Petreman *et al.*, 2014). The correlation between manual and semi-automated approach varied between datasets and was highest in the footage where short range was used and the image quality was high with no visible surface noise while the auto-processing performed very poorly in the dataset with longest (40 m) range (Faulkner and Maxwell, 2015). Fish density also has an effect, and high density of large fish observed at close range was found to cause the greatest disagreement between manual and automated tracking (Handegard and Williams, 2008). Compared to different sampling methods, automation-assisted subsampling was found to be the most cost-effective means to estimate the number of migrating fish in rivers (Petreman *et al.*, 2014). However, Peterman *et al.* (2014) report that the automatically produced numbers of downstream moving fish were highly inaccurate, especially because other downstream-moving objects, such as detritus and leaf-litter, are counted. Sources of error for the automated counts also include milling fish (*i.e.*, fish remaining in the sonar field for extended periods of time), gravel bars, and mobile sediment that can cause the software to count the same fish multiple times (Petreman *et al.*, 2014). A similar problem can occur in a case when a fish turns directly toward or away from the imaging sonar: a change in aspect angle reduces the amount of reflected energy and produces a poor image, and the fish may be detected only intermittently (*i.e.*, fish sometimes being lost from view), which makes it more difficult for the tracking algorithm to keep track of the fish, and subsequently resulting in the software to count the fish multiple times (Belcher *et al.*, 2002; Kang, 2011).

In this study, the automated data analysis method in Echoview (Kang, 2011) is adopted for analysing 1.1 MHz ARIS Explorer 1800 sonar data collected using the whole river width of approximately 30 m in the Little Southwest Miramichi River, New Brunswick, Canada. The aim of the study is to produce an accurate count of the number of fish passes through the sonar beam with fewer human interactions (*i.e*., more efficiently) than manual counting. To achieve this, the objectives were to predict if a fish is moving up- or downstream and to remove erroneous fish tracks using the Echoview summary tables; predict if a downstream moving object is a fish; and finally, to produce timely fish counts of similar accuracy and processing time to fish counts produced manually from sonar footage. We hypothesized that the computer-generated counts are similar to human-generated counts of up- and downstream moving fish; that the computer-generated and multiple human-generated fish counts are in agreement with each other; and computer-generated counts can be produced faster than human-generated counts.

3.2 Materials and methods

Data collection and datasets

The data were collected as a part of an Atlantic salmon (*Salmo salar*) monitoring project using an imaging sonar (ARIS Explorer 1800 with a standard 14° lens), Sound Metrics Corp.; www.soundmetrics.com) at a fixed location near the mouth of the Little Southwest Miramichi River (known by local Mi'kmaq as Tuadook), New Brunswick, Canada (46.957673, -65.860730). The sonar was set aiming across the river using 1.1. MHz frequency and the range was set to cover the whole river width of approximately 30 m (Table 6). Autofocus was used and the sonar automatically sets the sound velocity parameter based on water temperature (Table 6). The ARIS sonar uses 16 active channels to receive, and therefore the number of transmit-receive periods (pings) per each frame is six in 96-beam mode (Sound Metrics Corp., 2019) *i.e.*, the ARIS images (*e.g.*, 2.7 and 4.4 frames per second) are not true snapshots in time but composites built over a series of transmit-receive cycles. This reduces cross-talk between adjacent beams and reduces the energy consumption (Belcher *et al.*, 2002) but also makes the images susceptible to motion artifact. The beam spreading makes the acoustic beams wider with increasing distance from the transducer, thus the resolution is range-dependent and highest close to the transducer.

Common fish species in at the study site are Atlantic salmon, American eel (*Anguilla rostrata*), Striped bass (*Morone saxatilis*), American shad (*Alosa sapidissima*), white sucker (*Catostomus commersoni*), alewife (*Alosa pseudoharengus*), and blueback herring (*Alosa aestivalis*) (Hayward *et al.*, 2014). All these fish species are commonly > 30 cm in length and exhibit seasonal migrations along the river corridor.

Two different full-day (24 hours) datasets (Table 6) were used for developing and testing the automation in Echoview (9.0.19) sonar data processing software. The automation was developed using dataset 1 that was collected on September 29th 2018 and then same automation was tested without any adjustments using the dataset 2 from the previous year on June 22nd 2017 (Table 6). A different year was used to test if the automation can be used to analyse footage collected in different monitoring years and conditions.

Table 6. The dates, water temperature, and settings (range, frame rate, detail, and focus) used in the ARIS in the two datasets.

Dataset	Date	Water temp. (°C)	Sound velocity (m/s)	Range (m)	Frame rate (fps)	Detail (samples / beam)	Focus (m)
Dataset 1	29 September 2018	11	1449	1.46 – 27.52	2.7	2568	22.30 (auto)
Dataset 2	22 June 2017	21	1484	1.32 – 27.32	4.4	1208	19.88 (auto)

Automation parameters

Following the workflow presented by Kang *et al.* (2011), a fish target echogram was created from the raw sonar data in Echoview where the fish were tracked using Echoview's fish tracking algorithm to produce a count of upstream and downstream moving fish. A multibeam "target" in Echoview is a cluster of data points (*i.e.*, echoes) that meets specified value and size thresholds, and is assumed to represent a cross-section of an individual object (*e.g.*, a fish or other object with a density sufficiently different to that of the surrounding water) at a given point in space and time (Dunlop *et al.*, 2018). The parameters for each operator were tested and selected visually, and additional steps were introduced to improve the fish count. The initial testing was done using the first hour of the dataset 1 and then applied to both datasets.

The workflow (Figure 14) in Echoview consists of four operators that were used to process the imagery in the following order:

1. Multibeam background removal operator (Figure 14b) was used to calculate and remove the static background using the mean of 15 pings around the current ping and to subtract the background from each ping using a minimum Signal-to-noise-ratio 11.00 dB as a threshold.
2. Cluster detection operator (Figure 14c) generated multibeam targets from groups of adjoining datapoints in multibeam data (Echoview, 2018), *i.e.*, during this step, fish targets are generated from echoes at each frame. Seed threshold of 200 cm^2, satellite threshold of 10 cm^2, and link distance of 0.4 m were used and linking satellite clusters was allowed.
3. Length Filter (Figure 14c) was used to remove targets shorter than 10 cm using the target property threshold operator. This was done to remove noise in the imagery. Because the length measurements are very variable in the long-range imaging sonar data (Helminen *et al.*, 2020), the threshold was set very low so that the fish are tracked throughout the sonar beam.
4. Target conversion (Figure 14d) was used to convert multibeam targets to single target data that allows the use of Echoview fish tracking feature (Echoview, 2018).

Next steps in the workflow involved the creation of fish tracks. The fish tracking algorithm in Echoview is an alpha-beta tracker that implements a fixed coefficient method that selects single targets as candidates for appending to a track (Blackman, 1986;

Echoview, 2018). The user can select sensitivity to unpredicted changes in position and velocity, minimum number of single targets and pings, and maximum gap between single targets (Echoview, 2018). The aim of fish tracking is to combine all targets from each fish to a single track and export the number of fish and combined information of each fish in a track as an outcome.

In initial tests, a problem similar to described in Petreman *et al.*(2014) was encountered where the fish was not trackable throughout the whole time it was in the beam. The fish tracking algorithm therefore either counted one fish multiple times, or, if the user selected settings where longer breaks in fish track were allowed, started to track multiple fish as the same fish (Petreman *et al.*, 2014). To overcome these challenges, a double-tracking procedure (A.-M. Mueller, Aquacoustics, personal communication) was executed where the fish tracks were first created using settings that allowed short fish tracks and less change in the position. The original data were then masked using the first tracking round (Figure 14d), thus resulting in a cleaner dataset. Another round of fish tracking was then used in the cleaned dataset, but this time allowing longer breaks in the fish tracks and larger change in the position (Figure 14e); due to the overall low-quality of the fish echoes and high amount of noise, many of the real fish targets were filtered out in the previous steps, causing the need for long missed-ping expansion. Thus, the next steps of the workflow included:

5. Fish tracking 1st round (Figure 14d, see also Appendix A5).
6. Masking using tracks from 1st round (Figure 14e).
7. Fish tracking 2nd round (longer missed-ping expansion and longer maximum gap between single targets, (Figure 14e, Appendix A5).

The created fish tracks were then exported from Echoview as .csv tables that included track summaries and information of individual targets in each track. The duration of the analysis was recorded using Echoview reports for fish tracking and exporting the files.

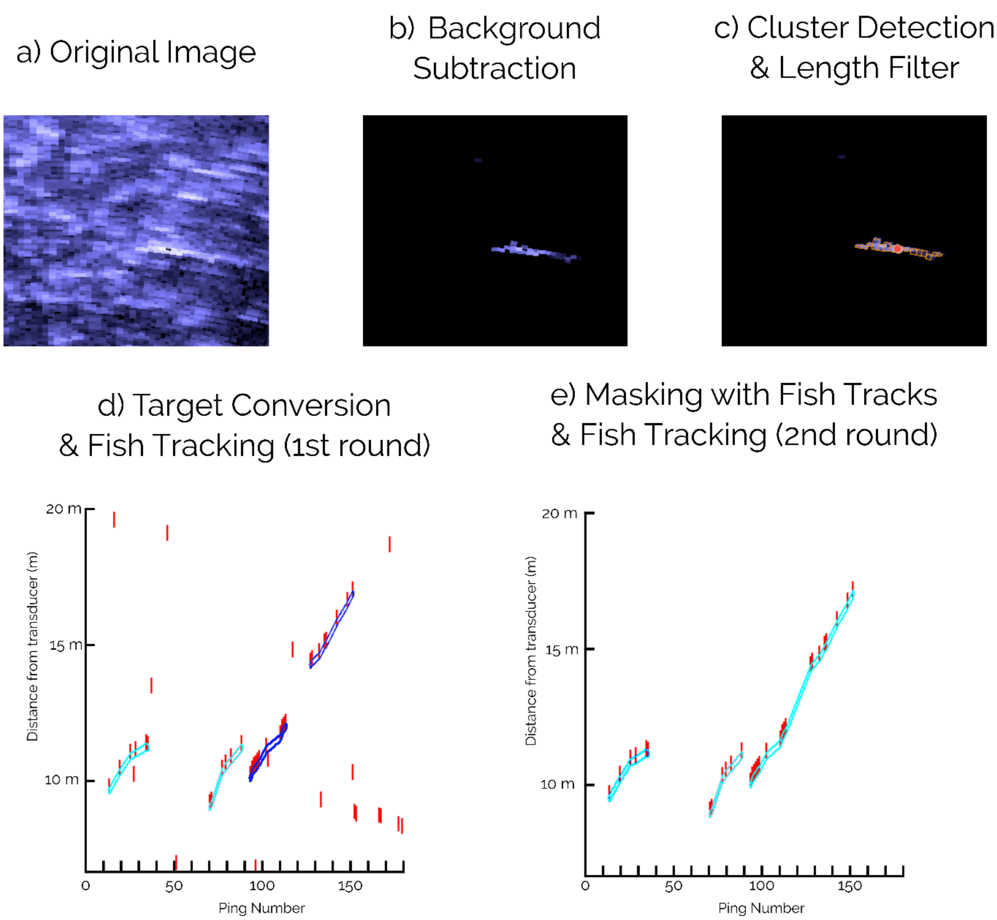

Figure 14. Workflow for image processing and fish tracking in Echoview. The background is subtracted (b) from the original image (a). Cluster detection is used to detect fish in the image and shortest clusters (<10.00 cm) are removed (c). Target conversion is used to allow fish tracking algorithm (d) where short tracks are created in the first round to prevent false tracking: the two light blue tracks are true fish tracks, the two dark blue tracks are incomplete fish tracks generated by one individual fish, and red lines outside the fish tracks are noise and potential source for false tracking. The fish tracks from the first round are used to mask the original data, and second fish tracking round is used to create three complete fish tracks (e).

Direction calculations & filtering of milling fish and dynamic noise

Echoview calculates the direction of a fish target using the angle of a line between the first and the last target in the track as a default. Because we were only interested if the targets were moving up- or downstream, we calculated the direction directly using change in Major Axis Angle (Figure 15). For each frame in the fish track, Echoview exports the angle values as angle difference from the center beam (0°) and it is calculated for the geometric center of a target (Echoview, 2018). To make all values continuous and positive, we added 14° (half of the 28° horizontal field-of-view) to all the major axis angle (MAA) values. A new variable (Major Axis Distance, MAD) was then calculated by subtracting the 14+MAA value of the last target of the fish track from the first target of the fish track as follows:

$MAD = (14 + MAA_{i=1}) - (14 + MAA_{i=nframes})$ || Where *i* is the frame number.

The up- or downstream direction is defined based on the sign (*i.e.*, positive or negative) of the MAD value; in this study, values > 0° represent downstream movements (Figure 15AB) and values < 0° represent upstream movements (Figure 15EF). Opposite signs are recorded if the sonar is placed on the other side of the river.

When a fish is successfully tracked through its whole pass in the sonar field, only one fish track is created. However, if the computer cannot track the fish throughout the whole pass, it starts new tracks and thus, creates multiple counts of the same fish. A total of 465 tracks in the dataset 1 were analysed by watching the raw footage and the fish tracks were manually classified as dynamic noise (*i.e.*, caused from a rock creating turbulence, n= 81), milling fish (not moving fish, n=75), and tracks that were created from real objects (fish or non-fish, n=309). When a fish created multiple tracks (by *e.g.*, turning and changing position quickly or milling), the longest track was chosen in the "real objects" category and the other tracks were discarded in the milling fish category. The MAD value of the fish tracks was then compared graphically, and the 5th percentile of the real objects class and 95th percentile of the two other groups were calculated to find a threshold between real objects category and the two other categories.

The identified threshold value was used to filter the tracks by removing all fish tracks with MAD value lower than the threshold. The direction (upstream or downstream) of the rest of the tracks was analysed by watching the raw footage and the sign of the MAD-value of each of the tracks (Figure 15) was compared to the human-defined up- or downstream direction of the track.

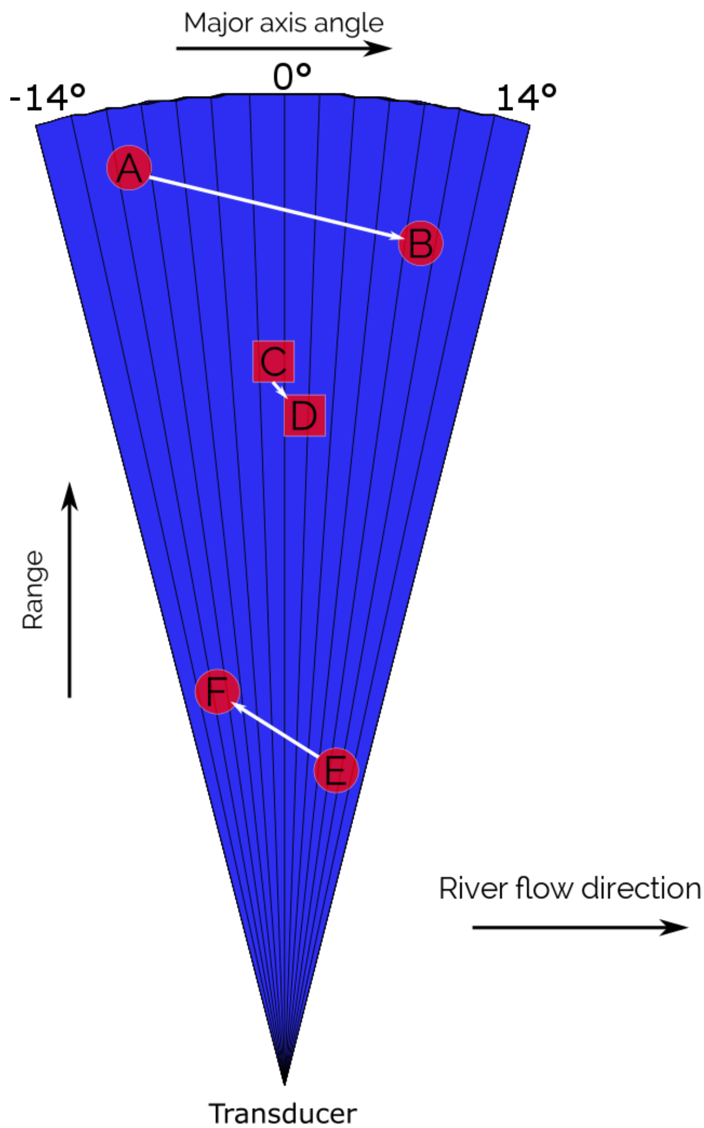

Figure 15. Direction and milling fish calculations in the sonar field based on the difference in Major Axis Angle (MAA) of the first and last frame in a fish track. With the addition of a factor 14° to MAA values stemming from the angle of the sonar field, the difference is defined as Major Axis Distance (MAD). In the example, the absolute MAD values of A-B (downstream) and E-F (upstream) are the same, but the sign is different because the objects are moving to opposite directions. The change in C-D is short and it is filtered out as indicative of “milling”.

Differentiating downstream moving fish from other objects

After filtering the fish tracks in the previous step, we classified 231 tracks of downstream moving objects into fish (n=76) and non-fish (n=155) categories manually by watching the raw footage in the dataset 1. We then used the measurements available from the Echoview-exported data to create a model that predicts the downstream moving objects into these classes. One of the true fish tracks could not be used for analysis, because Echoview reports the values in the summary tables erroneously as “-9999” when more than one target is included in the same ping in a track (Faulkner and Maxwell, 2015) and thus, it was removed before the analysis.

A logistic regression model was used for making binary predictions from the variables. The data were split to train (70 %) and test (30 %) datasets using caTools package (Tuszynski, 2020) in R, and the dependent variable (fish or non-fish) and a seed (that is used to ensure same random numbers are always generated) of 100 were used for randomizing the split between the training and test data.

The initial modeled set predicting downstream moving fish was created by including ten variables from existing Echoview fish track summary statistics. The variables in the initial modeled set included Average and Maximum speed 4D (accumulated distance between targets in the track over the time (Echoview, 2018); in ARIS data the speed is calculated in two spatial dimensions over time), Fish track change in range (the distance from the transducer of the first target minus the range of the last target in the fish track (Echoview, 2018)) converted to absolute values to represent the change both ways, Tortuosity 2D and 3D (sum of the distances in a track divided by the distance from the first to last target in the track (Echoview, 2018)), Distance 3D unsmoothed (sum of the distances between adjacent targets (Echoview, 2018)), Time of the day in seconds, Mean target strength (TS), Number of Targets in the fish track, and Time in Beam. In addition, the MAD value and average of target length were calculated from individual targets in each fish track; therefore, a total of 12 variables were included in the modeled set.

The model selection was done using the glmulti package (Calcagno and de Mazancourt, 2010) in R. With 12 variables, there were $2^n = 4096$ *a priori* candidate models without interactions. Model selection was initially conducted using variable interactions, but it resulted a lower test-set accuracy indicating model overfitting, and because there was no theoretical reasons for including interactions, they were left out from final model selection. The relative fit of each of the *a priori* candidate models was assessed using Akaike information criterion (AICc) corrected for small sample bias (Burnham and Anderson, 2002). Models that were within 2 AIC units above the best model (*i.e.*, model with the lowest AICc) were considered as the final model set (Calcagno and de Mazancourt, 2010); model weights and evidence ratios were then calculated separately for the final model set that also corresponded to the Kullback-Leibler 95% confidence set (Burnham and Anderson, 2002). The correlation between the variables was inspected and the test-set accuracy for predicting downstream moving fish was also calculated just for the final model set. For calculating the accuracy, the threshold for the predictions was set to 0.5 because we had no preference on predicting negative or positive outcomes. The relative importance of each predictor variable was assessed by summing the AICc weights across the models in the confidence set where each variable occurred. The (individual) model with the lowest AICc value (*i.e.*, the Kullback-Leibler best model; Burnham and Anderson, 2002), and also corresponding to the highest test-set accuracy, was selected for predicting the downstream moving objects in both datasets and the final downstream fish count was calculated for datasets 1 and 2 (in lieu of resorting to multimodel inference).

Comparison of automatically generated counts to human-generated counts

Sound Metrics ARISfish (versions 2.5 and 2.6) was used to manually count and measure the fish from the sonar data. Both datasets were analysed in a salmon monitoring project for the count and length of fish (human-generated monitoring counts). The users had previous experience in analysing imaging sonar footage in the same project and they were instructed to find fish in the background subtracted echogram and measure them using the raw sonar footage. The users were instructed to focus on fish longer than 30 cm but to not delete any shorter fish if they were measured. In addition, the dataset 2 was analysed by eight other users, all with previous experience analysing imaging sonar footage (additional human-generated counts, U1 to U8). The time it took for the users to analyse the footage was measured as the time difference between the first and last file using the timestamps on Microsoft Windows Explorer.

All the human-generated and computer-generated datasets were split into 15 min sections and the 15-minute tallies were used for comparing the different methods. Bland-Altman method (Bland and Altman, 1986) was used to compare the computer-generated counts and the human-generated monitoring counts in both datasets. The computer-generated counts for dataset 2 were also compared to the additional human-generated (U1-U8) counts. Bland–Altman bias was defined as the mean difference between the two methods, and the limits of agreement are the bias ±1.96 SD of difference (Bland and

Altman, 1986). The limits of agreement define the range within which 95 % of the differences fall (Bland and Altman, 1986). Up- and downstream counts were compared separately and because there was a trend in difference and magnitude, a proportional y-axis was used where the difference ($Count_{computer} - Count_{manual}$) is presented as % of average (Dewitte *et al.*, 2002). Intraclass correlation (ICC) was computed to assess the agreement between all the ten counts in the dataset 2, separately for the 15-min tallies of up- and downstream counts. R package *psych* (Revelle, 2018) was used to calculate the two-way random effect models and "single rater" unit was used. The ICC value was interpreted using Koo and Li (2016) suggestions: poor (<0.5), moderate (0.5–0.75), good (0.75–0.90), and excellent (>0.9). R software version 3.6.1 (R Core Team, 2019) was used for all calculations.

3.3 Results

Direction calculations and thresholding

The 5th percentile of the MAD value of the real objects group was 2.43 (Figure 16). When calculated separately by direction, the 5th percentile of the MAD was 3.98 for upstream and 1.40 for downstream fish tracks in the real objects group. The 95th percentile of the dynamic noise group was 3.98, and the 95th percentile of milling fish group was 6.42 (Figure 16).

Because the purpose of thresholding was to remove most of the dynamic noise and milling fish tracks without removing the true fish tracks, 2.43 was selected as an overall representative threshold. With the selected threshold, 89 % of the dynamic noise and 67 %

of the milling fish tracks were removed, and the total number of fish tracks was reduced from 1511 to 1006.

After filtering the tracks using the threshold, the direction calculations were correct in 96 % of the fish tracks (91 % of upstream tracks, n= 53 and 97 % of downstream tracks, n = 255). In the instances when the direction was incorrect, the tracking was influenced by another object that had entered the field or the object was not completely tracked through the field.

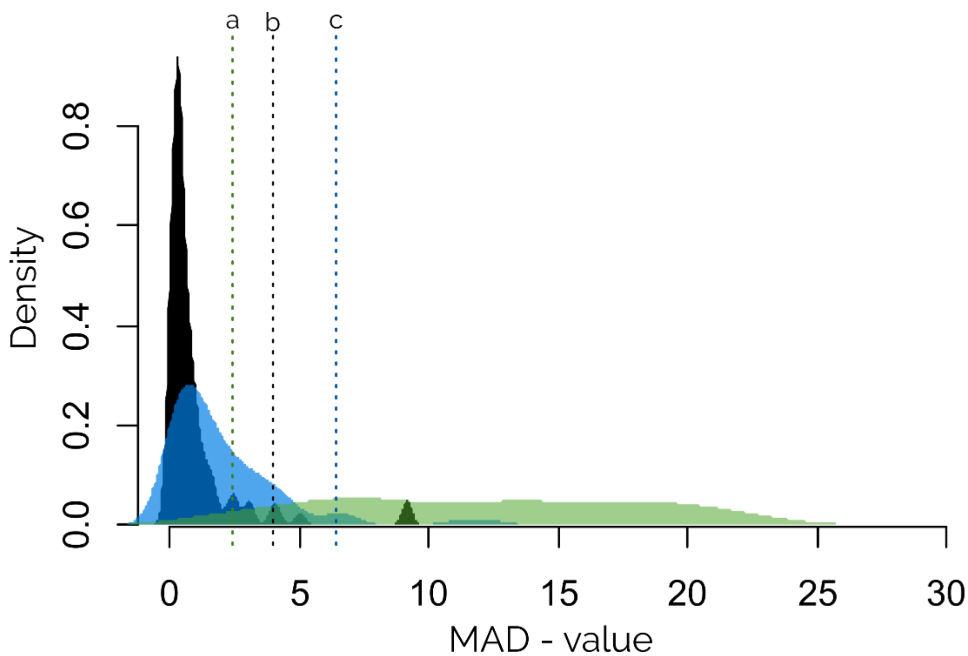

Figure 16. A density plot of absolute Major Axis Distance (MAD) values of fish tracks classified as dynamic noise (black, n = 81), milling fish (blue, n = 75) and true objects (green, n = 309). The 5th percentile of the true objects (a = 2.43) and the 95th percentiles of the dynamic noise (b = 3.98) and milling fish (c = 6.42) tracks are indicated with dashed lines.

Predicting downstream moving fish from other objects

Of the 4096 candidate models in the initial set, 11 models were within 2 AIC units from the lowest AICc value and were therefore considered as the final modeled set for which weights and evidence ratios were calculated (Table 7); all 11 models were within the Kullback-Leibler 95 % confidence set. The average target length, average speed 4D, and absolute fish track change in range were the three most important variables and were included in all models in the confidence set, resulting in 1.0 relative importance by AIC weights. In addition, Tortuosity 3D also had a much higher importance than other variables (0.84 relative importance; (Table 7) and was included in 9 of the models in the confidence set. Speed had a negative effect on the possibility of target being a fish; other variables had a positive effect in the 11 models in the confidence set (Table 7).

The model with lowest AICc (148.9) also provided the highest test-set accuracy (84 %; Table 7) and therefore, it was selected for future steps (Table 7). The sensitivity of the model was 82 % (n=23 true fish) and the specificity was 85 % (n=47 non-fish objects) in the test-set.

Table 7. The 11 logistic regression models in final AICc modeled set with their AIC weights, evidence ratios, test-set accuracies and included variables and their coefficients ± standard error.

AICc	AIC Weight[1]	Evid. ratio	Test-set (n=70) acc.	Intercept	Average Speed	Absolute Change in Range	Avg. Target Length	Tortuosity 3D	Other Variables	
148.9	0.18	1	0.84	-3.75±1.68	-3.29±0.99	0.46±0.19	0.13±0.03	2.13±1.23	-	
149.8	0.12	1.57	0.81	-3.64±1.69	-3.51±1.03	0.43±0.19	0.13±0.03	0.06±0.07	Tortuosity 2D	2.05±1.23
150.15	0.10	1.87	0.83	-4.45±1.96	-3.31±0.99	0.48±0.19	0.12±0.03	2.49±1.34	MAD	0.04±0.05
150.27	0.09	1.98	0.83	-3.57±1.71	-3.39±1.04	0.5±0.21	0.12±0.03	1.89±1.29	Max. Speed	0.18±0.38
150.36	0.09	2.08	0.81	-0.97±0.67	-4.11±0.91	0.4±0.17	0.13±0.03	-	-	
150.72	0.07	2.48	0.80	-0.97±0.67	-4.33±0.94	0.38±0.17	0.13±0.03	-	Tortuosity 2D	0.08±0.07
150.79	0.07	2.57	0.84	-3.68±1.72	-3.29±0.99	0.45±0.19	0.13±0.03	2.11±1.23	Time of Day	0±0
150.80	0.07	2.59	0.80	-3.76±1.68	-3.27±1	0.53±0.22	0.12±0.03	1.84±1.26	Distance	0.12±0.13
150.86	0.07	2.66	0.84	-3.82±1.74	-3.28±0.99	0.46±0.19	0.13±0.03	2.16±1.25	TS Mean	0.01±0.06
150.89	0.07	2.70	0.83	-3.74±1.69	-3.16±1.05	0.49±0.21	0.12±0.03	1.96±1.3	No. of Targets	0.02±0.06
150.90	0.07	2.72	0.83	-3.74±1.69	-3.16±1.14	0.47±0.2	0.12±0.03	1.99±1.35	Time in Beam	0.02±0.07

[1]Note: Relative importance of individual variables can be derived as the sum of AIC weights of the models in the confidence set where the variable is present.

Agreement between manual and automated counts

The mean of differences between the computer-generated counts and human-generated monitoring counts for the upstream migrating fish was -32 % in the dataset 1 and 36 % in the dataset 2 (Figure 17). For downstream data, the mean of differences was 115 % (dataset 1) and 73 % (dataset 2); the computer-generated counts were equal or higher in all instances for dataset 1 and similarly, equal or higher in all but two instances for dataset 2 (Figure 17). The mean of differences for upstream counts varied between -39 % and 65 % in the dataset 2 where the computer-generated count could be compared to eight additional human-generated counts (Table 8). The mean of differences was negative in five comparisons, meaning that the computer was typically counting less fish than the human (Table 8). For the downstream counts, the mean of differences was positive in all eight comparisons and the mean of differences varied between 14 % and 73 %.

There was a good absolute agreement between the ten different analysis outcomes for the upstream fish counts in the dataset 2 (ICC = 0.79, 95% CI: 0.74–0.84, p <.05). In the downstream fish counts, there was no agreement (ICC = 0.03, 95% CI: 0.0–0.07, p < .05).

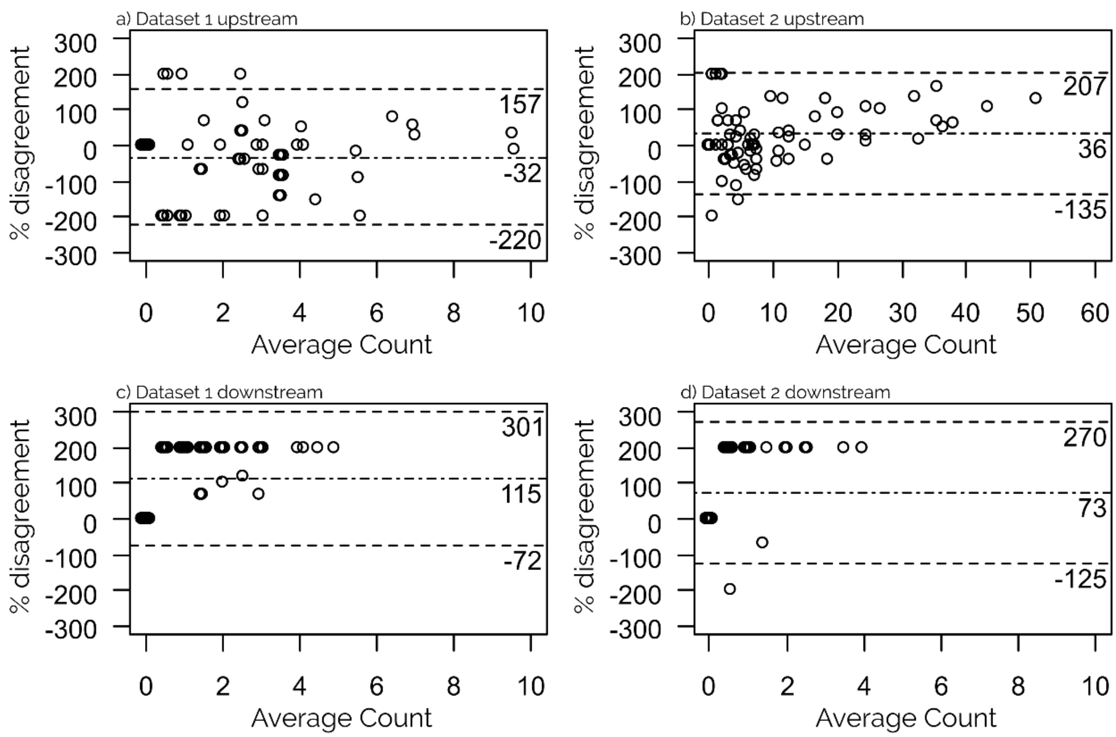

Figure 17. Bland-Altman graph using proportional y-axis where the difference ($\text{Count}_{\text{computer}} - \text{Count}_{\text{monitoring}}$) is presented as % of average in a) dataset 1 upstream fish, b) dataset 2 upstream fish (note larger x-axis), c) dataset 1 downstream fish, and d) dataset 2 downstream fish. The dashed lines represent the upper and lower limits of agreement and the dash-dotted line is the mean of differences.

Table 8. Bland-Altman mean of differences and limits of agreement (LOA) for upstream data and downstream data in monitoring counts and additional human-generated counts (Users 1-8) in the dataset 2. Agreement values are calculated relative to the computer-generated results.

Direction	Statistic	Monitoring	U1	U2	U3	U4	U5	U6	U7	U8
Upstream	Upper LOA	207%	293%	200%	137%	153%	186%	165%	111%	129%
	Mean of Dif.	36%	65%	39%	-33%	-16%	17%	-13%	-24%	-39%
	Lower LOA	-135%	-163%	-122%	-202%	-186%	-152%	-191%	-158%	-207%
Downstream	Upper LOA	270%	277%	261%	262%	276%	270%	265%	262%	269%
	Mean of Dif.	73%	69%	63%	14%	68%	73%	20%	62%	36%
	Lower LOA	-125%	-138%	-135%	-234%	-140%	-123%	-226%	-137%	-196%

Processing time

The processing time of the computer-generated data was 604 minutes for the 24 h dataset 1 and 486 minutes to process the 24 h dataset 2 (Table 9). The two tracking rounds took approximately same time to process within each dataset with only 6-8 min difference between rounds. The human-generated monitoring count took 240 min for the dataset 1 and 343 min for the dataset 2 (Table 9). The additional human-generated counts took between 173 and 605 minutes to process (Table 9).

Table 9. Processing time (in minutes) in each dataset. The three different steps (1st round, 2nd round, and exporting) and total processing time in the computer-generated counts (highlighted in gray), monitoring count, and eight additional human-generated counts (U1-U8) for the dataset 2.

Dataset	1st round	2nd round	Exporting tables	Computer total	Monitoring	U1	U2	U3	U4	U5	U6	U7	U8
Dataset 1	274	266	64	604	240	-	-	-	-	-	-	-	-
Dataset 2	228	234	24	486	343	601	591	605	186	173	477	246	571

3.4 Discussion

Upstream direction and filtering milling fish and noise

Using the MAD-value proved to be a rapid and effective way of recording the direction of the fish and filtering fish tracks caused by milling fish and dynamic noise from the data. The upstream direction calculation using the MAD-value was correct in 96 % of the fish tracks. The direction was incorrect in the instances when another object entered the field and the tracker had followed it through the field to other direction. Such instances are difficult to avoid and represent a source of error for the overall automated fish count. This approach is quick to calculate, but it only works in installations where the fish are passing the site across the beams to up- or downstream direction; if the fish are swimming to multiple directions and in many angles, using Echoview's direction calculation (0-365°) can be used.

The MAD-value was used to remove the erroneous fish tracks (milling fish and dynamic noise) without removing the true fish tracks. In this study, a conservative threshold (5^{th} percentile of MAD-value of the true fish tracks) was chosen, and it reduced the total number of fish tracks in the dataset 1 by 33 %. By removing the true fish tracks with the 5 % lowest MAD value, the filter removed most (89 %) of the fish tracks caused by dynamic noise (*e.g.*, turbulence caused from a rock) in the footage. Another method to clear such noise would be to filter out the area in the sonar field where the noise occurs, however, this method applies the same condition everywhere in the sonar field and therefore also removes randomly occurring noise. The filter also removed 67 % of the milling fish tracks. In addition to milling fish, this approach works in cases where a fish enters the field but turns back to the original direction of entry. Despite the filter, double counts of fish still occur in cases when fish entry and exit are tracked in separate fish tracks that both have a large MAD-value. Despite the high accuracy of filtering, it is still important to ensure high data quality during collection and prefer study sites where the fish are mostly swimming through without milling, as recommended by *e.g.*, Pipal *et al.* (2010).

Predicting downstream moving fish from other objects

One significant advantage of imaging sonars compared to other types of sonars is that it provides shape information that makes it easier to distinguish between downstream moving fish and other objects (Hateley and Gregory, 2006). However, automatically produced counts are found to be highly inaccurate, especially because the software includes other downstream-moving objects, such as detritus and leaf-litter in the counts (Petreman *et al.*, 2014). Classification of objects to different types of fish or debris based on their shape has been previously presented for data collected at a hydroelectric power plant (Bothmann *et al.*, 2016; Mueller *et al.*, 2008).

When downstream movement is of interest, a modelling approach can be used to create accurate counts of downstream moving fish. The model created to predict whether a downstream moving object was a fish or not correctly predicted 84 % of the objects to the right category in the test-set. With the used 0.50 threshold, the total number of predicted fish (26 in the test-set) was close to the true number of fish (23). All model parameters were easily calculated from the exported Echoview fish tracks and they all responded to measurements in a natural river where fish are often larger than debris (Average of Target Length), can move across the stream (Absolute Fish Track Change in Range), and move at different speed (Average Speed 4D) than objects that are carried by the current. Because all the monitoring sites are different, it is recommended to adjust the model in each monitoring site and possibly for different environmental conditions. Of the variables shown to be of importance for correctly predicting downstream moving fish *vs* debris, the speed of the object can especially vary as the water velocity changes at the study site.

Echoview reported one fish track in the summary table as "-9999" and was thus removed before analysis. Such error occurs when more than one target is included in single ping (any ping in a fish track) and can occur in up to 11.5 % of tracks (Echoview, 2018; Faulkner and Maxwell, 2015). Despite the erroneous ping, these fish tracks may include real fish tracks. Therefore, because the summary table information is used in the model that predicts downstream moving fish from other objects, it is recommended that summary data are calculated by manual means in such instances, without including the ping where multiple targets are measured.

Fish count agreement and processing time

The 15-min tallies of computer-generated upstream fish counts were on average -32 % (dataset 1) and 36 % (dataset 2) different when compared to 15-min tallies of human-generated upstream fish monitoring counts. Because the true number of fish was not known in the datasets, the computer-generated counts were compared to multiple human-generated counts: the dataset 2 was analysed by eight additional technicians and the ten analysis outcomes had a good absolute agreement (ICC = 0.79), suggesting that different users or automation can be used interchangeably for upstream counts. Despite the good absolute agreement, there was variability in the agreement between the computer-generated and additional human-generated upstream counts: the computer, on average, counted more fish in three datasets and less fish in five datasets in comparison to the human-generated count.

There was a larger difference in the downstream counts. The computer-generated downstream-moving fish counts were always higher than the human-generated counts, and the mean of differences was 115 % (dataset 1) and 73 % (dataset 2) when compared to the human-generated monitoring counts. Large differences between manually and automatically counted downstream data has been reported previously (Petreman *et al.*, 2014), however, because of the high accuracy of the downstream model presented here, the large difference was surprising. Because there was no agreement (ICC = 0.03) between the ten datasets for the downstream counts, it indicated that the downstream counts were very different in all datasets. However, it was known that the computer was counting true downstream-moving fish in the dataset 1 because there were multiple true fish tracks that were confirmed as downstream moving fish when creating the downstream model. Therefore, it is suspected that the number of downstream-moving fish was underestimated in the human-generated datasets. Knowing the number of downstream moving fish may not always be of interest if the focus of the study is on migrating fish that are known (by *e.g.*, tracking studies) to pass the study site directly to *e.g.*, spawning areas in headwaters. However, the movement of the fish may be more complicated than typically assumed (*e.g.*, Pipal *et al.*, 2010), and, as in the Miramichi River, other fish species may be passing the study site up- and downstream, and the number of such passages should be known so that they can be removed from the end-of-the-season estimate of the studied species.

The differences in the human-generated counts could be a result of the instructions where the technicians were told to focus on fish > 30 cm and if this threshold was estimated differently by the users due to the high variability in the length measurement (Helminen *et al.*, 2020). Another potential explanation for the discrepancy is a human-error related to the marked direction of the fish; while this was not the focus of this study, fish tracks were identified in the human-generated datasets where the fish direction was marked upstream by the user although further inspection showed the fish actually moving downriver. This would explain higher upstream counts and lower downstream counts in the human-generated counts compared to computer-generated counts. The variation in the results in the dataset 2 indicates that using multiple users in a monitoring study can introduce variability in the fish counts, as also reported previously for counting and measuring the fish (Hakkola, 2011; Keefer *et al.*, 2017). The used frequency (1.1 MHz) likely influences the accuracy and precision as well, as defining the targets is much easier with higher frequencies and high precision and accuracy has been reported with higher frequency (1.8 MHz; Holmes *et al.*, 2006). Automated methods can have an advantage over multiple human analysers, as the error of the counts over the season would be constant in stable environmental conditions. Moreover, the automation has an advantage when the research focuses on multiple fish species as counting fish of all sizes (as opposed to using a size limit) would be very labor intensive manually, but a computer can measure all fish in the dataset. However, accurate length measurements should only be expected when using short ranges, *i.e.*, the length measurements become less accurate in ranges > 15 m (Helminen *et al.*, 2020).

Processing time is an important logistical factor when assessing the efficiency of an analysis method. The required time for generating automated counts was 486 and 604 minutes which was longer than the human-generated monitoring counts in either dataset. In the dataset 2, half of the additional human-generated counts were produced faster than the computer-generated counts. The speed of the automation is dependent on many variables such as frame rate, fish abundance, and computing resources. As an example, Boswell *et al.* (2008) mention approximately 1.5 h processing time for 1 h of DIDSON data (high-frequency; 1.25–12 m range, 7 fps), while Bothmann *et al.* (2016) report real-time tracking (faster processing capacity than file length) utilizing a newer computer. In our dataset, if the tracking was done in one round instead of two, the processing time would reduce significantly because the two tracking rounds required approximately equal amount of time (200-300 min); however, the outcome would have been less accurate. Despite the long processing time, the automation can be run in the background and thus it requires less involvement of a technician in comparison to manual count where analysis requires the full attention of the analyst. Echoview also uses a Component Object Model (COM) interface that allows user scripting that can streamline the automated processing (Eggleston *et al.*, 2020). In regular operation, analysing a 24-hour dataset may require less than one hour of the technician's time, from bringing the data to the office to recording the number of fish, if the dataset is clean and no adjustments are needed.

Improvements and modifications to fish tracking

Improvements to different parts of the automation can be implemented depending on the study site and environmental conditions. The automation presented here involves multiple steps, and changes in each step can affect both accuracy and processing time. As an example, pre-processing the data using ARISFish software's background subtraction feature instead of in Echoview's could shorten the processing time, especially when combined with empty frame removal (Helminen *et al.*, 2020; Mueller *et al.*, 2010; Shahrestani *et al.*, 2017).

Fish tracking is the step that requires the most processing time, and it has a large influence on the final fish counts. In Echoview, one algorithm is available for tracking with user-defined settings. Echoview uses an alpha-beta tracker that selects single targets as candidates for appending to a track (Blackman, 1986; Echoview, 2018). A problem arises when setting the limit for the duration of the track: targets closer to the transducer create shorter tracks than targets farther out where the beams are wider. While many false negative tracks could be removed at far ranges by only accepting longer tracks, the approach would also remove real tracks close to the transducer. To circumvent this problem, we found that using double-tracking was a good method for creating fish tracks that included most of the fish targets but was not affected by targets outside of fish tracks. However, the additional tracking round almost doubled the analysing time. When faster processing is desired, using only one tracking round may still produce acceptable results with other filtering, such as the MAD-value presented here. Other tracking options, such as range-dependent filtering used by Handegard and Williams in MatLab (2008) can compensate for beam spreading, and could thus improve both the accuracy and efficiency of tracking. Recording the sonar data with a shorter end-range than in our datasets would also advance tracking performance because the beam spreading would have lesser effect (higher resolution) and because it would allow using higher frame rates and thus improve tracking by creating more frames where each target would be present.

Management implications

Although the automation presented here produced counts that are comparable to manually produced counts, one important factor to consider when deciding between the manual or automated counts is the difficulty of the analysis. Running the automation algorithm requires well-rounded understanding of sonar data processing, computers, and fish; therefore, in short-duration studies, it may be more cost-efficient to count the fish manually as it requires far less training and can be done using free software. Because of the cost of the required software and the need of specially trained personnel and specifics in study site, the automation is most suitable for long-term monitoring projects where dedicated sonar expertise can be devoted to developing functional project-specific automation.

Echoview allows data processing without programming, but the same operations can be implemented in other software (Boswell *et al.*, 2008) and the automation procedure can be used with any multibeam imaging sonar (Kang, 2011). Recently, consumer-grade fishfinders have also been used in research such as bathymetric and vegetation mapping (Helminen *et al.*, 2019), and their recent development includes live-view imaging similar to the data used here; although the image resolution is lower compared to scientific equipment, a combination of consumer-grade fishfinder and automated data processing would provide a very cost-effective monitoring method.

While the methods presented here are used to remove many of the issues regarding falsely tracked objects, erroneous tracks slow down the automation process and, if possible, should be avoided by other methods such as site selection. In the tested datasets, one cause of noise was from turbulence by a rock that was exposed during low water levels; removal of such noise-generating objects from the study site should be prioritized and would often be relatively easy. Similarly, shifting of the substratum (Petreman *et al.*, 2014) and turbulence at hydroelectric dams (Mueller *et al.*, 2010) have been previously recognized as an error source. Some sources of error indicated in other datasets but not tested here include: cross-talk from other nearby sonars, sonar shifting either by the force of the water or by humans, sonar beams reflecting from the water surface causing movement in the image, boats and birds moving on the surface, vegetation, and sea lampreys (*Petromyzon marinus*) holding on rocks (Helminen, unpublished data). Modifying the substrate within the ensonified area and building a sandbag ramp at the study site as described by Enzenhofer *et al*. (2010) would assist the detectability and tracking of fish (Petreman *et al.*, 2014) and although costly, it is recommended in long-term monitoring programmes. Because conditions in the river can change quickly, continuous quality control is important for ensuring data collection in the field and automation accuracy in the office.

Compared to monitoring programs that focus on other fish such as Sockeye salmon (*Oncorhynchus nerka*) (Faulkner and Maxwell, 2015), our dataset represents a fish run with relatively low fish densities, and only a small amount of fish are typically in the sonar field at the same time. This allowed us, and likely any other Atlantic salmon monitoring application, to create the targets and fish tracks using settings that will allow more variation. When more fish are present, different parameter values will likely have to be used to better detect fish that are travelling together. Large schools of fish will itself present challenges for automation, however, if they are not target species, school detection algorithm could be used first to mask (and count, if desired) those sections of the data before further analysis.

Overall, automating data analysis for making Atlantic salmon counts can improve the efficiency of the counts in long monitoring programs where otherwise multiple different users are needed for analysing the data manually. However, understanding of the software, sonar technology, and fish migration is required so that adjustments in the automation can be made accordingly. The workflow presented herein can be used to improve automated imaging sonar fish counts in rivers.

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4. Measuring tailbeat frequencies of three fish species from Adaptive Resolution Imaging Sonar (ARIS) data

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Abstract

Imaging sonars, such as the Adaptive Resolution Imaging Sonar (ARIS), provide high-resolution sonar data that is used in fisheries research and management. While sonar methods have enormous potential for making population estimates, species identification via sonar remains an unresolved challenge. One method that may overcome this challenge involves measuring tailbeat frequencies to guide species differentiation. The tailbeat frequencies of three commonly sympatric anadromous fish species of eastern North America, Atlantic salmon (*Salmo salar*), striped bass (*Morone saxatilis*), and American shad (*Alosa sapidissima*), were measured from imaging sonar data collected in an experimental low-flow, short-range setup. The frequencies were significantly different between the species (mean ±1 SD beats per second: 0.6±0.3 (Atlantic salmon), 0.9±0.2 (striped bass), and 1.4±0.3 (American shad)) when measured using a previously established manual method. Building on this, an automated method was developed and tested, and the method showed promising results. However, when compared to manually identified number of beats the error was large (on average, 1.1 beats in a fish track (Atlantic salmon), 4.8 (striped bass), and -0.4 (American shad)), especially in high fish densities. Despite the limitations, the automated method has utility in fisheries management when high-quality data can be collected of species with differing tailbeat frequencies.

4.1 Introduction

Sonar methods are commonly used in fisheries applications. Sonar uses sound to produce the image, rendering it applicable in deep and turbid waters as well as overnight as light is not required for the operation (Simmonds and MacLennan, 2005). They are non-invasive and do not require physical handling of fish unless it is required for additional sample collection (Foote, 2009). A limitation of sonar research in systems with diverse fish populations, however, is the difficulty of distinguishing between fish species (Horne, 2000; Martignac *et al.*, 2014). Fishing, typically trawling, is a commonly used method for identifying acoustic recordings (Misund, 1997), but other methods, such as underwater cameras are also used (Andrews *et al.*, 2020; Wolff and Badri-Hoeher, 2014). Combining multiple methods is laborious and costly, and determining fish species directly from the acoustic data has been of interest for decades (Horne, 2000; Misund, 1997), yet the true identification of fish species using only acoustic waves is difficult and remains unresolved (Horne, 2000; Martignac *et al.*, 2014; Misund, 1997).

A multibeam imaging sonar, such as the Adaptive Resolution Imaging Sonar (ARIS; Sound Metrics Corp.; www.soundmetrics.com) and the Dual-frequency IDentification SONar (DIDSON; Sound Metrics Corp.) uses multiple narrow beams and high frequencies (0.7 MHz to 3.0 MHz) to produce high-resolution underwater imaging (Moursund *et al.*, 2003). The high image resolution and high frame-rate have induced the development of species identification methods using measurements such as length and other morphometrics, and behavioral characteristics (Burwen *et al.*, 2007; Martignac *et al.*, 2014; Mueller *et al.*, 2008). Langkau *et al.* (2012) revealed that acoustic shadows produced to a projection plate 2 m away from the transducer can be used to distinguish between four morphologically distinct species. However, they state that using the method with large species at far ranges could be challenging as the resolution would be lower (Langkau *et al.*, 2012), and would require a specific study site in field studies.

Observing swimming behaviour of fish from the imaging sonar footage has been presented as a species-identification tool (Bothmann *et al.*, 2016; Kirk *et al.*, 2015; Kupilik and Petersen, 2014b; Mueller *et al.*, 2010, 2008). Tailbeat-frequency measurements have been successfully used for distinguishing between Chinook salmon (*Oncorhynchus tshawytscha*) and sockeye salmon (*O. nerka*) using an echogram that presents the maximum intensity value for each pixel (Mueller *et al.*, 2010). The most promising results have been found for distinguishing eels (*Anguilla spp.*) and lampreys (*e.g.*, Pacific lamprey; *Entosphenus tridentatus*) from other fish species, based on their distinct swimming pattern (Bothmann *et al.*, 2016; Kirk *et al.*, 2015; Mueller *et al.*, 2008; Yin *et al.*, 2020).

Automatic sonar data processing methods are increasingly used for rapidly processing imaging sonar data (Boswell *et al.*, 2008; Han *et al.*, 2009; Handegard and Williams, 2008; Helminen and Linnansaari, 2021; Kang, 2011; Petreman *et al.*, 2014; Yin *et al.*, 2020). Automation is typically used to count the fish from the footage, but other information, such as fish size (Han *et al.*, 2009; Helminen *et al.*, 2020) or the tailbeat-frequency (Kupilik and Petersen, 2014b) can also be generated. The tailbeats can also be calculated automatically by observing changes in body concavity throughout the fish passage in the sonar beam (Kupilik and Petersen, 2014b).

Multibeam imaging sonars are commonly used in rivers for monitoring migrating fish populations (Martignac *et al.*, 2014). To support a monitoring program that aims to make estimates of the annual run size of Atlantic salmon, (*Salmo salar*), in the Miramichi River, New Brunswick, Canada, the objective in this study was to test a tailbeat frequency method for distinguishing between Atlantic salmon and two similar-sized sympatric fish species, striped bass, (*Morone saxatilis*), and American shad, (*Alosa sapidissima*). Our second objective was to develop and test a method to automatically calculate the tailbeat frequency from the sonar data. It was hypothesized that the tailbeat frequencies significantly differ between the three fish species when counted manually from the maximum intensity echogram and that the automated method would produce tailbeat counts that closely approximate the manual method.

4.2 Materials and methods

Data collection

The sonar data were collected in an experimental pond (width: 6.5 m, length: 46 m, depth: 0.8 m). The velocity regime of the experimental pond was slow and relatively constant (0.08 – 0.14 m/s: measured using a SonTek FlowTracker). An imaging sonar (ARIS Explorer 1800, Sound Metrics Corp.; www.soundmetrics.com) was set facing across the pond and perpendicular to the current. The transducer was mounted 0.05 m below the water surface using a Sound Metrics Ar_2 rotator that was used to tilt the transducer down 14 °.

The sonar was set to record at 1.8 MHz using ranges up to 5.9 m (Table 10). Automatic focus and maximum frames-per-second (15 fps) was used in each experiment, as they are typically used in monitoring studies (e.g., Burwen *et al.*, 2014; Miller *et al.*, 2015). The sound velocity value used by the ARIS for producing the footage is dependent on the water temperature, and automatically set by the device (Table 10).

The data for each of the three fish species were collected at separate times (Table 10) by releasing a single species into the experimental pond and recording for at least 8 hours. The care and use of experimental animals complied with Canadian animal welfare laws, guidelines, and policies. Hence, the number of animals used in this study as well as the total time the fish were kept in the pond was kept as small as possible. The fish were sourced from the adjacent Miramichi River. The striped bass and American shad were captured using a commercial (American shad) and research (striped bass) fyke nets, transported to the location, and released to the pond. The striped bass were simultaneously used in another study where environmental DNA was collected using water samples downstream of the experimental pond, *i.e.*, the swimming behaviour of the fish was not affected. The Atlantic salmon were used for broodstock collection at the fish hatchery located on the site, and then released to the pond after the hatchery procedures. Because the fish were collected from different sources and only the American shad were caught specifically for this study, the numbers of individuals used in the study varied. After the fish were released in the pond, their behavior was visually observed for at least an hour to ensure there were no injured individuals or fish whose swimming capabilities would have been compromised due to the handling. The direct observation period was concluded when it was confirmed that all fish were using the whole pond and were likely swimming through the sonar field during the subsequent recording period.

Table 10. The fish species in the experiment and their respective dates of data collection, water temperature, sound velocity used in ARIS recording, range (m), number of fish and mean length (±1 standard deviation).

Species	**Date**	**Water temp. C°**	**Sound velocity m/s**	**Range (m)**	**n of fish**	**Fork Length (cm) Mean±1SD**
Atlantic salmon	24 Oct 2017	9	1441	1.0 – 5.8	43	66.7±13.2
Striped bass	17 Oct 2017	9	1441	1.0 – 5.9	100	44.1±7.6
American shad	19 Jun 2018	14	1462	0.7 – 5.8	13	43.3±3.4

Sonar data processing

The sonar files were processed following approaches used previously for tailbeat frequency identification and calculations (Mueller *et al.*, 2010) and for automatically processing sonar files (Helminen and Linnansaari, 2021; Kang, 2011). The files were background subtracted using Sound Metrics ARISfish version 2.6.2 (CSOT function: cluster sizes >200 cm^2, remove speckles under 10 cm^2) to remove targets that were not in motion (Sound Metrics Corp., 2019b). The background subtracted files were then processed in Echoview software (Echoview Software Pty Ltd; www.echoview.com, Version 9.0.333.35479).

A total of 50 fish passes were selected systematically for each fish species by choosing tracks where the fish was visible throughout the whole time it passed the field and it could be separated from other fish. As an example, the passes where the fish were mostly moving parallel to the center beam did not produce clear images in the echogram and were therefore not included. Some of the selected passes were undoubtedly produced by the same individual, but because the observations were sparsely distributed in time, it was assumed that observations construed independent datapoints for the purposes of tailbeat calculations. In other words, the tailbeat frequency was assumed to be a property of a 'fish species' rather than a property of an individual.

Manual tailbeat definition and fish length measurements

The tailbeat frequencies were analysed as per Mueller *et al*. (2010). The Maximum intensity operator was applied to the background subtracted data in Echoview to produce an echogram where each sample at range R (*i.e.,* each pixel from the start to end range from the transducer in one beam; the downrange resolution) contained the maximum value of all the corresponding multibeam samples that were in range R (*i.e.*, all pixels at that range across the multibeam array; the cross-range resolution) (Echoview, 2018), making the tail extensions visible in a two-dimensional plane (Figure 18, Mueller *et al.*, 2010). The start, end, and every tailbeat within the fish tracks were marked using define region feature and the marked data were exported as .csv tables using Analysis By Regions – Integration feature in Echoview (Figure 18). The markings were used to calculate the time difference between the start and the end of the tracks and to calculate the number of tailbeats within each fish track. The number of tailbeats in each track was divided by the duration of the track, to calculate the tailbeat frequency. The fish lengths were then measured manually by selecting a frame where the fish was visible from head to tail and following its body shape using Echoview´s Tape measure tool that measures the two-dimensional distance between the points.

After outliers were removed (three from Atlantic salmon and striped bass datasets, two from the American shad dataset), the normality was tested using Shapiro-Wilk test and the homogeneity of variances was tested using Levene’s test in R version 3.6.1 (R Core Team, 2019) and *CAR* package. Subsequently, Welch’s ANOVA, followed by Games-Howell post-hoc tests was used to determine if the tailbeat frequencies varied significantly between the different fish species. Finally, Pearson´s correlation was used to evaluate the relationship between fish length and tailbeat frequency.

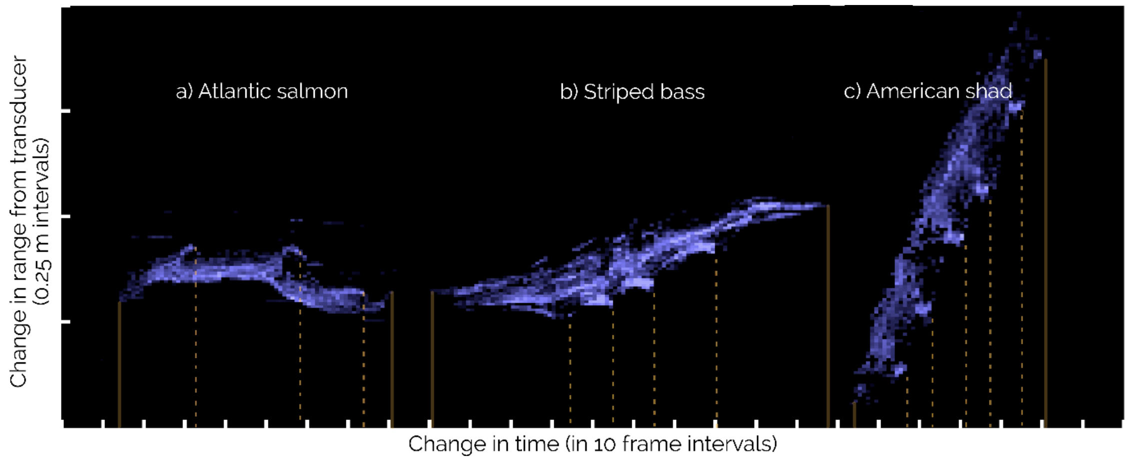

Figure 18. Examples of Maximum intensity echograms of A) Atlantic salmon, B) striped bass, and C) American shad. The start and end of the fish tracks are identified with solid vertical lines and the tailbeats are identified with dashed vertical lines. Y-axis indicates the change in range and X-axis identifies the change in time (recorded at rate of 15 frames per second). The tracks are not to scale (range nor time) between species.

Automated tailbeat calculations

Automatic fish counts can be produced from imaging sonar data in Echoview using a workflow where the imagery is processed and fish are tracked throughout the passage in the sonar field (Kang, 2011). To test if the tailbeat frequencies could be calculated automatically using target properties that are created in Echoview when counting fish automatically, a similar workflow as presented previously in Kang (2011) and Helminen *et al.* (2020) was generated (Table 11). The workflow and each operator´s parameter values were selected manually by viewing a section in the datasets that was not used in the tailbeat analysis and the same values were applied to all the datasets.

Table 11. The workflow used in Echoview for fish tracking. The operators are applied in the numbered order.

Operator	**Description and parameter values**
1. Beam median filter	Corrects the imagery by applying a 3x3 median filter to each ping; *i.e.*, the filter replaces each data point with the median of the data points in the surrounding cells (Echoview, 2018).
2. Cluster detection operator	Generates multibeam targets from groups of adjoining datapoints in multibeam data, *i.e.*, fish targets are generated from echoes at each frame (Echoview, 2018). The values used in cluster detection were: seed threshold 60 cm^2, satellite threshold 1.5 cm^2, link distance 20 cm, and satellite cluster linking enabled.
3. Target property threshold operator	Thresholds targets using a specified target property range (Echoview, 2018). All targets with a length <10.00 cm were filtered out, to remove reverberation and noise from the data.
4. Target conversion	Generates single target data from multibeam targets, allowing the use of the Echoview fish tracking feature (Echoview, 2018).

Similar to the tailbeat measurement approach in Kupilik and Petersen (2014b), the method applied herein utilized metrics of measurements extracted from each frame rather than applying the maximum intensity echogram. To combine all frames where a fish was visible during its passage through the sonar field a fish tracking feature was used in Echoview. All fish track information was exported as .csv tables that included information (*e.g.*, time, target length, target range, and target range extent) about the fish in each frame within the fish track. In this exercise, the Target Range Extent -value was analysed. The Target range extent is the difference in range (in cm) between the samples in the target that are closest and farthest from the transducer (Echoview, 2018). When the fish bends its tail, the range extent is different (Figure 19a) compared to when the fish is fully extended and straight (Figure 19b).

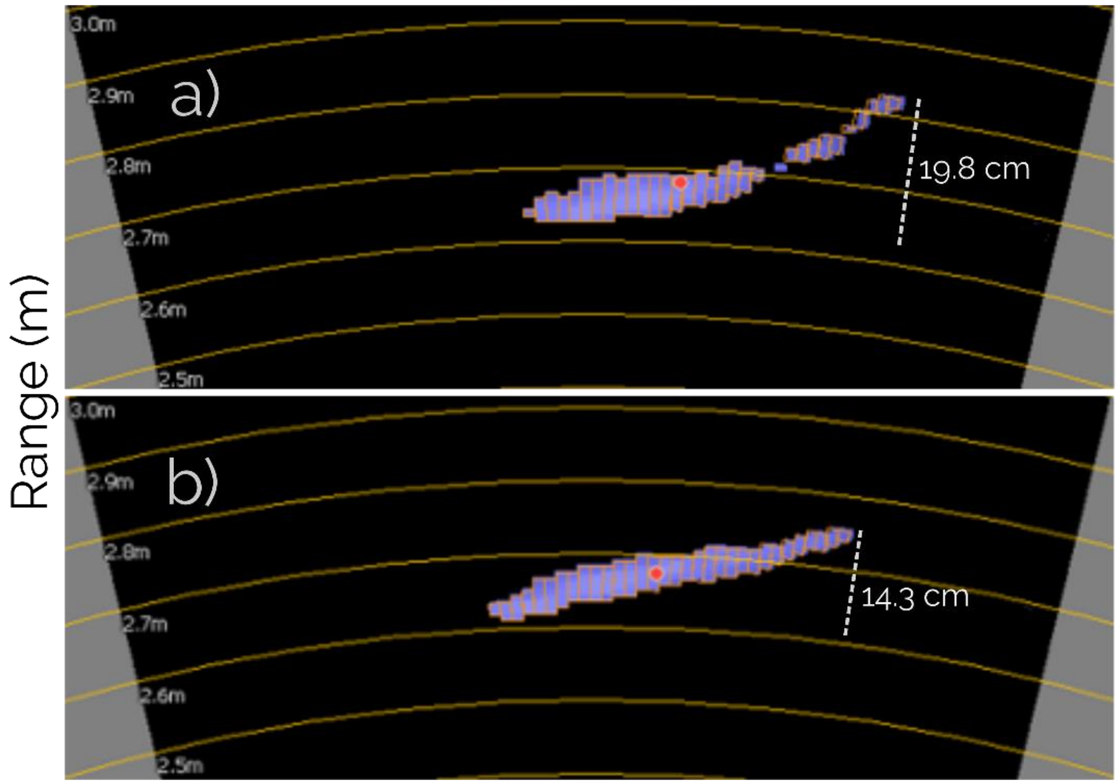

Figure 19. The target range extent measures the difference in range (distance from the transducer) between the closest and farthest samples. In (a) the fish is bent, and the target range extent is 19.8 cm. In (b) the fish is straight, and the target range extent is 14.3 cm. The red dot indicates the geometric center of the target.

A signal peak detection algorithm (Anonymous 2014) was used to analyse the time-series data of the Target Range Extent. The algorithm indicates when a datapoint is a given number of standard deviations away from a moving average (Anonymous 2014). A moving average was used because the range extent varied due to the movement of the fish (changing position and angle in relation to the center beam), and therefore the (mean) range extent as well as the height of the peak varied over time. The algorithm requires three inputs: lag (the lag of the moving window), threshold (the z-score at which the algorithm signals), and influence (influence of new signals to the mean and standard deviation) (Anonymous 2014). The whole dataset in this study was analysed using the same parameter settings. The settings were chosen by visually testing them in the first three (ordered by time) tracks of each species. By considering that the peaks were variable in height, and that the mean also varies during the tracks, the following inputs were used in this dataset: lag 10, threshold 0.2, and influence 0.5. The analysis was run separately for each fish track. One fish track in the selected n=50 salmon dataset could not be analysed because there were less than 10 frames in the track and four salmon fish tracks could not be analysed automatically because all the tailbeats were manually identified within the calculation period of first 10 frames.

Each change in the signal detection output to 1 or -1 were calculated (i.e., two contiguous same-output signals are counted as one), separately for the negative and positive signal output, to calculate the number of positive and negative peaks in the data. The number of negative peaks in each track was then compared to the number of manually measured tailbeats within the peak detection period (tailbeats within the first 10 frames not included as these data were used for calculating the moving average) using the Bland-Altman method (Bland and Altman 1986) where the difference between the two methods is plotted against their average to define bias (mean of differences) and the limits of agreement (LOA; mean ±1.96 standard deviation). An ordinary least squares (OLS) was used in the Bland-Altman graph to detect proportional bias. All calculations were made in R (R Core Team 2019) and the tracks were further visually inspected to understand when the algorithm worked well and when it produced different numbers compared to manually defined tailbeat calculations.

4.3 Results

Comparison of Tailbeat Frequencies Using Manual Measurements

American shad and striped bass typically produced clear tailbeat patterns in the Maximum Intensity echogram and thus, were easier to analyse than salmon tracks that had a lower number of tailbeats. The salmon were often gliding through the sonar field and moving their tails less. Additionally, some of the salmon tail movements were not full tail extensions thus the tailbeats were not as easily identifiable in the Maximum intensity echogram. Overall, the tailbeat frequency was significantly different between the three fish species (Welch's One-way ANOVA, $F(2, 89) = 73.8$, $P<.001$; Figure 20) and the post hoc comparison indicated differences between all groups ($P<.001$ for all three post-hoc comparisons). The mean tailbeat frequency (±1 SD) was 0.6±0.3 beats per second (bps) for Atlantic salmon, 0.9±0.2 bps for striped bass, and 1.4±0.3 bps for American shad (Figure 20). The fish length measured from sonar data (mean ±1 SD: Atlantic salmon: 62.6±13.0 cm, striped bass: 43.5±6.7 cm, American shad: 48.4±4.4cm) and tailbeat frequency were not correlated in American shad ($r(46) = -0.07$, $P=.621$) or Atlantic salmon ($r(45) = -0.02$, $P=.909$) datasets, but there was a weak negative correlation in the striped bass dataset ($r(45) = -0.33$, $P=.023$).

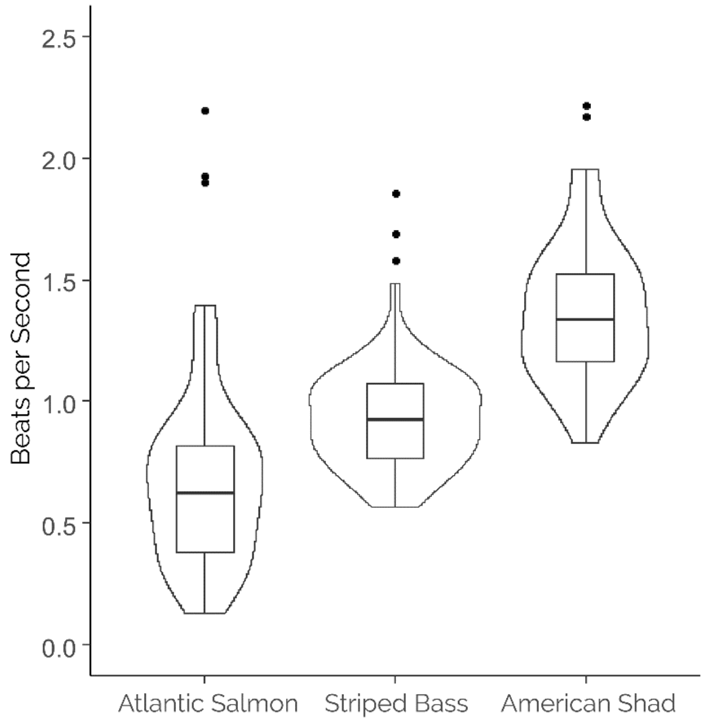

Figure 20. Violin plot of the tailbeat frequency of Atlantic salmon (n=50), American shad (n=50), and striped bass (n=50).

Automatic Tailbeat Detections

The automated method calculated the same number of peaks as the manual method calculated tailbeats in 27 % (Atlantic salmon), 22 % (American shad), and 10 % (striped bass) of the instances, and there was a one beat/peak difference in 42 % (Atlantic salmon), 40 % (American shad), and 18 % (striped bass) of the instances. The Bland-Altman plot revealed differences between the two methods in all datasets (Figure 21). The lowest bias (-0.4) and smallest difference in the limits of agreement (lower: -3.5; upper: 2.6) was in the American shad dataset where neither of the methods produced substantially higher counts than the other (Figure 21). The peak counts were typically higher than tailbeat counts in the Atlantic salmon (bias: 1.1) and striped bass (bias: 4.8) datasets, and therefore the bias was positive in both datasets (Figure 21). The ordinary least squares regression revealed a positive proportional bias (relationship between difference and magnitude) in all the datasets; it was clear in the striped bass dataset (R^2 = 0.90, *P*<.001) and Atlantic salmon datasets (R^2 = 0.73, *P*<.001), but lower in the American shad dataset (R^2 = 0.37, *P*=.008).

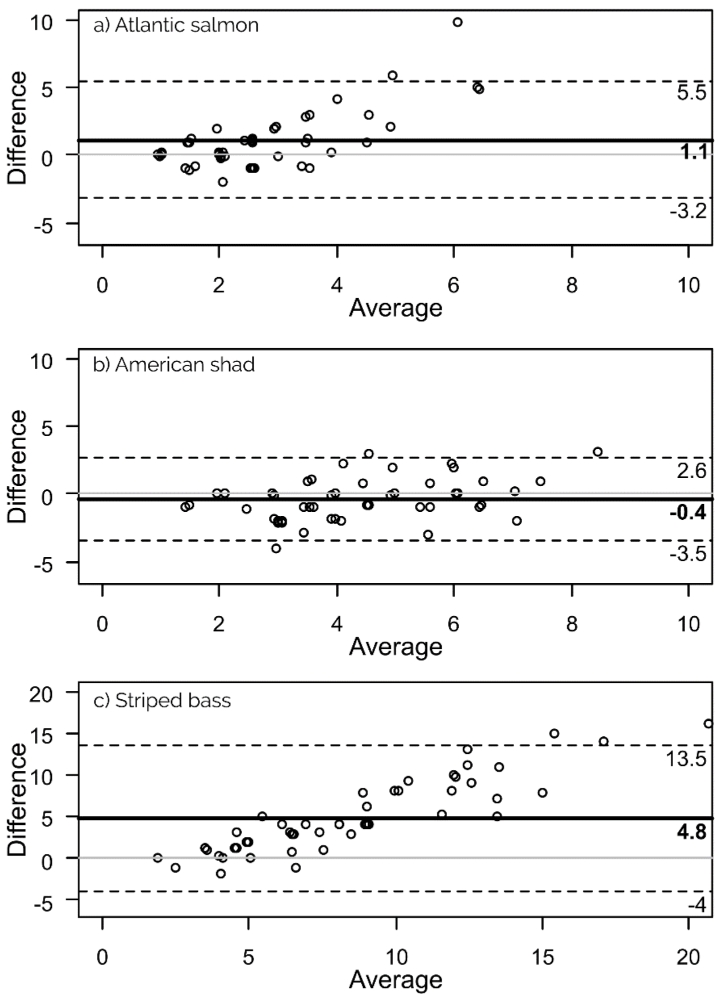

Figure 21. Bland–Altman plots of the difference between the peaks in Target Range Extent and manually calculated tailbeats ($\boldsymbol{n_{peaks}} - \boldsymbol{n_{tailbeats}}$) in a) Atlantic salmon (n=45), b) American shad (n=50), and c) striped bass (n=50) datasets. The dashed lines show the limits of agreement, the black line is the bias (mean of differences) and the light grey line shows the no-bias (0) line for reference. X-axis is the average count of the two methods. Note the different scale in the axes in the c) striped bass dataset.

Graphical inspection showed that the peak detection algorithm detected peaks at similar frames as the manually detected tailbeats in the instances when the two methods agreed (Figure 22). A common source for automation to miss a detection was when the tailbeat was in the later part of the fish track when the fish was leaving the sonar field and only partially measured, resulting in shorter range extent measurement (See frames >25 in Figure 22).

A common source for false detections was noise or reverberation in the sonar footage that had resulted in erroneous detections when the targets were created in Echoview (Figure 23). The target detection either included other echoes (noise or other fish) in the target or missed parts of the fish, and when these occurred in any frame, that frame would then signal in the peak detection. This was the main source of error (evident in approximately 85 % of the fish tracks) in the striped bass dataset where the automation was least likely to detect a similar number of tailbeats as manual detection (Figure 23).

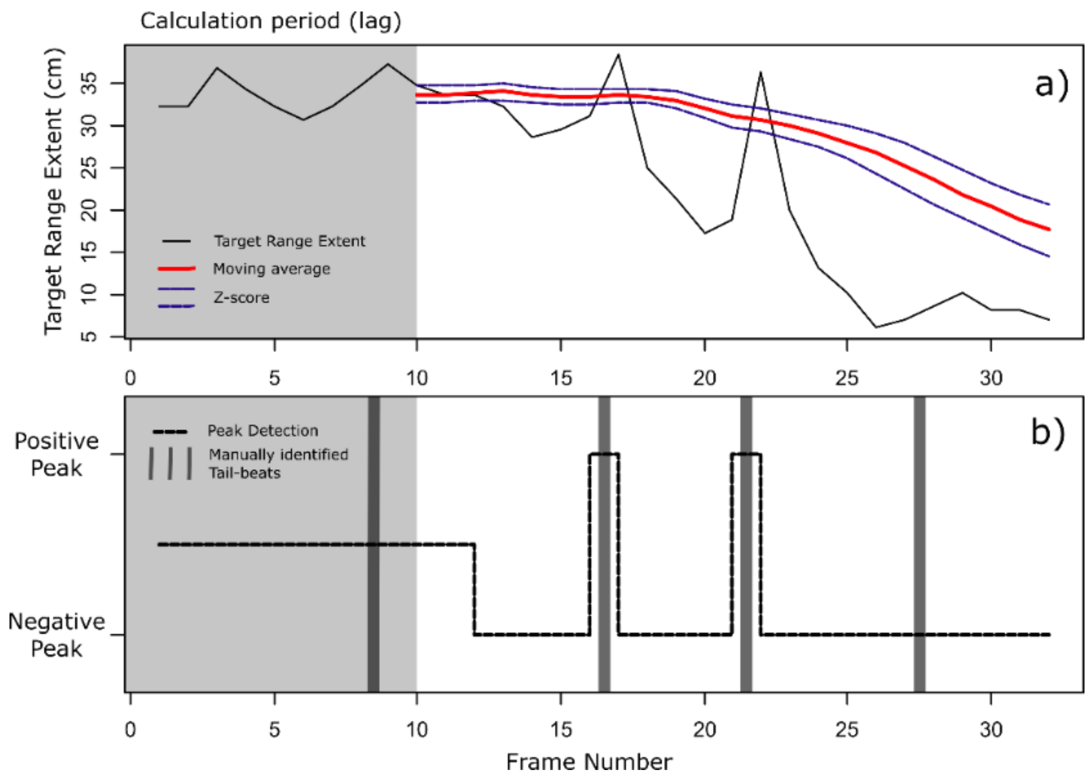

Figure 22. Example of peak detection from American shad data. a) The peak detection algorithm calculates a moving average and a Z-score (number of standard deviations) from the target range extent data and b) signals when the range extent value is above (positive peak) and below (negative peak) the z-score calculated for the frame. The gray bars in (b) indicate where the tailbeats were manually identified and the first 10 frames are the calculation period where no tailbeats are detected.

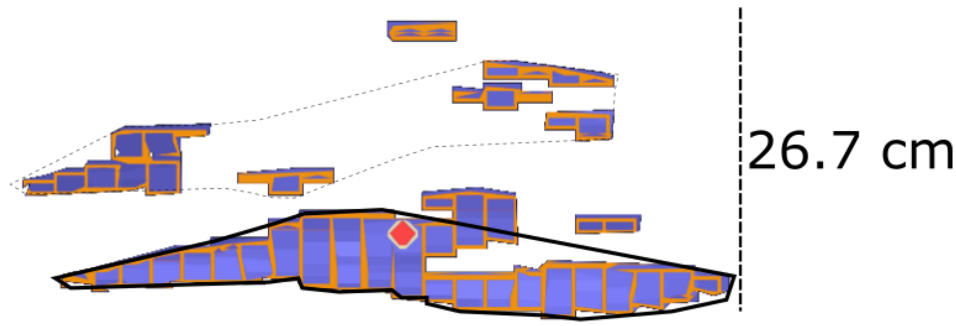

Figure 23. Example of a source of error in target range extent method for detection of tailbeats from imaging sonar data. A fish (approximately outlined in black) is erroneously detected as echoes from another fish (approximately outlined in dashed line) are included in the detected target. In the example, all pixels are included in the target and the target range extent (26.7 cm) is calculated for the whole target—causing a peak in the range extent calculation although the fish is actually stretched out.

4.4 Discussion

Tailbeat Frequencies of the Three Fish Species Using Manual Measurements

The first objective of the study was to test if the tailbeat frequencies differ between Atlantic salmon, American shad, and striped bass. When counted from the maximum intensity echogram, the tailbeat frequencies of the three species significantly differed from each other, and the fish length was only weakly correlated with the tailbeat frequency in one of the datasets. This is in line with the previous findings, where the tailbeat frequencies of Chinook salmon (1.0-2.0 bps) and sockeye salmon (2.0-3.5 bps) were found to be different using the same method, and the tailbeat analysis was shown to be independent of the fish length (Mueller *et al.*, 2010). However, the tailbeat frequencies in this study were much lower (on average 0.6 ± 0.3 for Atlantic salmon; 0.9 ± 0.2 striped bass 1.4 ± 0.3 for American shad) than the frequencies found in Mueller *et al.* (2010). In addition to species, the tailbeat frequency is influenced by many factors such as current velocity, swimming speed, and temperature (Cheong *et al.*, 2006; Stevens, 1979). The tailbeat frequencies presented here were measured in low velocity conditions and in a controlled setup while the data in Mueller *et al.* (2010) were collected in a river. As an example, the Atlantic salmon in the experimental ponds used in this study exhibited swim-glide behavior (see *e.g.*, Handegard *et al.*, 2009) through the sonar field with very few tailbeats; such behavior is not expected when swimming against higher currents.

Many other parameters can also affect the swimming behaviour but were difficult to control in an experimental study setup where logistics such as catching method of the fish and animal welfare defined the timing of the experiment. For example, the American shad dataset was collected in the summer when the water temperature and day length were different compared to the previous autumn when the other two datasets were collected. The three fish species were also originally caught for different purposes and using different methods, which may, in addition to different inherent behaviour and stress factors in the experimental pond, affect the swimming behaviour.

While it is expected, then, that the absolute magnitude of the tailbeat frequency would change if the physical setting changes, it is nevertheless important that the three species studied herein exhibit differences in tailbeat frequency in a "common garden" set-up and that the difference can be inferred from the sonar data. This means that the premise of using tailbeat frequency to differentiate between the three species studied herein should be transferable and scalable to another physical setting. However, it is recommended that study site specific calibration datasets are collected for different environmental conditions and fish species to ensure accuracy specific in the applied conditions.

One application of this tailbeat calculation method is in population monitoring studies, where information about fish species is often needed, and the ability to distinguish species using only the sonar imaging would have several advantages over other methods, such as laborious fishing apportionment programs (Mueller *et al.*, 2010). While the tailbeat frequencies differed significantly between the fish species, there was some overlap in the tailbeat frequencies between the three tested species. The outliers in all datasets also indicated that on occasion, the tailbeat frequencies are higher than the typical values for each fish species. Therefore, the utility of tailbeat frequency as a discriminate characteristic is likely restricted to study areas where only a low number of sympatric species are present at the same time. Hence, it is advisable to include collection of parameters (*e.g.*, migration timing or fish size, see Martignac *et al.*, 2014) and a statistical framework when predicting fish species using the sonar data. Tailbeat frequencies are also of interest in bioenergetics studies (Mueller *et al.*, 2010; Standen *et al.*, 2002; Steinhausen *et al.*, 2005), where sonar and the presented tailbeat calculation method can be used as a data collection method in natural conditions even at night and in turbid waters.

The setup used in the current study ensured that only individuals of one species were recorded exclusively at any given time, removing any ambiguity in species identification. However, it should be noted that tailbeat frequency was measured repeatedly for some individuals. The chance of recording tailbeat frequency from an individual multiple times was highest in the American shad data that had the lowest number of individuals in the pond. To minimize the effect of repeated data from same individuals, the fish behaviour was observed at the beginning and end of the experiment to ensure that all the fish were using the entire pond, thus ensuring each fish was as likely to pass the sonar field. As the selected dataset (n=50 observations for each species) consists of observations sparsely distributed with regard to the time it was collected, we maintain that the observations that were used are unique tailbeat “events” (fish randomly passing sonar unit) that are independent despite the potential that certain fish could have contributed more than one of these unique datapoints.

Automatic Peak Detection

In a monitoring study where large amounts of data are collected, automated methods for species identification are desired. It was hypothesised that the automated method would produce tailbeat counts that would closely approximate the counts from the manual method. The two methods produced the same or similar (±1) number of peaks/tailbeats in 68 % of comparisons for Atlantic salmon and in 62 % for American shad. However, clear and large differences were present especially in the striped bass dataset where only 28 % of the tracks produced the same or similar number of peaks/tailbeats. The limits of agreement were higher than ±1 in all datasets, and therefore the automated method cannot be fully used to replace the manual method in counting tailbeats. Nonetheless, the peak-detection algorithm showed promising results as an automated tailbeat detection tool, especially when the indicated sources of error can be minimized and when high accuracy is not needed (*e.g.,* when predicting fish species with largely different tailbeat frequencies). As the Target Range Extent can be included in the automatic fish detection procedures with very little additional computing in Echoview or other software, it could also be used in concert with other parameters, *e.g.*, length and schooling behaviour to predict fish species.

The limits of agreement were large, especially in the striped bass (-4 to 13.5) and Atlantic salmon (-3.2 to 5.5) datasets, where the fish densities were higher than in the American shad dataset. Most of the automated peak detection counts were higher than the number of manually identified tailbeats in both datasets. A source for false detections likely resonates from the sonar data processing stage in Echoview. In the tracks where the two methods did not agree, the peaks in the target range extent were typically variable, causing frequent signaling in the peak detection algorithm. This was most evident in the striped bass dataset where the fish density was highest and the fish were shadowing and swimming close to each other, thus resulting in varied shapes of the clusters. Similar issues can arise in high-noise environments, such as hydropower dams where turbulence prevents the collection of high-quality images; thereby, affecting tailbeat measurements (Mueller *et al.*, 2010). Setting a maximum linking distance when creating the clusters may improve the results but it can also influence the peak detection readings. Relatively high fish densities, such as used in this study, may not manifest in a monitoring situation in nature where the fish are allowed to progress at their own pace.

In the American shad dataset where the fish density was lower, the limits of agreement were the smallest (-3.5 to 2.6) and the mean of differences was close to zero (-0.4), indicating that neither method was constantly producing higher counts, but also that the peak detection algorithm was missing some tailbeats. A common source for the peak detection algorithm to miss a tailbeat was identified at the end of fish tracks. When the fish was close to the edge of the sonar field, its range-extent measurement became shorter, and the peak-detection algorithm could not adjust to the change. This could be avoided by discarding the last frames when enough tailbeats are recorded during the mid-section of the frame. In this study, the lengths of the fish tracks were already trimmed at the beginning to calculate the moving average and shortening the tracks from the back end was not feasible in our datasets where fish were recorded in close proximity of the transducer, hence the relatively short overall tracks. Ensuring long fish tracks during data collection will improve the automatic fish tracking. The longest tracks are produced when the fish are at the far end of the acoustic field and additional lenses or different sonar transducers can be used to widen the field.

Future Research and Management implications

Data quality directly affects the results in both the manual and automated tailbeat detection methods, highlighting the necessity for field-based calibration data. Our data suggests minimising noise is important and smaller fish densities can produce more accurate results. The most accurate results were attained when the entire fish was detected throughout its passage in the sonar field, and nothing else (*e.g.*, echoes of other fish or other noise) is included in the detected cluster. In this study, the application of homogenous parameter values in all datasets for the processing methods, such as the CSOT method used for removing the background, target detection algorithm, and tuning of the peak detection algorithm, undoubtedly affected detection efficacy, and it is probable that more accurate detection models will arise from dataset-specific algorithm tuning. The use of differing algorithms may also increase detection accuracy: for example, the inclusion of fish morphology, extracted via object-based image analysis (see for example, Blaschke, 2010), may provide additional data texture thereby improving model outputs.

Some salmon were observed gliding in the acoustic field, and thus limiting the number of measurable tailbeats in the short timeframe when the fish was visible in the data. Future studies and monitoring operations would benefit from including additional data relating to fish species, classification of swimming modes, and a comparison of tailbeat frequencies as a function of swimming mode. Another swimming-behaviour related question would be to study the straightness of swimming trajectory and its possible influence in the tailbeat frequencies: the applied moving average in the peak-detection algorithm adjusts for different heights of the peaks, however, the aspect angle of the passing fish needs to be considered, and ideally every fish would swim perpendicular to the acoustic axis to produce clear and constant tailbeats; the tracks where the fish were mostly moving parallel to the center beam did not produce clear images in the echogram and could not be included in the analysis.

It is also important to ensure that the recording frame rate is higher than the expected tailbeat frequency so that all beats are recorded (Kupilik and Petersen, 2014b; Mueller *et al.*, 2010). The used end-range in ARIS largely influences the frame rate as well as the resolution (Sound Metrics Corp., 2019a), and therefore, for most fish species, much longer ranges than used herein would likely not produce desired results. An example of the end-range and its influence on the resolution is the length measurement accuracy in different sonar datasets. High measurement accuracy has been typically reported in studies that used short ranges (*i.e.*, < 15 m) and high (*i.e.*, ≥1.8 MHz) frequencies (*e.g.*, Burwen *et al.*, 2007; Martignac *et al.*, 2014). Similarly, in this study, the difference between the lengths measured from the sonar data and lengths measured in the field was -4.1 cm (Atlantic salmon), -0.6 cm (striped bass), and 5.1 cm (American shad). In comparison, the lengths measured by four different users from longer end-range (29 m) and lower frequency (1.1 MHz) data were more variable, *i.e.*, mean of differences between -9.9 cm and 7.8 cm when compared to true fork lengths) and a modelling approach had to be used to predict the size category of Atlantic salmon (Helminen *et al.*, 2020).

The tailbeat frequencies were different between the three fish species, and therefore the information can benefit fisheries management for example by improved species differentiation from imaging sonar data. Overall, the automated method presented here should not be considered as a method that can alone be used for differentiating between fish species. However, as an easy-to-calculate method it can provide additional information in predictive models especially when the data quality is high and the sources of error are minimized. It is especially useful when the tailbeat frequencies of the target species are very different from each other.

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5. Combining imaging sonar counting and underwater camera species apportioning to estimate the number of Atlantic salmon (*Salmo salar*) in the Miramichi River, New Brunswick, Canada

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Abstract

The size of the adult Atlantic salmon (*Salmo salar*) population in the Miramichi River, New Brunswick, Canada, is currently assessed annually using a combination of trap net catches and a Bayesian mark-recapture model. Due to the uncertainty of the accuracy and the invasiveness of the current method, a combined imaging sonar and underwater camera method was tested in one of the main tributaries of the Miramichi River. The numbers of Atlantic salmon and striped bass (*Morone saxatilis*) at the study site in October were calculated by apportioning the sonar fish count using species ratio from the underwater camera data. The combined method estimated 358 Atlantic salmon and 255 striped bass when the species ratio was applied every day, and 274 Atlantic salmon and 337 striped bass when the monthly species ratio was applied. The counts were compared to catches in a downstream index net using estimated values for catchability of the trap net and for proportion of fish ascending to the same tributary. As an example, the sonar/camera count was 1.01 times the trap net catch that was adjusted with values similar to previous knowledge (10 % catchability and 50 % proportion). For striped bass, the same catchability and proportion values produced a lower agreement (*e.g.*, sonar count was 13 – 16 % of the adjusted catch) because unlike salmon, striped bass are not deterministically migrating up the tributary in the autumn. The trends in daily numbers of fish detected with the combined sonar/camera method were similar to the fish catches at the index net, with most Atlantic salmon being detected mid-month and most striped bass at the end of the month, and the fish were mostly detected overnight. In conclusion, the sonar and underwater camera

combination is a non-invasive method that can provide timely information of the salmon population in the Miramichi River in the tributaries that are currently unmonitored.

5.1 Introduction

The Miramichi River, New Brunswick, Canada, is a renowned Atlantic salmon river where the salmon run was historically the largest in the eastern North America, with returns exceeding 100,000 adult salmon until early 1990's (Chaput, 2010; Chaput *et al.*, 2016). Like majority of the salmon populations in continental North America, Miramichi population declined in the late 1990's (Chaput, 2010; Chaput *et al.*, 2016). Such trend not only poses a serious concern for the integrity of the conservation of this species *per se* but also has significant socio-economic ramifications for the province of New Brunswick where the value of recreational fishery alone is estimated $54 million annually (Gardner Pinfold, 2011).

The annual returns of adult salmon population in the Miramichi River are currently assessed using a mark-recapture model that combines catches at estuary index nets, (mark-) recaptures at in-river monitoring facilities, and directed capture programs (Chaput, 2010). The estimate is stratified separately for two main branches of the river that flow to a common estuary: the Main Southwest Miramichi River (SW; *i.e.*, one marking facility - Millerton trap) and the Northwest Miramichi River (NW; *i.e.*, one marking facility - Cassilis trap) (Chaput, 2010). Since 1994 (SW) and 1998 (NW), these index nets have been used to mark captured Atlantic salmon with either Carlin tags or caudal fin punching (Chaput, 2010).

The population is estimated using a model where the standard assumptions of a mark-recapture study are applied (Chaput, 2010). The proportion of the catches on the total returns (*i.e.*, fishing gear efficiency or catchability) is estimated annually using the recaptures for the two index nets and two size groups (1 sea-winter (1SW) salmon < 63 cm and multi sea-winter (MSW) salmon ≥ 63 cm) separately. The catchability has typically varied between 5 % and 15 % in the NW (Cassilis) index net (DFO, 2020a). The model also assumes a 10 % tagging and handling mortality and a closed population *i.e.*, all fish marked in a facility remain in the same branch of the river (Chaput, 2010). Additionally, tag loss was estimated to be 18 % for small salmon and 14 % for large salmon in 2009 (Chaput, 2010). For a successful mark-recapture study, a high proportion of the population should be marked and recaptured (Southwood and Henderson, 2000), which is difficult to achieve in a large natural river with migrating fish of multiple species.

Other factors complicating the estimate include potentially different capture probabilities (catchability) of the trapping gear between the branches (Chaput, 2010) or within branch over time due to the *e.g.*, environmental conditions or the changing number of fish passing the capture site. Particularly, equipment washouts can be problematic and prevent using the index nets during the time when the water is high and highest fish counts may occur (Chaput, 2010) as adult Atlantic salmon river entry has been shown to be in part triggered by increases in flow (Carrow, 2021). High water temperatures also prevent the use of index nets due to concerns with respect to salmon well-being, especially in recent years (DFO, 2020a).

Thus, the current population estimate relies on modelling approach, and a hierarchical model that includes multiple years is currently used (Chaput, 2010). The hierarchical model works well in estimating the uncertainties: as an example, the uncertainty in the probability of capture of the fish at the index nets is lower (coefficient of variation up to 33 %) than when using annual modeling where the uncertainty is high especially in the years with low number of recaptures (the coefficient of variation up to 161 %) (Chaput, 2010). However, the time lag to improved estimates of the population due to the need of multiple years in hierarchical model makes fisheries management decisions slower as well. A number of recommendations for the mark-recapture model, such as using other data sources and exploring other modelling options, have been discussed in an internal Fisheries and Oceans Canada peer-review meeting (DFO, 2010).

While there are limitations in the accuracy of the mark-recapture method, another consideration is the invasiveness of the capture, tagging, and recapture. The need to tag a large proportion of the population for a successful population estimate (Southwood and Henderson, 2000) combined with the estimated 10 % tagging and handling mortality (Chaput, 2010) is problematic in a vulnerable population where between 520 and 2921 salmon are being tagged annually (Chaput, 2010). These concerns in the current assessment method, as well as the downward trend of the salmon population size, have sparked the need to test other population assessment methods to support the current mark-recapture method.

In many rivers around the world, sonar methods have replaced other methods, such as mark-recapture programs in estimating the returning adult populations (Burwen and Bosch, 1998; Romakkaniemi *et al.*, 1997). As an example, split-beam sonars have been used in several river systems in Alaska since the early 1970's (Maxwell and Gove, 2004; Ransom *et al.*, 1998), and within the last two decades, imaging sonars have become the standard of hydroacoustic monitoring of migrating fish populations in rivers (Martignac *et al.*, 2014; Maxwell and Gove, 2004). Imaging sonars are also used in Atlantic salmon research (Anonymous, 2019; Lilja *et al.*, 2010) and therefore, provide a promising option for monitoring the population size in the Miramichi River.

Imaging sonars have been shown to provide relatively accurate estimates of count and length of different fish species in rivers, especially in short range (Helminen and Linnansaari, 2021; Martignac *et al.*, 2014). They can remain operational over a broader range of stream conditions (*i.e.*, high flow periods) compared to *e.g.*, weir counting (Pipal *et al.*, 2012). Sonars also provide timely (*i.e.*, daily or hourly) estimates of the run size to benefit in-season management decisions, as opposed to *e.g.*, mark-recapture estimates. Hydroacoustic methods can be limited in the identification of fish species when multiple species are present (Helminen *et al.*, 2021; Martignac *et al.*, 2014). Combining sonar with other methods, such as fishing, underwater cameras, or tailbeat-frequency calculations is used to estimate the abundance of each species (Egg *et al.*, 2018; Helminen *et al.*, 2021; Martignac *et al.*, 2014; Mueller *et al.*, 2010, 2006).

The aim of this study was to assess if the imaging sonar method can be combined with underwater camera data to count fishes migrating in the Miramichi River. The objectives of this study were to estimate the number of fish of different species in the Little Southwest Miramichi River using sonar count and underwater video camera species apportion method ('the combined sonar/UWC method'), and compare results with annual index trapnet programme in the river to assess the value of the sonar/UWC for monitoring these migratory populations.

5.2 Materials and methods

Study area

The Miramichi River, New Brunswick, Canada, has catchment of about 14,000 km^2 (Chaput *et al.*, 2016). There are two major branches: the Main Southwest Branch (SW: about 7,700 km^2) and the Northwest Branch (NW: about 3,900 km^2) that drain into a common estuary and subsequently into the Gulf of St. Lawrence (Figure 24; Chaput *et al.*, 2016). Currently, two index nets are used for catching, tagging, and releasing Atlantic salmon: Millerton (SW) and Cassilis (NW) (Figure 24; Chaput, 2010).

The study site was located in one of the two major tributaries of the NW; the Little Southwest Miramichi River (LSW; known by local Mi'kmaq as Tuadook) (46°57'20N 65°51'40W; Figure 24) that has a catchment of about 1,300 km^2 (Chaput *et al.*, 2016). The LSW empties to the NW in an area that is under the tidal influence, *i.e.*, in the estuary. The monitored location was 4.5 km upstream from the LSW / NW confluence and 8 km upstream of the index net.

At the study site, the river is approximately 40 m wide during the summer low flow and during the study but can be up to 70 m wide in high water. The flow velocity varies throughout the season, but it was 0.4 ± 0.1 m/s (average ± 1SD) during these low flows of the study. The substratum at the study site is alluvial cobble and gravels.

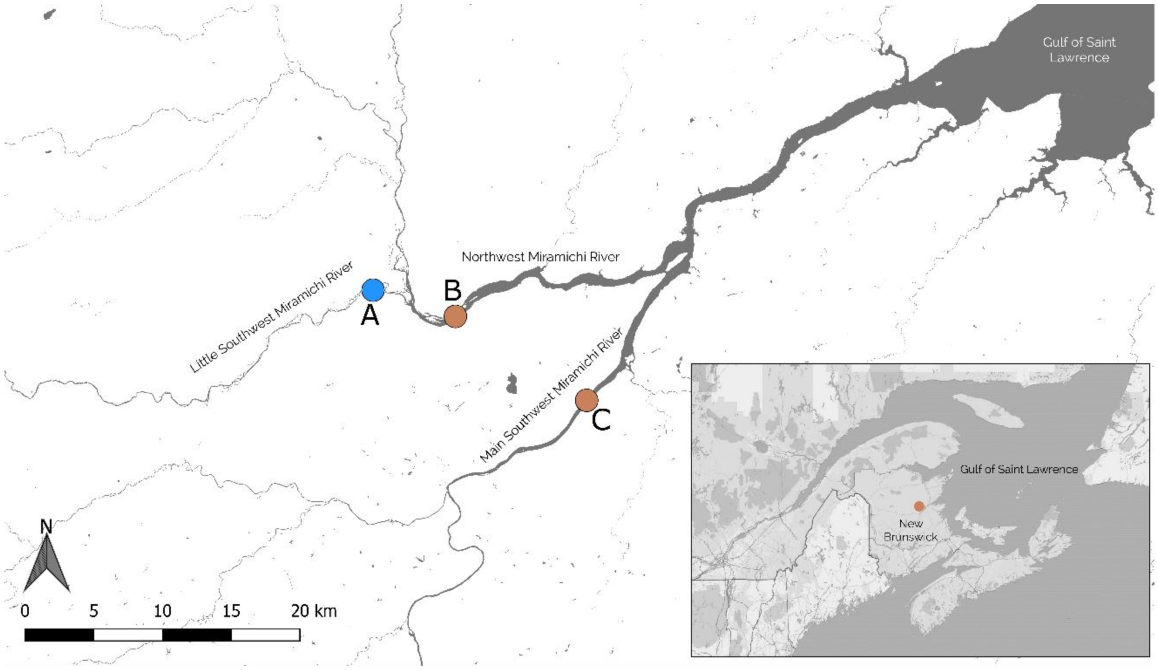

Figure 24. Map showing the location of the study site (A) in the Little Southwest Miramichi River and the index net locations in the Northwest Miramichi River (B: Cassilis) and Main Southwest Miramichi River (C: Millerton). The map data contains information licensed under the Open Government Licence – New Brunswick and OpenStreetMap contributors.

During the studied period (October 1 – October 24; see below), the water temperature was 3.4 to 13.3 °C, and the water level was approximately 0.7 m until October 17, 2019, after which it peaked twice and was up to 1.3 m (Figure 25).

Atlantic salmon return to the Miramichi River between the months of May and October (Chaput *et al.*, 2016) and during the same time period, various other diadromous species are also reported in the index net: striped bass (*Morone saxatilis*), American shad (*Alosa sapidissima*), American blueback herring (*Alosa aestivalis*), and alewife (*Alosa pseudoharengus*) which are abundant in the spring until July (DFO, 2020b). The striped bass return in October to overwinter in the estuary when they are counted in the facilities (DFO, 2020b) and some (an unknown portion) of them also explore the freshwater portions of the river as far upstream as the sonar study site. American eel (*Anguilla rostrata*) is also common in the area (DFO, 2020b).

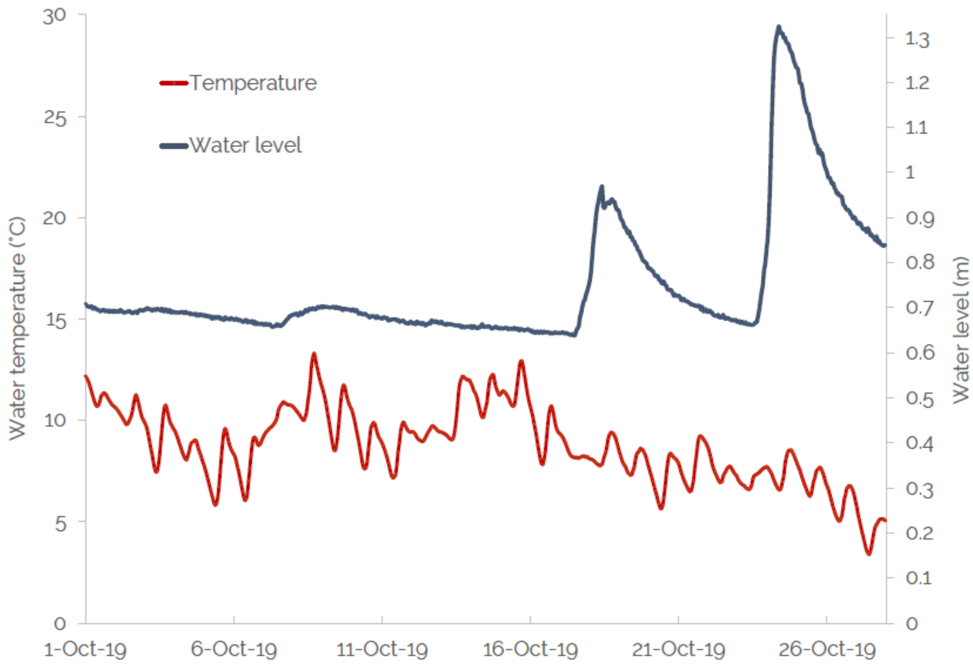

Figure 25. Water level and water temperature in October 2019 in the Little Southwest Miramichi River. Data from the Miramichi River Environmental Assessment Committee weather station located at the sonar study site.

The population size of Atlantic salmon is currently estimated for the NW (and SW) population, and there are no separate estimates of the salmon numbers ascending to the LSW or any other tributary. The last full salmon population assessment was completed in 2014 (DFO, 2014), and updates have been published annually; the latest update is for the 2019 season when 3900 adult salmon were estimated in the NW Miramichi (DFO, 2020a).

At the study site, an Adaptive Resolution Imaging Sonar (ARIS explorer 1800, Sound Metrics Corp.; www.soundmetrics.com) was installed facing perpendicular to the river flow using range 1.5 m to 11.1 m and frequency of 1.8 MHz. The sonar was aimed so that the river bottom was visible throughout the sonar field. All settings were kept at maximum (Frame rate and Transmit) or automate (Focus, Pulse width) throughout the monitoring period. From the opposite side of the river, a resistance board fish weir (*i.e.*, “floating fence”; Stewart, 2003) was installed to restrict the river width to approximately 10 m, and thus, to guide the fish to swim into the sonar field (Figure 26).

Four cameras (Zosi 1280TVL Surveillance system) in waterproof boxes were installed in the river, directly downstream of the sonar field and outside the sonar image (Figure 26). The cameras were spaced approximately 1.5 m apart from each other and faced across the river (i.e., the next camera in line was visible in the video). Video files were recorded using a motion detection in iSpy 64 v7.1.8 (DeveloperInABox ltd.; www.ispyconnect.com) software, and its sensitivity was adjusted such that normal “background” motion (*i.e.*, water flow and light reflection) was insufficient to trigger recording, and only triggered by objects passing a camera. Underwater lights (Q-Led III floodlight, 7500 Lumen) were attached to all mounts and a timer was used to switch the lights on at 1800 hours and off at 0600 hours.

For the purpose of this study, the sonar and video camera data were collected from October 1 until October 25, 2019. The monitoring season in the Miramichi River typically lasts until mid- to end of October and in 2019, the last day of catch at DFO’s NW Cassilis index net was October 24.

Figure 26. Study site at the Little Southwest Miramichi River. The Resistance Board Fish Weir (A) guides fish to one side of the river, where an ARIS sonar (B) is recording with 11.1 m end range (C) and four underwater cameras (D) are aimed to the middle of the river. The flow direction indicated with an arrow.

The sonar data were analysed manually in ARISfish 2.6.2 (Sound Metrics Corp.; www.soundmetrics.com) software for count and size of fish by an experienced sonar technician. Background subtracted echogram was used to find the fish and lengths were subsequently measured from the raw footage as explained in Helminen *et al.* (2020). All (motion detection triggered) videoclips that were recorded by the underwater camera were analysed and when a fish was seen, its species, time, and possible external fish tags were recorded. The daily fish counts from the sonar data were then summarized and all the fish with length ≥ 48 cm were grouped into up- or downstream moving fish. The threshold of 48 cm was based on the minimum fork lengths of adult Atlantic salmon captured in the NW Cassilis index net in 1992 to 2013 (Chaput *et al.*, 2016).

Species apportion method

The sonar count was considered a total count of fish at the study site and the underwater camera footage was considered a species sampling method and used to apportion the sonar counts between the species. There were mainly two species, Atlantic salmon and striped bass, in the underwater videos. Two different methods were tested: daily apportion (*i.e.*, the proportion of each fish species in the underwater camera data applied directly to the sonar fish count of the day) and monthly apportion method (*i.e.*, the counts of each fish species was accumulated for the whole month, and the monthly proportion was applied directly to the sonar fish count of the month). Using these methods, the total number of fish of each species in October was calculated. In the days with no fish seen in the underwater camera footage (n=4 days), the average number of fish per species of the previous and next day was calculated and used for apportioning the sonar count. No adjustments were made for the sonar data for the days when the sonar had stopped working and had not collected data (n= 4 days).

Comparison to index net data

Because the (true) number of fish in the LSW is not known, the index net catches from downstream Cassilis index net were used for comparison (DFO, 2020b). Because the trap net ($Catch_{trapnet}$) only samples a proportion of the fish population ($Catchability_{trapnet}, between\ 0\ and\ 1$), and because it is located downstream of two river branches between which the fish will be divided ($Propotion_{Branch}, between\ 0\ and\ 1$), the number of fish in the LSW (n_{LSW}) is estimated as:

$$n_{LSW} = \frac{Catch_{trapnet}}{Catchability_{trapnet}} * Proportion_{LSW}$$

The equation assumes that the fish are actively migrating and not staying in the estuary, thus it can be reliably used to estimate only the salmon population, while other fish species (*e.g.*, striped bass) are more likely to stay in the estuary or move back and forth between the areas.

The proportion of the adult Atlantic salmon that ascend to the LSW from the NW estuary was estimated based on habitat availability and information from a radiotracking study. The LSW has approximately 50 % of the juvenile salmon habitat in the NW system (Chaput *et al.*, 2016) and an ongoing study from 2019 indicates that approximately 39 % of adult salmon from the NW Cassilis net exclusively enter the LSW with additional adult salmon swimming between the LSW and other river branches (Scott Douglas, Fisheries and Oceans Canada, Gulf Region Science Branch, pers. comm.).

The catchability in October is not known, but it has been estimated to range from 5 to 15 % in the NW Cassilis index net (DFO, 2020a). In 2019, the estimated proportion of total population caught in the index net (median) was approximately 8% for large salmon and 11 % for small salmon (DFO, 2020a).

Assuming that the sonar is counting all the fish ascending into the LSW, the total number of fish remaining upstream of the study site is calculated by subtracting the descending fish from the total number of ascending fish ($n_{sonarUP} - n_{sonarDown} = n_{sonar}$). The ratio between the two methods is therefore calculated:

$$\frac{n_{sonar}}{\frac{Catch_{trapnet}}{Catchability_{trapnet}} * Proportion_{LSW}}$$

To produce example ratios, Proportion_{LSW} values 40 % and 50 % were used with catchability values 5 %, 10 %, and 15 %, and the ratios between the combined sonar/UWC method and the index net catch for October 2019 were calculated for the two most common species (Atlantic salmon and striped bass). Additionally, using the sonar/UWC estimates and the index net catch, a regression line was plotted to estimate the catchability using different Proportion_{LSW} values and compared to values from the literature.

Observed fish behaviour and the number of externally tagged fish

To assess if the fish were similarly active throughout the diel period, the hourly fish counts were tabulated for all days when sonar data were collected. To avoid the influence of large schools in the dataset (*i.e.*, multiple fish seen in the same hour causing bias in the data), the frequencies of binary outcomes (fish or no fish) per hour every day (24 hours and 25 days, n=600), were used in the comparison instead of the total number of fish. Fisher's exact test was used to test if there was a difference between the frequencies in different hours and pairwise Fisher's test with Bonferroni corrections was calculated for all hours using package *fmsb* (Nakazawa, 2019) in R software 3.6.1 (R Core Team, 2019). The hour 0 (midnight – 1 am) was used as a baseline; the frequencies in other hours were compared to the frequency in hour 0.

Similarly, the time of the day was analysed from the underwater camera observations, separately for Atlantic salmon and striped bass. Fisher's exact test was used to test if there was a difference between the hourly distribution of the two species.

To compare the daily estimates of the daily numbers of Atlantic salmon and striped bass at the sonar study site and in the index net catches, the daily numbers of fish of each species were compared graphically in Microsoft Excel (MSO 365 version 16).

External fish tags were detected and recorded from the underwater video footage. The salmon that had a visible dorsal fin were counted and the tagged/not tagged ratio was calculated.

5.3 Results

A total of 579 fish ≥ 48 cm were recorded moving upriver (Figure 27) and forty fish moving downriver in October 2019. The underwater camera recorded 62 salmon, 67 striped bass, and 2 American eels (*Anguilla rostrata*). There were 59 salmon and 464 striped bass caught in the index net. The other species caught in the index net were brook trout (*Salvelinus fontinalis*, n=1), fallfish (*Semotilus corporalis*, n=4), and white sucker (*Catostomus commersoni*, n=3).

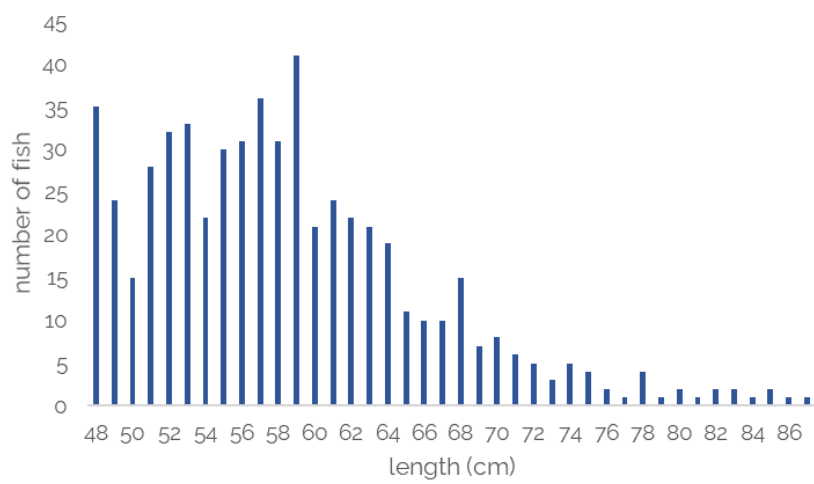

Figure 27. Length distribution of upstream moving ≥ 48 cm fish recorded in the sonar footage (n=579).

By combining the sonar and underwater camera data using daily fish species apportion method, there were 358 salmon (n_{up}=328, n_{down}= 30). Using the monthly apportion method, the number of salmon was 274 (n_{up}=256, n_{down}= 18). The same numbers for striped bass were 255 (n_{up}=245, n_{down}= 10) when using the daily and 337 (n_{up}=315, n_{down}= 22) for the monthly apportion method. Additionally, 6 (n_{up}=6, daily apportion) and 9 (n_{up}=8, n_{down}= 1, monthly apportion) eels were detected, but no eels were captured in the index net in October.

If the number of fish destined to LSW (n_{LSW}) from the index net was produced independently of the combined sonar/UWC method by applying the true captures at the index net, and simply varying values for index net catchability and $Proportion_{LSW}$, it was observed that the sonar/UWC count estimates were within 40 % and 190 % of the estimated Atlantic salmon numbers in the (adjusted) index net and within 5 % and 24 % of the striped bass numbers (Table 12). There was a good agreement (close to 1:1 ratio) between the combined sonar/UWC method and index net data for adult Atlantic salmon when values that were realistic, based on *a priori* data, were applied: For Atlantic salmon, the closest ratio to 1:1 (*i.e.*, 101 %) was achieved when using the daily apportion method, 10 % index net catchability and 50 % $Proportion_{LSW}$, followed by 103 % agreement when using the monthly apportion method, 10 % index net catchability and 40 % $Proportion_{LSW}$ (Table 12). For striped bass, the ratios between combined sonar/UWC and index net catches were considerably lower. The highest agreement between the two methods for striped bass (*i.e.*, 24 % for monthly apportioning, or 19 % for daily apportioning) was achieved using 15 % index net catchability, and 40 % $Proportion_{LSW}$ (Table 12).

Table 12. The level of agreement (ratio) of the sonar count / index trap net LSW estimate, where the example values for catchability and $Proportion_{LSW}$ are applied to the index net catch and the underwater camera species data are applied to the sonar count using D = Daily apportion method and M = monthly apportion method.

Catchability	**5 %**		**10 %**		**15 %**	
$Proportion_{LSW}$	**40 %**	**50 %**	**40 %**	**50 %**	**40 %**	**50 %**
Salmon / D	63 %	51 %	130 %	101 %	190 %	151 %
Salmon / M	50 %	40 %	103 %	81 %	151 %	121 %
Striped bass / D	6 %	5 %	13 %	10 %	19 %	15 %
Striped bass / M	8 %	6 %	16 %	13 %	24 %	19 %

Using the fish counts from the sonar (by applying either daily or monthly apportioning method), and further assuming equality of the sonar and the index net method, and the estimated 39 % $Proportion_{LSW}$ (as per preliminary radiotracking data), the index net catchability can be estimated as 7.7 % and 9.7 % for salmon using the daily and monthly apportion methods, respectively (Figure 28). Alternatively, if the index net catchability was (arbitrarily) fixed 10 %, the $Proportion_{LSW}$ at the index net could be estimated as 50.5 % (daily) and 40.3 % (monthly) for salmon (Figure 28). For striped bass, if using the same assumptions, the index net catchability was estimated as 77.0 % and 61.7 % ($Proportion_{LSW}$ at 39%), and alternatively, fixing the index net catchability at 10% resulted in $Proportion_{LSW}$ as 5.1 % (daily) and 6.3 % (monthly) for striped bass (Figure 28).

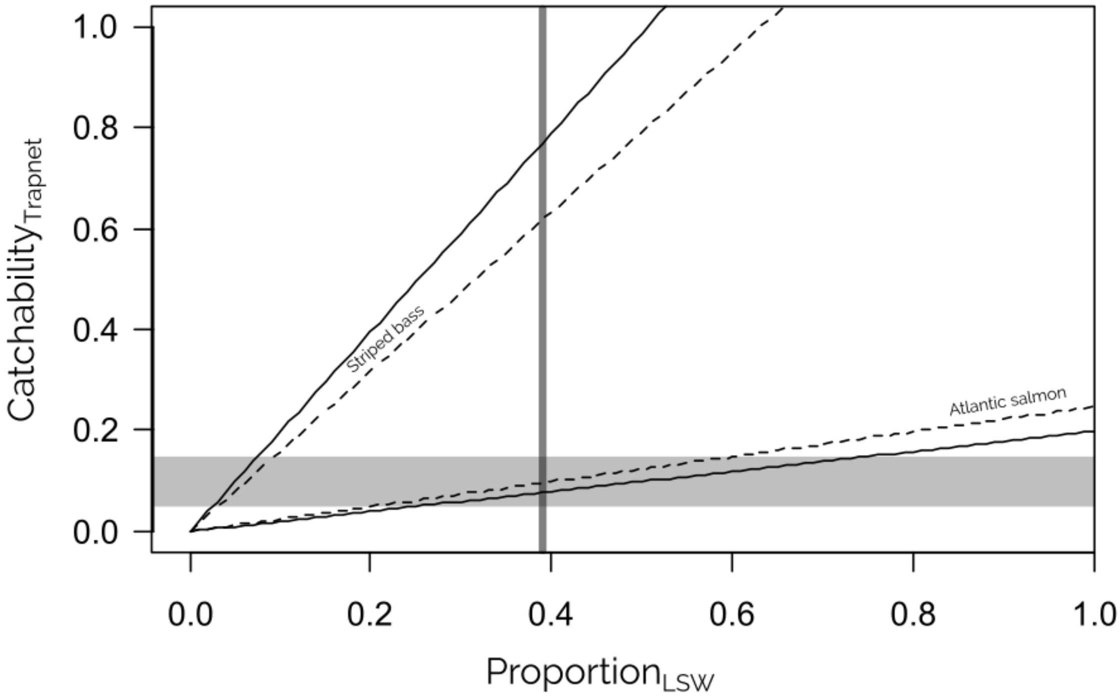

Figure 28. The regression lines estimating the index trap net catchability using different proportion values (proportion of all fish from the Northwest Miramichi system swimming to the Little Southwest Miramichi (LSW)) for Atlantic salmon and striped bass. The solid line uses the daily apportion method and dashed line uses the monthly apportion method. The gray lines indicate values from previous knowledge: 0.39 proportion and 0.05 – 0.15 catchability.

Observed fish behaviour and tag identification

Based on the sonar data, the fish were most active between 1900 – 0800 hours; in those hours, the fish were detected in 36 % - 68 % of the days (Figure 29). The fish were least active in 0900 – 1600 hours, when fish were only detected in 0 % – 12 % of the days (Figure 29A). The Fisher's exact test for count data indicated a difference (p<.05) between the frequencies of fish seen in different hours (Figure 29A). The pairwise comparison showed differences (p<.05) between hour 0 and hours 9 to 16 (Figure 29A). For the other hours, the Bonferroni corrected p-values were p=1 except for hour 8 (p=.07), hour 17

(p=.23), and hour 18 (p=.63). The other pairwise comparisons indicated differences between the same or similar hours (Appendix A6).

In the underwater camera data, all striped bass were detected overnight between 2200 and 0400 hours (Figure 29C), when also 68 % of the Atlantic salmon were detected (Figure 29B). Most (95 %) of the Atlantic salmon were detected after sunset and before sunrise (between 1800 and 0700 hours), but three salmon were also detected after sunrise, in the hours 9, 11, and 15 (Figure 29B). The Fisher's exact test therefore indicated a difference (p<.05) between the hourly distribution of the Atlantic salmon and striped bass detections (Figure 29B,C).

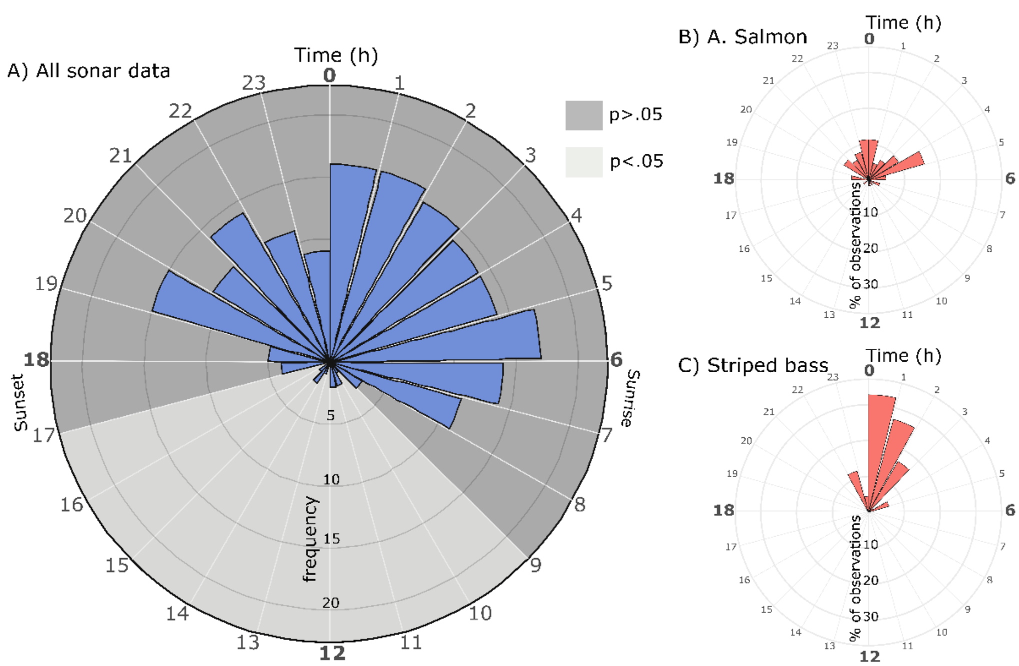

Figure 29. Circular bar-plots of fish detections each hour. A) The blue bars represent the number of days with fish detections in the sonar data (max=25) every hour (using 24 h clock). The hours with significantly different (p<.05) fish detection probability compared to hour 0 are highlighted in light gray. The red bars represent the percentage of fish detections each hour of the day in the B) Atlantic salmon and C) Striped bass underwater camera datasets. The sunset and sunrise hours are also highlighted for reference.

Using the combined sonar/UWC method, most (89 %) of the salmon were detected during October 8–18, and only 0-2 salmon per day were detected at the beginning of the month (October 1–5) and after October 23th (Figure 30A). There was a similar trend in the index net catches, as most (93 %) of the salmon were caught before October 15th (Figure 30A).

The combined sonar/UWC method detected most of the striped bass (73 %) at the end of the month (after October 18; Figure 30B). Striped bass were also counted at the beginning of the month, but not between October 4 and 17 (Figure 30B). Similarly, most of the striped bass (80 %) were caught in the index net at the end of the month after October 17th, and there was a period (October 11 – 16) when striped bass were not caught (Figure 30B).

Of the salmon observed in the underwater video cameras, the dorsal fin was visible in 38 salmon of which 11 (29 %) were tagged.

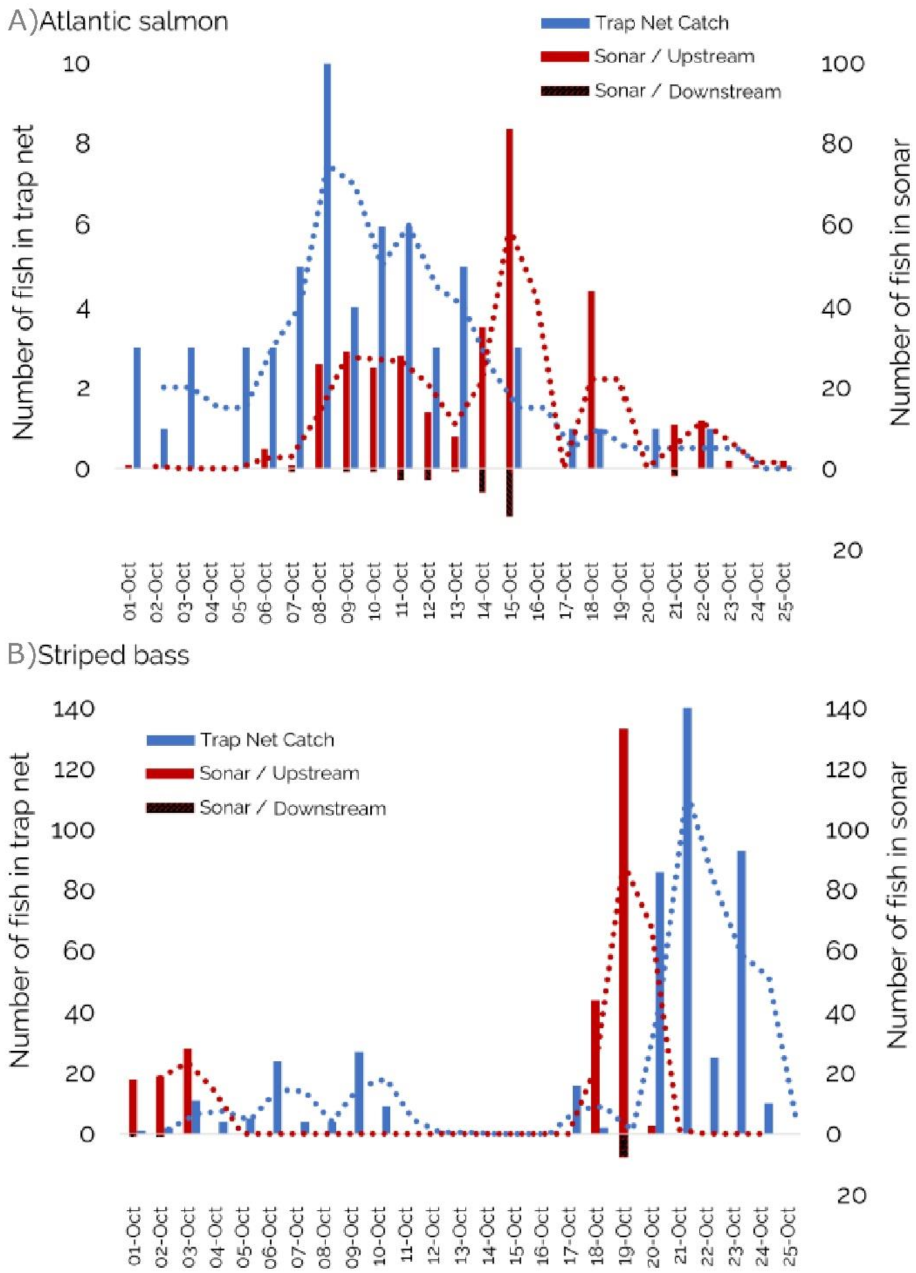

Figure 30. The daily numbers of (A) Atlantic salmon and (B) striped bass caught in the Cassilis index trap net and seen in the sonar and divided to species using daily species ratios based on the underwater camera footage, separately for up- and downstream moving fish. The dotted lines represent two-period moving mean trends. Note the differences in Y-axis ranges between panels.

5.4 Discussion

Estimating the numbers of fish of different species and comparison to index net catches

The combined sonar/UWC method resulted in 358 (daily apportion method) and 274 (monthly apportion method) Atlantic salmon in October, which is approximately 4.4-5.8 times more than the number of salmon caught in the index net in the same time period. Upscaling the index net daily catch using catchability rates and proportion of catch destined to LSW using realistic *a priori* estimates from existing DFO data, the estimates of the methods were very close to each other, *e.g.*, the best estimate of sonar/UWC salmon count was 101 % of the estimate using index net catch adjusted with values from DFO data. However, there are uncertainties in both methods and in both estimated parameters for the index net method, and a change in either catchability or Proportion_{LSW} yield a large difference in the ratio between the two methods. Nevertheless, the outcome points to the fact that the combined sonar/UWC method assesses the salmon population at least similarly as the index net and encourages to continue the monitoring using the combined method, to gather a larger dataset for a more thorough comparison. Importantly, tributary-specific population estimates are currently not produced for either in the Northwest or Southwest Miramichi River, but as is demonstrated herein, an effective method of doing so now exists, and could be tasked to be undertaken by the fisheries management agency or be outsourced to local non-government organizations or First Nations.

While the literature-adjusted index trap net salmon count and the combined sonar/UWC salmon count were in high agreement, the case was not the same for striped bass. The combined sonar/UWC method counted 255-337 striped bass in the LSW in October, and the estimate was at best only 24 % (monthly apportioning) or 19 % (daily apportioning) of the estimates that were made using index net catches. However, the large disagreement between the two methods was expected, and as such, is not an indication of inaccuracy or failure of the sonar/UWC method for estimating striped bass population ascending to LSW. The discrepancy between the two methods is borne from the fact that the striped bass do not migrate to the river to spawn in the autumn but rather, use the estuary as overwintering ground where they can aggregate in high numbers in late autumn. Any movement to LSW by striped bass is exploratory in nature, rather than facultative, and therefore, they are more likely to be moving back and forth in the estuary–freshwater interface area. Thus, the catchability and proportion of the stiped bass migrating to the LSW is very different than with salmon and, in addition, the striped bass are more likely to be caught/detected multiple times because they are not actively migrating upriver whereby they would be passing the study site only once. Thus, due to the sonar study site location in the river rather than in the estuary, the combined sonar/UWC method does not attempt to estimate the size of the striped bass population, but we believe it can be reliably used to better understand migration behaviour of striped bass including estimating the number of fish that go upriver temporarily for *e.g.*, feeding and used towards a better understanding their impact on salmon and other fishes (Andrews *et al.*, 2018; Daniels *et al.*, 2018).

Atlantic salmon and striped bass were the two most common species in October, as detected by both the combined sonar/UWC and index net methods. Small number (<10 individuals per species) of other fish species were caught in the index net but not seen in the combined UW/sonar data, and a small number of eels were seen in the combined data but not caught in the index net. Similarly to striped bass, these fish are not actively migrating and therefore not expected to be detected at both study sites at all times.

Observed fish behaviour

In the sonar data, the fish were mostly detected moving between hours 1900 and 0800, with little or no activity from 0900 and 1700 hours. We are uncertain if the artificial lights used for the underwater camera recording influenced the migration after dark, however, no difference was found in the numbers of fish when the lights were on and off in an experiment conducted over six nights in October 2018 at the same study site (Laiho, 2019). The movements are therefore likely related to the photoperiod at this shallow site, but the behaviour may be different in other, deeper parts of the river. For sites where the fish will be moving (*vs.* holding), there are some advantages for operation, such as saving data storage (no recording during inactive hours) and focusing maintenance periods during the daytime, but it also addresses the limitations of the underwater cameras as additional lights are needed.

The underwater camera data similarly showed that most of the striped bass and Atlantic salmon were detected during nighttime. All striped bass were seen at hours close to midnight while Atlantic salmon were detected throughout the nighttime hours and sometimes also in the daytime; therefore, there was a difference between the hourly distribution of the species. This could be a result of the small sample size; however, it is also possible that Atlantic salmon were more active around sunset and sunrise than striped bass.

Both the index net and the combined sonar/UWC method detected most of the striped bass at the end of the month and had a period of no striped bass detections/catch in the middle of the month. Similarly, most of the Atlantic salmon were detected/caught mid-month, with less salmon detected/caught at the beginning and end of the month. A lag time (*i.e.*, the time it takes to swim from the index net to the sonar site) between the index net and the sonar site was not applied to the data as the distance was only ~8 km (compared to *e.g.*, Faulkner and Maxwell (2020) where a lag time of roughly 32 km/d was used). The matter of lag may further be complicated by the fact that Atlantic salmon that are handled at the index net for biological measurements and tagging may spend a longer time in the estuary recovering from sampling (*e.g.*, avg. lag in estuary of 8.3 days for LSW salmon, with up to 50 days; Carrow, 2021) in comparison to unsampled Atlantic salmon, and the fact that environmental conditions triggering freshwater entry from the estuary (water temperature and flows; Carrow, 2021) may vary over time. However, an interesting question in future studies would be to compare the index net and combined sonar/UWC counts over the whole season to gain a better understanding on the time Atlantic salmon spend in the tidal water after being caught in the index net and before entering the river.

It is remarkable that, in either of the methods, there was little overlap in the days when the two species were seen. This could partially be a bias in the methodology, if abundance of one species results in lesser detection rate of the other species, especially in the combined sonar/UWC method, where the number of fish detections in the underwater camera was low. However, because similar trends were seen in the index net data, it is more likely related to true natural movement and migration patterns. For instance, in a radio telemetry study, most of the salmon entered the river in the autumn mainly after the water temperature had fallen below 15 ℃ (Carrow, 2021). Striped bass start to seek overwintering habitats in the estuary and leave the river before the water temperature declines below 10 ℃ (Andrews *et al.*, 2019). For salmon monitoring purposes, it is also notable that less salmon were detected at the end of the month using both methods, which indicates that most of the individuals would have passed the sites before the end of the monitoring period: similarly in a radio telemetry study in 2018, all Atlantic salmon had entered the river by October 18th (Carrow, 2021).

Proportion of tagged fish in the underwater video footage.

A large percentage (29 %) of salmon were Carlin-tagged in the underwater videos. These tags were likely inserted at the Cassilis index net that is close to the study site, although salmon may have also been tagged at the Millerton index net and switched the river branch after tagging. The high re-encounter rate of tagged salmon could indicate that the catchability at the Cassilis is, in fact, much higher than the estimated 5 % -15 % - assuming there is no difference in the behaviour (proportion of fish swimming to the LSW) between the tagged and untagged salmon. However, in our dataset, a catchability value 29 % would not produce a result (*i.e.*, proportion value would be >1), and, as an example, the high encounter rate of tagged salmon could be an artefact wherein a salmon carrying a flashy tag were more likely to trigger the motion detection of video recording than a salmon without the tag. The small dataset does not allow further inspection of the cause, but the finding warrants future research.

Management implications: Miramichi River

Due to the similarity of the literature-adjusted index net salmon count and the combined sonar/UWC salmon count, and the similarity of the daily trends throughout the month of October, the new method would add to the current knowledge about the salmon population size and migration timing without complicating the comparison to historical index net data. Although the values for catchability and proportion will likely slightly vary over the years and even within a year, the values found in this study can be used as a baseline for statistical models in future studies, even in the years when only one method (either sonar or trap net) is used.

The sonar monitoring method could be used to gain a better understanding of the populations in all the tributaries of the Miramichi River. The populations within tributaries are important to consider in management strategies, because they can act as independent, closed populations and the health of the populations of different tributaries may vary largely (Anonymous, 2019; Vähä *et al.*, 2007). Using an imaging sonar would also benefit in-season management, as the information from the studied site(s) can be available timely (*e.g.*, daily), rather than after the season as with the current mark-recapture method.

An important benefit of using the combined sonar/UWC method is its non-invasiveness. Currently the tagging and handling mortality at the index net is estimated as 10 % for salmon (Chaput, 2010), and, depending on the catchability of the index net, it therefore varies between 0.5 – 1.5 % of the salmon population annually. Even if the true salmon mortality was lower than estimated, large amounts of other species are also caught and the impact of the index net to them is unknown, but it is probably not 0. With sonar, it is not possible to collect “hands-on” biological characteristics data, namely the sex ratio that is of important role in estimating the total egg deposition annually (DFO, 2020a). Perhaps the same information could be collected using the combination of underwater camera footage (sex information based on images), sonar (length data) and *e.g.*, information from recreational angler or First Nations fishery catches (all biological data, including scale and tissue samples).

The sonar has an advantage over traditional trap-fishing methods in changing environmental conditions (*e.g.*, in high flow periods; Pipal *et al.*, 2012). In Miramichi, the sonars can be used during high water temperatures when the index nets are not in use. To achieve the advantage in high water levels, the sonar study site needs to be built so that the equipment remains functional in strong flow, but it can be easily removed before the river freezes. As an example in October, the sonar study site was disassembled in the same week as the index net, because the rising water levels increased the risk of not being able to remove the equipment (fence and sonar transducer) before significant ice build-up. Additionally, there were four days when the sonar data were not recorded. The cause of the issue was a software error that had caused crashing either in the operating system or the recording software. More frequent (daily) checks are needed to ensure continuous recording and quicker reaction time to errors, to gain the advantage of better temporal coverage. The sonar system is easily connected to remote control capabilities via internet, so monitoring of functionality, or adjusting parameters can be easily achieved without field trips.

Current mark-recapture modelling would also benefit from the information (count and proportion) of the fish tags seen in the underwater video footage in different tributaries, and a better understanding of the distribution, movements, straying rates, and catchability of the fish could be achieved by tagging the fish using different types of tags (*e.g.*, coloured Floy-tags) in different index net locations and different times.

Future improvements

The combined sonar/UWC method assumes that all species have the same probability of detection (detectability), and higher detection rates will improve the estimate. The number of detections in the underwater video camera dataset was clearly lower (21 % of the sonar data) than the number of fish detections in the sonar footage. Some difference between two methods is expected in natural river conditions, but a higher agreement is desired for higher confidence in the method.

The high proportion of tagged fish in videos raises questions about the motion detection used during recording, as it is possible that notable features (*e.g.*, fish tags or colours of fish) or behaviour (*e.g.*, different swimming patterns) may trigger the motion detection at different rates. While it was not tested, it was common to see the fish moving slowly in the videos, and perhaps the fish that were moving slowly were more likely to trigger the motion detection than fish that swam quickly past the study site. In retrospect, 24-hour recording should have been collected and motion detection applied on recorded data instead of using the motion detection to record the videos. A potentially better solution would be to combine the sonar data and underwater camera data together in the same software, allowing simultaneous analysis of the two. Automatic fish tracks could be used to detect the fish in the sonar files (Helminen and Linnansaari, 2021), and the video files from the same timestamp analysed either by user, or using an automated approach (*e.g.*, Ditria *et al.*, 2020).

In real life, a defining factor when deciding the assessment methods is the cost-efficiency; while running a sonar site can be more cost-effective than running an index net, running multiple sonar sites may be challenging and expensive, especially if the sites are spread through the catchment. Potentially, some cost effectiveness could be reached through only using underwater video cameras at some of the tributaries (*e.g.*, Borgstrøm *et al.*, 2010) and with the development of stereo-camera systems the fish lengths can be measured (Letessier *et al.*, 2015), and therefore, similar information could be produced as with the combined sonar/UWC system. The results in this study show that such information can be collected using underwater cameras in the Miramichi, but more research is needed to test the accuracy of the count with more emphasis on the accuracy of the motion detection.

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6. A practitioner's guide for monitoring fish populations in rivers using imaging sonars – Case study: Monitoring adult Atlantic salmon (*Salmo salar*) run in rivers using an ARIS

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Abstract

Imaging sonars are used for monitoring migrating fish in rivers and provide accurate and timely counts of fish in low-light conditions and turbid waters. Many organizations have recently shown interest in monitoring Atlantic salmon (*Salmo salar*) populations with imaging sonars but due to the high cost of the equipment, an initial understanding of the limitations and total resource requirements to run a monitoring program is necessary to make an educated decision. This paper reviews the recommended practice and cost for selecting the study sites, designing and building the site equipment, choosing analysis methods, and daily operational tasks. Insights are added from our experience from running an imaging sonar monitoring project in the Miramichi River, New Brunswick, Canada from 2016 to 2019. Study site selection is arguably the most important factor for successful sonar monitoring project and careful *a priori* testing is recommended before investing in the study site. A team of personnel are needed for ensuring the operation of the site and trained people are needed for analysing the data. Large amounts of data are collected, and thus automated data analysis methods may provide a cost-effective option, especially if many sonars are simultaneously used for collecting the data. Additional costs will occur if the application requires species identification and behaviour analyses. This paper reviews the factors that need to be considered before investing in a sonar-based monitoring program for fish population estimates.

6.1 Introduction

Fixed-location sonar methods have been used for monitoring fish populations in rivers for decades (Maxwell and Gove, 2004; Ransom *et al.*, 1998), and within the last 20 years, the imaging sonar systems have become the standard for hydroacoustic monitoring of migrating fish populations in rivers (Martignac *et al.*, 2014; Maxwell and Gove, 2004). They can be used for estimating the number and length of fish over a broad range of stream conditions (*i.e.*, turbid rivers and in complete darkness; Mueller *et al.*, 2006). Currently, the main limitation of hydroacoustic methods is the identification of fish species, and sonars are often combined with other methods to estimate the abundance of each species (Martignac *et al.*, 2014).

As an anadromous species, Atlantic salmon (*Salmo salar* L.) populations are monitored with imaging sonars during their spawning migration when they return to rivers to reproduce (Gurney *et al.*, 2014; Lilja *et al.*, 2011, 2010). Compared to other species that are commonly monitored using imaging sonars, adult Atlantic salmon have a relatively long migration period and the absolute density (frequency) of fish is generally lower than *e.g.*, Pacific salmonids (*Oncorhynchus* spp.). As an example, the Atlantic salmon monitoring period in the Northwest Miramichi River, New Brunswick, Canada, in 2019 was approximately five months with an estimated total run of 3900 salmon (one-sea-winter and multi-sea-winter salmon combined; DFO, 2020a). Similarly, approximately four months of monitoring in Tana/Teno River in Northern Norway/Finland, resulted in a count of 21,000 Atlantic salmon (Anonymous, 2019). In comparison, in Kenai River, Alaska, United States, the early run (1.5 months) of all salmon (primarily sockeye salmon, *Oncorhynchus nerka*) was estimated 26,256 and 1,439 for Chinook salmon (*Oncorhynchus tshawytscha*), and the late run (1.5 months) was estimated 313,277 for all salmon and 15,185 for Chinook salmon (Key *et al.*, 2016). Long monitoring period increases the operational costs and a low total number of fish underlines the importance of monitoring the whole population rather than sampling temporally or spatially, because each fish has a proportionally large value in the total count. Accuracy and precision are more critical in smaller, often depressed, populations (Pipal *et al.*, 2010).

The intention of this paper is to update the current knowledge on the operation of imaging sonars in rivers with a specific focus on Atlantic salmon. This document focuses on using the Adaptive Resolution Imaging Sonar (ARIS, Sound Metrics Corp.; www.soundmetrics.com) and Dual-frequency IDentification SONar (DIDSON, Sound Metrics Corp.) that are the two most common imaging sonars used in salmonid monitoring. The practice described here can be applied in any imaging sonar types and for example, five other commercially available systems are potentially appropriate for monitoring use (Campbell, 2015): some have lower price-tags (*e.g.* 50 % - 75 % lower than the price of DIDSON), but not all systems have adequate resolution for the species and location under study. Additionally, consumer-grade fishfinders are also being used in fish and fisheries research (*e.g.*, Andrews *et al.*, 2020; Helminen *et al.*, 2019) and the newest consumer-grade fishfinders include a multibeam 'live' view that has potential for low-cost fish monitoring purposes.

The use of imaging sonars in shallow waters for monitoring migratory fish populations has been previously reviewed by Martignac *et al.* (2014) who describe the advantages and disadvantages of common hydroacoustic methods, including the technology and examples of the use of imaging sonars in fish monitoring. Operational recommendations were provided in Maxwell (2007) for site selection, equipment selection, and field/office methods. Additional approaches using a DIDSON system in three different systems on California's central coast are described in Pipal *et al.* (2010).

Building on the previous work and reviews, we aim to provide an operational manual and an estimate of costs in 2021 for those interested in using imaging sonars for monitoring Atlantic salmon populations in rivers. In addition to a literature review, we expand the previous work by providing our own experience from the Miramichi River, New Brunswick, Canada, where ARIS sonar systems have been tested since 2016 and we discuss how to overcome logistical and biological challenges to improve outputs (*e.g.*, data quality) and outcomes (*e.g.*, management decisions). The article first describes proper selection of a study site, and then it outlines the operation of sonar systems, specifically recording data, large data set transfer options, and data analyses methods. Finally, the cost associated with starting and running a sonar-based monitoring program are discussed.

6.2 Study site selection

Selecting an ideal study site is an important early factor for a successful monitoring study as it optimizes data collection and minimises problems with sonar operation such as wash outs or dry outs, obstacles creating unwanted echoes or blind spots, and fish milling behaviour (Martignac *et al.*, 2014; Maxwell, 2007; Pipal *et al.*, 2010). Overall, seven considerations should always be assessed prior to selection of a sonar monitoring study site (Figure 31). Four initial steps for successful hydroacoustic monitoring of migrating fish populations were cited in Maxwell (2007) and included (1) consideration of the bottom profile and flow fields of the site, (2) active and unidirectional migration of studied fish (3) fish must cross the sonar beam at the site, and (4) the species of interest is the only species present in the assessed size range or shape; otherwise, an alternative technique is needed for species identification. Additionally, it is advisable that (5) prior knowledge, especially with regard to flow events (high or low discharge) is available for site selection (Pipal *et al.*, 2010). Finally, consideration should be allowed for 6) site accessibility and security and 7) power availability. These seven main considerations are further elaborated below.

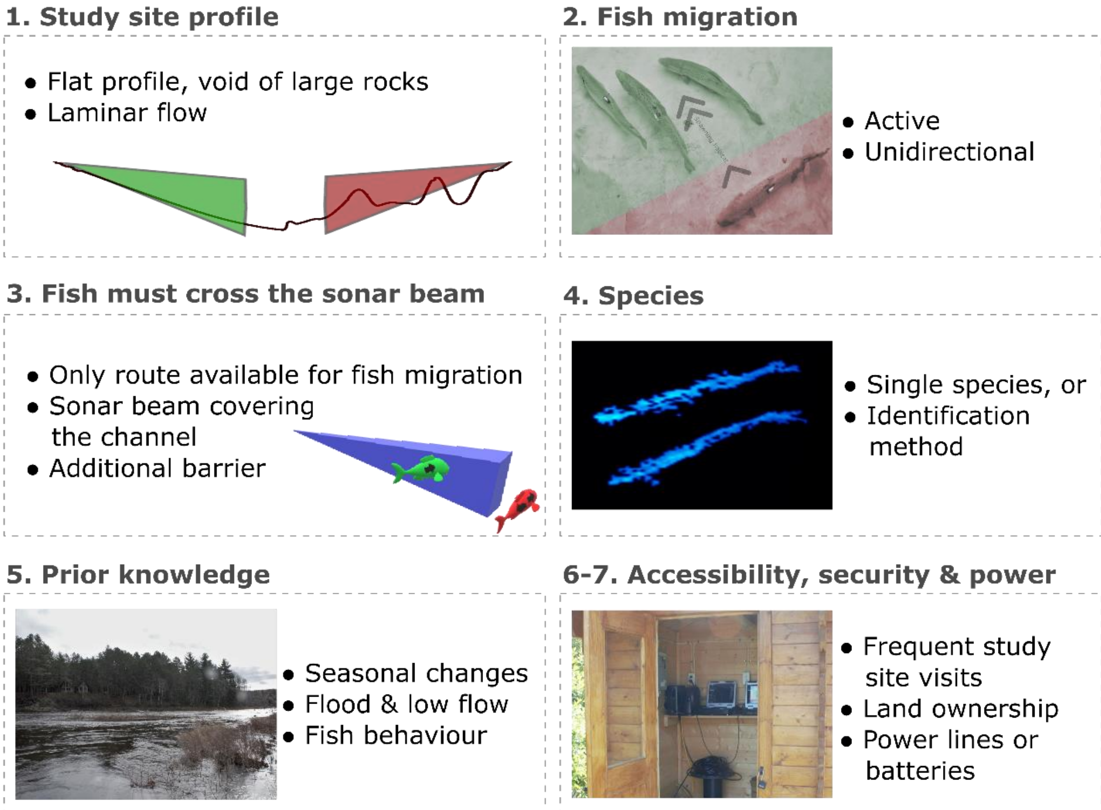

Figure 31. Framework for sonar monitoring study site selection.

Considerations 1 and 2: Study site profile and active fish migration

The study site profile is the most important factor of site selection as it defines the quality of the collected data footage. Overall, the site should be flat and the flow should be laminar (Maxwell, 2007). Collecting river bathymetry at a potential study site helps preventing the presence of the blind zones in the sonar image. At a fixed location, the sonar is aimed across the river and a clear image with no obstructions should be ensured

(Maxwell, 2007). Suitable substrate types are mud, sand, gravel, or small cobble (Pipal *et al.*, 2010). Large rocks and vegetation should be avoided as the fish can migrate behind them unnoticed and they can complicate fish detection by creating additional movement (*e.g.*, turbulence from a rock or vegetation moving with the current) in the sonar data (Helminen and Linnansaari, 2021). Level and soft surfaces, built from *e.g.*, sand or sandbags, are less reflective of sound than rock, and increase the signal-to-noise ratio for improved fish detection (Enzenhofer *et al.*, 2010). An aiming protocol has been developed that imaging sonar operators can use for aiming the device (Maxwell and Smith, 2007) and, after installation of the sonar, beam mapping is done to assess the sampled volume and to aim the sonar so that the wanted section of the river is covered.

At a good sonar monitoring site, fish species of monitoring interest are actively and unidirectionally moving so that they can be successfully counted (Maxwell, 2007). The idea behind monitoring diadromous species in a river is that the whole population will have to pass one location where they are counted during their migration; if a population of non-migrating species is spread throughout the river and migration does not occur, methods other than stationary counting stations must be considered. The fish movements at the study site should be unidirectional (mostly upstream) and preferably without stops or turns in the sonar field. Stopping and hiding may cause the fish being missed in the sonar imagery and milling behaviour complicates both manual and automated tracking and bias may be introduced from fish passing back and forth in the detection beam (Helminen and Linnansaari, 2021). For example, fish are easily detected when moving on rocky and concrete bottom types, but holding- and sliding behaviour was more common on rocky substrate (>10 % of the fish) than on concrete (< 1% of the fish) (Maxwell and Gove, 2004).

If the monitoring site has species that are moving both up- and downstream, it is possible to record the swimming direction of the fish when processing the imaging sonar files. Therefore, for the end-of-the-season estimate, the total number of downstream moving fish can be subtracted from the number of fish moving upstream to estimate the number of fish upstream of the study site at the time of *e.g.*, spawning (Xie *et al.*, 2005). However, because an error is associated in the fish counts and the error rate are not necessarily the same for up- and downstream counts (Helminen and Linnansaari, 2021), an accumulation of errors may be induced when the same fish are detected multiple times. As an example, Pipal *et al.* (2010) reported that the anadromous rainbow trout (steelhead; *Oncorhynchus mykiss*) movement was more complicated than typically assumed and the fish were not always swimming directly to desired spawning grounds but a high degree of milling behaviour occurred instead. Similarly, Atlantic salmon typically migrate directly upstream until in close proximity of putative spawning areas but once there, they can exhibit local movements up- and downriver at or close to the position held at spawning (Carrow, 2021; Økland *et al.*, 2001). Altered migration behaviour has also been observed where Atlantic salmon descended downstream after recapture and release (Karppinen *et al.*, 2004), relocated to another branch after initially ascended to one branch of a river (Carrow, 2021), or even moved to a different river after being tagged in the fjord (Erkinaro *et al.*, 1999). It is important to consider these local movements and behaviors of the species of interest when designing a sonar monitoring site as they can greatly complicate the data processing or induce count errors.

Consideration 3: Fish crossing the sonar beam

Only the fish that cross the sonar beam can be counted. This means that 1) the physical location of the study site should be downriver from any known spawning areas of the population (Maxwell, 2007) and 2) the sound beams will have to cover the whole width (and depth) of the river that is available for target population migration. It is also important to inspect potential sites for temporary side channels or fish barriers that form under different water levels and would either prevent fish from entering the monitoring site or offer an alternate path to avoid the site entirely.

A study site relatively close to the ocean is recommended so that it is downstream from any spawning tributaries, but upriver from tidal influence (Maxwell, 2007; Pipal *et al.*, 2010). When the focus of the study is on a single population in the tributaries rather than mixed population of the main stem (see *e.g.*, Anonymous, 2019 for examples of exploited stocks with contrasting stock status within the same river) or if other fish species are abundant in the lower stretches and might therefore complicate the operation of the sonar, a study site further upstream from the sea/ocean may be warranted (*e.g.*, Lilja *et al.*, 2010).

The study site must be compatible with the sonar beam such that all fish swimming through the site will be detected in the sonar. The dimensions of the beam vary between different types of imaging sonars and should be selected according to the needs. Because DIDSON and ARIS use lenses to form the acoustic beam (Belcher *et al.*, 2002), different kinds of lenses are available for *e.g.*, shallow water and long-range setups. The river depth can be an issue if the river is deeper than the beam dimensions (*i.e.*, beam angle). Commonly, the sonars are aimed to ensonify the areas close to the bottom, where the velocities are lower and where most Pacific salmonids and Atlantic salmon are detected in split-beam sonar studies (Pipal *et al.*, 2012; Ransom *et al.*, 1998; Romakkaniemi *et al.*, 2000; Xie *et al.*, 2005). Optionally, the sonar can be set to sample different depths by alternating between different tilt angles throughout the recording period.

The range (the distance from the transducer face to the other end of the sonar field) can be adjusted and set to cover the river width available for migration. As an example, and depending on the sonar make and model, ranges up to 80 m are used (Lilja *et al.*, 2010). The sonar resolution is higher when using short ranges and information such as the length measurements or (possible) species identification become less accurate, or even impossible, in longer ranges (Helminen *et al.*, 2021, 2020). Therefore, ranges less than 15 m are most common (Grote *et al.*, 2014; Holmes *et al.*, 2006; Moursund *et al.*, 2003), as 15 m is the distance where *e.g.*, ARIS Explorer 1800 units switch between the lower (1.1 MHz) and higher (1.8 MHz) frequency when using automatic settings (Sound Metrics Corp., 2019a). Sampling by alternating between long- and short ranges is also used (Enzenhofer *et al.*, 2010), but in rivers with low fish abundance, this may not be feasible if it is important to collect recordings of all migrating fish. In our experience in the Miramichi River, ranges > 15 m should only be used if a generic fish count (irrespective of species) is the single data needed; short range and high frequency should be used for any information about fish species or accurate information about fish length.

Moreover, if only long ranges are used, other manufacturers may provide a more cost-effective option compared to DIDSON or ARIS. For instance, the data quality of the BlueView sonar (Teledyne Technologies; www.teledyne.com) was reported to be similar to the DIDSON in low-frequency setting, but with significantly lower cost (Braun *et al.*, 2016). Other imaging sonars, such as the Gemini (Tritech International Ltd.;

www.tritech.co.uk/) and Oculus (Blueprint Design Engineering Ltd.; www.blueprintsubsea.com/) have also been used in biological research recently (*e.g.*, Maki *et al.*, 2020; Parsons *et al.*, 2017), and the newest consumer-grade fishfinders offer a 'live' view that could be applied in fisheries monitoring. A direct comparative study using various sonar products is warranted to better understand the cost-benefit ratio of these different sonars.

One way to use shorter range sonar is to only sample parts of the river (Figure 32A,B). In Alaska, 18-67 % of the river width is ensonified because the Sockeye salmon are using only a portion of the river width to migrate upstream and prefer the areas near shore (Enzenhofer *et al.*, 2010; Faulkner and Maxwell, 2020; Maxwell *et al.*, 2013; Xie *et al.*, 2005). Similarly, in river Tornionjoki (Finland/Sweden), sonars are set on each side of the river (Figure 32A), but a 15-20 m wide area in the middle is not covered with sonar beams because only a small percentage (< 5 %) of the Atlantic salmon use the mid-channel (Vähä *et al.*, 2013). On the contrary, Enzenhofer *et al.* (2010) found that a small number of fish were consistently observed beyond the typically monitored range during gillnet fishery openings; however, the behaviour did not persist outside of fishing periods, indicating that the fish were changing their behaviour due to fishing that therefore impacted the success of the monitoring project.

Multiple transducers can be used for larger coverage. As an example, one sonar on each side of the river (Anonymous, 2019; Vähä *et al.*, 2013) can cover both shores (Figure 32A) and more coverage and/or a higher resolution can be achieved by a combination of offshore and inshore sonars (Burwen *et al.*, 2014; Figure 32C). When multiple sonars are used, the possibility of one fish showing in multiple sonars will also need to be considered.

For the highest resolution at longer ranges, lenses that reduce the width of individual beams can be used; by reducing the beam width, the resolution is higher at long ranges but the field of view also becomes narrower, complicating fish identification near the transducer (Burwen *et al.*, 2014). In areas with high water level fluctuation, the nearshore and offshore sonars can also be mounted together (Figure 32C), one aiming to the shore to account for changing tide and another aiming offshore (Faulkner and Maxwell, 2020). To avoid crosstalk (*i.e.*, transducer inference from other transducers), the transducers can be set to record using different frequencies (*e.g.*, Burwen *et al.*, 2014) or the transducers can be placed in the river so that they are not directly facing each other (Anonymous, 2019; Figure 32A).

The channel width can be restricted for the purpose of easier monitoring using a physical barrier (*e.g.*, a fence) which can guide fish to the sonar field (Figure 32D). Commonly, deflector fencing is installed to prevent fish from swimming behind the transducer (Enzenhofer *et al.*, 2010; Lilja *et al.*, 2010; Pipal *et al.*, 2010). It should reach from the shore to the transducer, but typically it is several meters longer to prevent fish from swimming within the first 1-3 meters of the sonar field (Figure 32D), where the beams are narrow and fish may not be fully ensonified at once (Enzenhofer *et al.*, 2010; Faulkner and Maxwell, 2020). Larger fence structures are also used to reduce the river width (Figure 32D), or to block the entire river for complete control of fish access. Fencing materials are commonly metal or plastic. T-posts with plastic fencing is effective in low to moderate flows, but is not resilient in higher flow events and it is susceptible to clogging with leaves and other debris, and it is more difficult to clean than 5 cm 'chicken wire' that can be easily adjusted (Pipal *et al.*, 2010). In larger rivers, more robust structures such as metal conduit fencing or resistance board weirs (*i.e.*, “floating fence”) are used (Enzenhofer *et al.*, 2010; Holmes *et al.*, 2006; Stewart, 2002; this study).

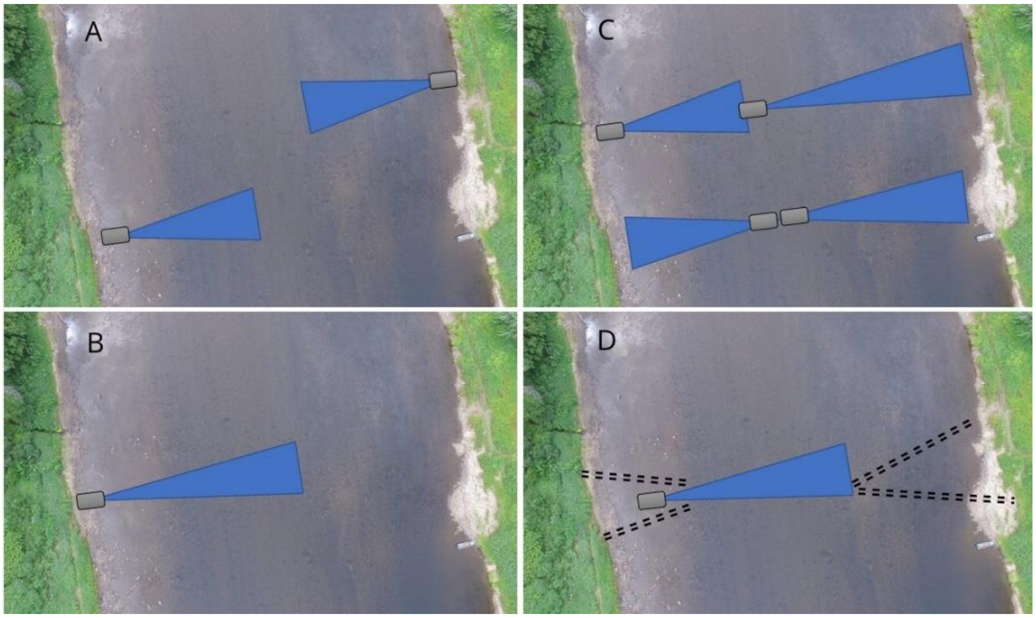

Figure 32. Different sonar monitoring setups. In (A), transducers are set on both sides of the river, not directly facing each other to avoid crosstalk. In (B), part of the river is sampled using one sonar. In C, two sonars are used in line (top) and mounted together (bottom). In (D), barriers (black lines) are used to guide fish to the sonar field and protect the sonar from large debris floating from upriver.

In the Miramichi River, one transducer (end range 11.1 m) with a barrier fence was used to cover the river width of approximately 45 meters (Figure 33). Because of previous experience using conduit pipe fence and a high risk of washouts (*e.g.*, Chaput, 2010), a resistance board installation (floating fence) (Helminen and Linnansaari, n.d.; Stewart, 2002) was tested. Following the instruction of the setup (Stewart, 2003), a series of 1.2 m by 3 m PVC pipe fence panels were built and attached within the river to form a 35 m wide PVC pipe fence. Initially, the installation was done on bedrock; however, the attachment to bedrock was complicated due to the sandstone composition cracking during drilling such that the earth anchors were impossible to set. Additionally, the narrow and shallow site had very high velocities at the end of the monitoring season making removal of the fence difficult and dangerous. The study site was moved to a new location, where the substrate was alluvial cobble rather than bedrock and the flow velocity was lower, allowing for much easier installation and removal. Overall, the floating fence proved to be a durable solution and stayed in position throughout the monitoring seasons although the whole fence was below the water surface in high water periods. The majority of debris would float over the fence, making it possible to maintain the fence even in high water conditions with minimal maintenance in comparison to normal conduit fence. The main issues were related to installation and removal of the fence. Installation was only possible in mid-summer during low flows after the spring flood and removal, although easy to do before high-water events, was difficult during the highest flows. Even though it is more costly than other fencing options, in more permanent study site setups the floating fence is a durable and low-maintenance option; however, the setup should be built so that easy installation and removal in high water is possible.

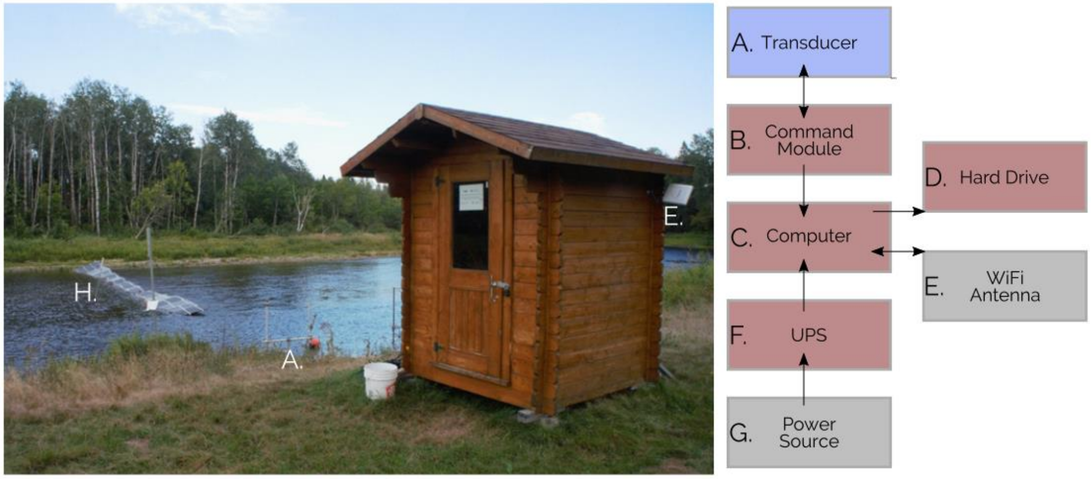

Figure 33. Study site at the Little Southwest Miramichi River (known by local Mi'kmaq as Tuadook). ARIS transducer (A) is in the river (marked in blue) and communicates with the command module (B) that is located in a dry shed on the shore. Other devices stored in the shed (marked in red) are computer (C), hard drive (D), and an Uninterruptible Power Supply (UPS; F). Devices outside the shed are marked in grey: the computer receives and sends data through a Wi-Fi antenna (E) and power lines (G) are extended to the shed. A fence (H) is used to guide the fish to the sonar transducer side of the river.

Consideration 4: Single species vs species apportion methods

A challenging limitation of the imaging sonar programs is the difficulty of distinguishing between fish species (Horne, 2000; Martignac *et al.*, 2014). Often in imaging sonar programs, the target species is the only species present or the target species is the only species within certain size range and/or it has a run timing that is different from other fish species (Faulkner and Maxwell, 2020; Kajtaniak and Easterbrook, 2019; Lilja *et al.*, 2010; Maxwell, 2007). When multiple species of the same size and run timing are present, other methods need to be considered. Alternative techniques include a combination of sampling using fishing or underwater cameras, species identification using sonar data, study site relocation, and statistical modeling.

A solution in many studies (in *e.g.*, lacustrine and marine environment) is to sample the fish species using traditional fishing methods (Misund, 1997) such as gillnets to apportion the fish species in the sonar data (Schumann *et al.*, 2015). In some rivers, test fishing is used to determine salmon species composition in imaging sonar data (Enzenhofer *et al.*, 2010), but combining fishing and imaging sonar monitoring programs over a long monitoring period is costly (see *e.g.*, Faulkner and Maxwell, 2020) and often not possible when observing threatened species (Pipal *et al.*, 2010). Underwater cameras are an alternative sampling method (Helminen and Linnansaari, n.d. (submitted); Wolff and Badri-Hoeher, 2014), and the recent development of automated video analysing methods (*e.g.*, Ditria *et al.*, 2020) provides an interesting option for sampling, although the optical methods are limited to areas with high visibility and need additional lighting during night in most latitudes. Species identification directly and automatically from sonar imaging has been tested with some success (Bothmann *et al.*, 2016; Helminen *et al.*, 2021; Kirk *et al.*, 2015; Kupilik and Petersen, 2014a; Langkau *et al.*, 2012; Mueller *et al.*, 2010, 2008). In these studies, observations of fish swimming behaviour (*e.g.*, constant swimming vs. milling, and tailbeat frequency) and shape or size of fish (*e.g.*, using acoustic shadows) are used to distinguish between species, but the true identification of fish species using only acoustic waves has been deemed difficult (Helminen *et al.*, 2021; Horne, 2000; Martignac *et al.*, 2014; Misund, 1997; Mueller *et al.*, 2010).

In some instances, moving the study site to a location where other species are not, or are less, present can be a solution, however, a problem may arise if the site is moved upstream of potential spawning or utilized habitat, and therefore the whole population is not monitored as a consequence. As an example, in the Miramichi River, anadromous striped bass (*Morone saxatilis*), that co-exist with Atlantic salmon and overlap in both size range and migration timing, are mostly encountered in the estuary and not in the tributaries upstream – but monitoring multiple tributaries would be more expensive. In addition, the striped bass have been recently detected in new areas upriver where they had not been seen prior to starting the sonar monitoring project (Helminen and Linnansaari, n.d. (submitted)). As the spatial distribution of fish populations are fluid, and especially so in the changing climate, shifts in species composition (or in the knowledge of the current state) may trump the original assumptions of the study site suitability. A combination of all the above methods and a statistical framework is therefore recommended in many instances to successfully apportion fish species proportions observed in multi-species sonar data.

Considerations 5 to 7: Prior knowledge, site accessibility, security, and power

Prior knowledge can help selecting the site; thus, local knowledge and past research projects can provide invaluable insights to site selection. Understanding the typical changes in the river during high and low flows helps preparation for the season (Pipal *et al.*, 2010). Even with thorough preparation, change of study site might be needed. Pipal *et al*. (2010) reported that one of their study sites did not fully meet their expectations, and security concerns and excessive fish milling behaviour resulted in change of plans for future study years. Similarly, in the Miramichi River, after the first year of operation, we moved the study site approximately 500 m downriver to a location where the water velocity was not as strong and installing and anchoring the equipment was easier, however, the milling behaviour of the fish seemed to increase at the new location. Therefore, it is recommended that a trial year of sonar monitoring is conducted before installing all the expensive equipment, carrying out significant site manipulations (such as pouring concrete structures) and thus starting a long-term imaging sonar monitoring program in full. During the first trial year, the sonar can be moved around in search of the most suitable site without the pressure of losing data; not getting a complete dataset during first study year(s) is a worthwhile trade-off if it will increase the data quality and decrease the operation costs in the future monitoring years.

Site accessibility and security should be considered when selecting the location such that daily visit are possible (Pipal *et al.*, 2010). Data downloads are frequent (*e.g.*, the hard drives were swapped daily in the Miramichi case study), and the staff has to be able to respond rapidly to changing flow conditions (Pipal *et al.*, 2010). Daily re-aiming and re-positioning of the transducer may be needed during rain events (Pipal *et al.*, 2010) and when the water levels are changing quickly. Long drives to the study site increase the monitoring cost, while internet access can reduce the need to visit the study site by remote connection to determine the status of the site (Enzenhofer *et al.*, 2010), aiming the transducer, and even downloading the data. Land ownership issues are closely related to accessibility and can also be an important factor for consideration. As an example, state-owned land (*e.g.*, Burwen *et al.*, 2014) can be easier with regards to access and for building necessary structures at a study-site than privately owned land. On the contrary, security concerns are higher in areas with unrestricted public access compared to private property (Pipal *et al.*, 2010). System security is a concern especially because of the value of the equipment (*i.e.*, even innocent tampering with the equipment may cause an irreparable financial damage) and the possible downtime of the project. Extended cables and pad-locks are used to lock the equipment to trees or other permanent structures (Pipal *et al.*, 2010). In the Miramichi River, security cameras and signs mentioning video surveillance were also used to improve the security. The security cameras can be linked to the same system as the underwater cameras (if used for species identification) and therefore, used for monitoring the frequency of *e.g.*, boat traffic that can interfere with sonar beams.

Power availability is another important factor. Where reliable AC power is readily available or the power lines can be extended to the site, it is used for operating the sonars (Pipal *et al.*, 2010). Other sources of power such as solar, generators, and batteries, can be used in remote locations (Enzenhofer *et al.*, 2010; Kajtaniak and Easterbrook, 2019), and a detailed description of a remote power supply setup is described in Enzenhofer *et al.* (2007). The DIDSON and ARIS consume little power (Belcher *et al.*, 2002) and are therefore suitable for remote locations; the DIDSON system and a computer had a continuous draw of 7 Amps, and four solar panels of combined 20 Amp maximum output were sufficient to run the system for most of the study period barring occasional prolonged cloudy periods, when top-up charging were needed (Enzenhofer *et al.*, 2010). Other types of imaging sonars may have other requirements, and local electrical code and manufacturer recommendations should be considered during initial setup. As an example, due to work in and near water, additional protection such as Ground Fault Circuit Interrupter (GFCI) should be considered for user safety if it does not interfere with the sonar device.

While finding a perfect study site is difficult, balancing between all the factors is important. Additionally, and when possible, building a permanent structure for the study site should be considered. As an example, Enzenhofer *et al.* (2010) describe a very advanced setup with an adjustable pole mount, rail system, and sandbag ramp for clear footage and easy installation and adjustment. While building such infrastructure is often not feasible in short studies, it would be very beneficial in long-term monitoring studies. In the Miramichi River, most of the issues during the field work were experienced during the installation and removal of the sonar equipment and fence; by designing the structure so that the equipment can be easily installed and removed even in high water, a longer monitoring period and safer working environment can be achieved. In addition, ideal setup may benefit from creating a flow environment that is not preferred by the fish (*i.e.*, no rocks that will create microhabitat for milling Pipal *et al.*, 2010) and a more homogenous background for any additional video confirmation. Confirming that the study site is suitable for monitoring and that high-quality data can be collected is, however, essential before building any permanent structure.

6.3 Sonar monitoring equipment needs and considerations

Several types of equipment are needed for running an imaging sonar program. While this review focuses on Sound Metrics DIDSON/ARIS sonars, a similar set of equipment is expected when using other makes and models of imaging sonars. If more than one transducer is used, most of the listed items will have to be multiplied by the number of transducers used.

The basic equipment for operating a DIDSON or ARIS sonar is the sonar unit (transducer and command module), mount, rotator, laptop, data storage, associated cables, and a weatherproof storage box or building (Pipal *et al.*, 2010). An ARIS sonar consists of the transducer, a cable, and command module that connects to a computer. The transducer is in the water and connects to a computer on the shore. An appropriately sized metal box is commonly used for storing the computer and other equipment on the shore (Pipal *et al.*, 2010), but more comfort can be achieved with *e.g.*, trailers (Kajtaniak and Easterbrook, 2019), tent (Burwen *et al.*, 2014) or nearby buildings or storage sheds (this study; Figure 33).

A computer is used for recording the sonar files. The PC requirements are found from the sonar manufacturer and (automatically) analysing the sonar files may require a specific computer; however, no special computer is necessary for recording (*e.g.*, for ARIS Explorer 1800, the minimum PC requirements are Windows 7 SP 1 with 100BaseT Wired Ethernet). Weatherproof laptops are used (Pipal *et al.*, 2010; this study) but regular computers can be used as well if they are located in dry areas. Data is recorded to an external hard drive (*e.g.*, 1TB or 2TB) that is replaced with another when transferring data from the study site to the office for analysis. In the Miramichi River work procedure, the hard drive containing the data was brought to the office where the files were moved to a larger storage and where the files are analysed for count and measure of fish. The large storage was backed up every night into another storage device to prevent data loss due to hard drive failures. In some instances, transferring data over internet may provide savings in time and cost.

Power outages cause the sonar to turn off and a site visit is required for turning the unit back on. Similarly to Pipal *et al.* (2010), we also encountered several power outages throughout the monitoring season and installed a back-up battery source (Uninterruptible Power Supply; UPS) that keeps the unit in operation during power fluctuations. In case of longer power outages, the UPS would only keep the unit running for approximately an hour, but this often allowed sufficient time for sonar technicians to reach the site for proper shutdown and to prevent data loss if the power outage was likely to persist for several hours or even days.

A special cable is used in ARIS and DIDSON to communicate between the transducer (in the river) and command module. Due to the high cost of the cable, the needed length should be carefully measured prior to purchase. In the Miramichi River, up to 150 m cables were used and run across the river during two seasons. A protective plastic sleeve (*i.e.*, a garden hose) was wrapped around the cable to protect it from damage and pieces of metal chain were attached to it to help keep the cable on the river bottom even in faster flow. Earth anchors can be added upstream of the cable for additional support. The method worked successfully and the only issues were experienced while removing the cable at the end of the season if the cable had tangled to objects (*i.e.*, rocks or anthropogenic objects, such as bicycles, on the river bottom) and was difficult to retrieve. When cable is run underwater, it is recommended that regular checks are conducted during lower flows and to remove any objects that may make cable extraction at the end of the season difficult, if higher flow conditions are expected later. Another option for data transferring is a wireless connection across the river (Burwen *et al.*, 2014), and combination of cables and wireless connections can be used.

The transducer is held in place in river using special mounting. Two common mounting systems are described in the literature (Martignac *et al.*, 2014): the (scaffolding) H-mount (Burwen *et al.*, 2014; Lilja *et al.*, 2010; Maxwell and Smith, 2007) and a tripod (Burwen *et al.*, 2014; Pipal *et al.*, 2010; Schumann *et al.*, 2015)**.** Other types of mounting and modifications to the described mounting can be designed based on the needs. The mounts typically have adjustable height for easier aiming and they should be light, cost-effective, easy to move and adjust, and easily accessible during different flows and tides (Martignac *et al.*, 2014; Pipal *et al.*, 2010). Strong currents can tip the mount and the mounts are held in place using *e.g*., anchors and sandbags or metal rebar (Faulkner and Maxwell, 2020; Pipal *et al.*, 2010). Additional requirements may include prevention of tampering in public places, protection for large debris, etc. However, larger and stronger mounting structure may be more susceptible to collecting debris and therefore, require more frequent cleaning. In addition, removal of heavy equipment during high flows after the monitoring season is difficult, and is even more difficult if the equipment is attached and secured to the river bottom. As a solution, Pipal *et al.* (2010) describe a crank-pulley hoist system for a quick and safe removal during sudden high flows.

Silt accumulation can be an issue in rivers with high fine sediment load, and different boxes and covers are used to prevent it, however, they can be slow to remove which makes aiming the sonar slower and more problematic (Faulkner and Maxwell, 2020). While the sonar mounting can be designed so that the sonar can be adjusted manually, it is laborious because adjustments are needed throughout the season due to *e.g.,* changing water levels. A rotating device is important when operating an imaging sonar at a fixed location as it allows for small adjustments for aiming the beams correctly. Devices operating directly with ARIS that are controllable with recording software are available from the manufacturer, but other types of rotators are also used (Burwen *et al.*, 2014; Lilja *et al.*, 2010; Pipal *et al.*, 2010).

6.4 Operation of sonar

Setting up the sonar angle and file recording

After carefully selecting a study site and obtaining all necessary equipment, the task switches to ensuring the obtained imaging is optimal for the site. Aiming a sonar is a necessary skill for anyone responsible for the study site and data collection because the sonar image may still need adjustments after *e.g.*, changes in sonar position due to changes in water level or after a software issue (Martignac *et al.*, 2014; Maxwell, 2007; Pipal *et al.*, 2010; Schumann *et al.*, 2015). While the imaging sonar is an “easy-to-use” sonar compared to *e.g.*, split-beam sonars (Enzenhofer *et al.*, 2010), their use still needs thorough training and experience for finding and setting a clear image.

In a natural river setup, the sonar is typically aimed by “burying” the beam into the substrate (Pipal *et al.*, 2012) so that the bottom is visible in the footage throughout the whole ensonified range. The bottom is targeted because the fish are taking advantage of the lower velocities close to the bottom and are therefore more likely detected there than close to the surface (Pipal *et al.*, 2012; Ransom *et al.*, 1998; Romakkaniemi *et al.*, 2000; Xie *et al.*, 2005). With careful site selection or by “building” a suitable bottom, the image is clear throughout the footage, however, some variability in the bottom is often non-avoidable in a natural river (Figure 34A). Small obstacles such as rocks can cause shading (Figure 34D; right) and large structure, such as fencing or dams will block the signal completely (Figure 34D; left side), and either the transducer or the obstacles have to be moved. When the transducer is tilted upwards from the bottom, the bottom disappears at close ranges as the beams are covering only the water column (Figure 34B), and when the transducer is tilted down toward the bottom, the image disappears at far ranges (Figure 34C).

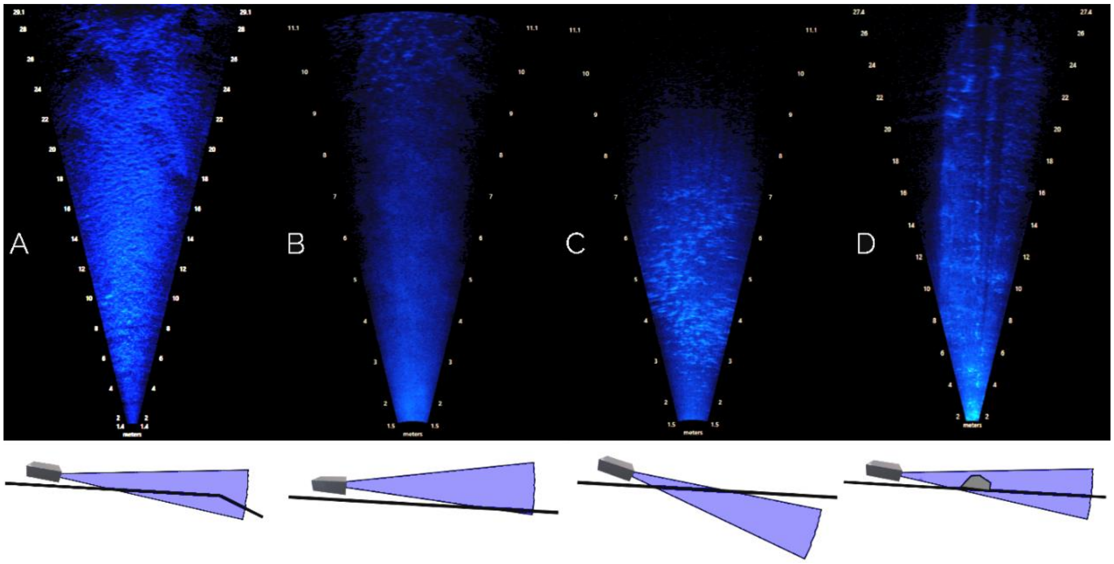

Figure 34. Aiming the transducer tilt so that the bottom is visible. A uniform bottom is desired; however, some variability is typically expected in natural river (A). Tilting the transducer upwards (B) will cause the image to disappear from close ranges and tilting the transducer down (C) will only show the close ranges. Big obstacles in the sonar field will cause shading (D).

Besides tilt, transducer location, transducer depth, and angle, there are several other settings that the sonar user defines. These settings are chosen at the beginning of the monitoring period, but they may need to be adjusted throughout the monitoring season depending on the environmental conditions or in case of software or hardware failure. Therefore, it is crucial that the technicians have a good understanding of the equipment and that the person responsible for the study has a quick access to the sonar either physically or online.

In typical monitoring projects, the automatic or highest available setting is used for most settings, (*e.g.*, Burwen *et al.*, 2014; Miller *et al.*, 2015), but specific settings may be required in special instances or when the available file storage size is limited. Because many settings are interconnected (*i.e.*, favoring one parameter will lower another parameter), selection will have to be based on the study needs. Different sonar types and software have different available settings, however, some important examples (frame rate and size, recording time, and synchronization) are discussed herein with the use of ARIS sonar and ARIScope software (Sound Metrics Corp., 2019a); more information on all settings is typically available in the help file(s) associated with each software.

The frame rate defines how often the image is updated in the sonar and higher frame rates create larger files. Typically, it is recommended that the frame rate is set to the highest available setting because it is needed for collecting additional information such as the tail-beat frequency and frequent updates may increase the accuracy of automatic tracking (Helminen *et al.*, 2021; Helminen and Linnansaari, 2021). The frame rate, however, is limited by increasing end range, ping mode, and frame size (Sound Metrics Corp., 2019a). The shorter the end range, the higher frame rates are allowed, but with limited coverage of the river. Ping mode sets the number of beams used, and more beams mean a higher cross-range resolution (*i.e.*, in a typical setup, the resolution in upstream-downstream direction) or a wider field of view, but lower frame rates (Sound Metrics Corp., 2019a). Higher cross-range resolution helps defining targets (*e.g.*, distinguishing downstream moving fish from debris or eels from other fish Helminen and Linnansaari, 2021; Mueller *et al.*, 2008) but as the range increases, and depending on the study focus, it may be beneficial to switch to lower ping mode for a higher frame rate. Similarly, the frame size is the number of samples per beam which defines the downrange resolution (*i.e.*, in a typical setup, the resolution across the river *i.e.*, between the start and end range) in combination with pulse width; higher resolution makes it easier to define targets, but large frame sizes will restrict the maximum frame rate. To determine the right balance, starting with automated settings is recommended and the settings can be adjusted as needed.

In addition to settings related to the sonar physics, the recording time is also set by the user. The length of the recordings vary in different studies and is typically between 10 and 20 minutes (*e.g.*, Burwen *et al.*, 2014; Faulkner and Maxwell, 2020; Kajtaniak and Easterbrook, 2019; Pipal *et al.*, 2010). Longer files are not recommended because the transfer and manipulation of files becomes difficult, and because of a higher risk of losing more data if the file becomes corrupted (Pipal *et al.*, 2010). Shorter files are also faster to use in practise because large files slow down the computer during analysis.

When multiple devices (*e.g.*, sonars, underwater cameras, or other devices) are used together, time synchronising becomes another important setting, as it ensures events detected on each system are comparable in time when analysing the data (*i.e.*, when a fish is detected in one system, it can quickly be identified in other data sets by the timestamp and data will be processed faster). Even if initially set to the same time, the computer time will drift during the monitoring project (Marouani and Dagenais, 2008) and when multiple systems are used, the recording laptop clocks should be synchronised. Global Positioning System (GPS) can be used for clock synchronization and is especially beneficial in remote locations (see *e.g.*, Burwen *et al.*, 2014) but if internet access is available, a protocol such as the Network Time Protocol (NTP) can be used for clock synchronization and it can be scheduled to update frequently in an operating system (*e.g.*, Microsoft Windows).

Study site visit and maintenance

The study site is typically visited either for maintenance or data download purposes (Enzenhofer *et al.*, 2010). Therefore, the frequency of the study site visits is defined by the need of the frequency of fish count updates (*e.g.*, if information of daily number of fish is needed for management purposes) and environmental conditions. During regular operation, technicians should be available to visit the site as often as every day to monitor the study site, maintain proper sonar image, clear debris, and exchange hard drives (Pipal *et al.*, 2010). Other maintenance can include cleaning the sonar lens of silt (Faulkner and Maxwell, 2020) or pollen (Lilja *et al.*, 2010) and the lens box in secure conditions under all possible environmental conditions. In long monitoring seasons, corrosion can also be an issue and the devices should be inspected to prevent it. Most tasks only need one person, however, due to safety reasons, more people may be needed when operating in the water. In our experience, remote (internet) connection that allows access to the recording computer and a security camera for monitoring water levels can significantly reduce the amount of study site visits. In the Miramichi River, daily remote checks over internet connection (evenings) were used in addition to daily visits (mornings) at the site. The online site-check concluded that sonar was operating and aimed correctly, ensured space availability on the hard drive, and allowed scrutiny of safety and security of the site based on security cameras.

The busiest time is during the deployment and take-downs, and during the months when the flows are high. Frequent visits may be needed during high water for ensuring safe operation of the equipment, transducer reposition, or moving the equipment on shore to prevent damage or loss of equipment. During high-flow periods it is important to have people on call to monitor and respond to possible equipment washout (Pipal *et al.*, 2010). Low water and online access to the site may allow for less frequent visits to the study site if there is no need to download the data and if there is no risk of exposing the transducer above water surface due to declining water level. During low-flow periods, check-ins can be as infrequent as once per week (Pipal *et al.*, 2010), however, in our experience other issues (*e.g.*, software, hardware, user error) demand more frequent visits (Table 13).

Throughout the monitoring in the Miramichi in 2016-19, multiple errors have been recorded that have influenced the data recording process (Table 13). Solutions have been provided for each error (Table 13) and it is important to frequently check the recording computer to be able to react quickly and prevent long-term data loss. Most of the errors can be solved remotely using a remote desktop in another device (laptop or smartphone), however, study site visits are required when the sonar has turned off. In the event of sonar equipment failure, the gap in data collection is often long: due to the high price of the equipment, it is often not feasible to have a spare unit that can be set up quickly, and local service for sonar units is not available for most locations.

Table 13. Common errors during sonar monitoring operation and their solutions.

Type of Error	Error	Solution
Software Error	Operation system updates & reboot	Disable automatic software updates in Windows.
Software Error	Automatic computer reboot for any other reason	Set ARISFish software to open automatically when the computer restarts.
Software Error	Software Crash	Install software that checks that ARISfish is running and opens it if it is not running. Inspect reason for (frequent) crash: *e.g.,* hard drive failure causes this.
Hardware Error	Power outage	UPS with backup battery. If sonar turns off, visit at the site is required.
Hardware Error	Hard drive failure (data loss)	Frequent data downloads, hard drive replacements.
Hardware Error	Sonar equipment failure	Inspect sonar equipment. Maintenance.
User Error	Transducer aiming failure	Frequent checks that the aiming is correct. Reminding technicians to always ensure this as the last step when doing a site visit.
Environmental/Hardware Error	High water causing sonar mount tilt	Monitor future weather daily for storms. Preparing for high water by moving the sonar shoreward out of potentially fast and damaging flow and monitoring site frequently to react to changes or equipment failures.
Environmental/Hardware Error	Low water causing the sonar transducer to be air exposed	Monitor rainfall predictions and local hydrographs for low water conditions and relocate the sonar to deeper water or shutdown the site until conditions are better.

6.5 Data storage, analysis and other considerations

Data volume and storage

The sonar files are very large and quickly fill hard drive storage space. The recording settings define the file size, and it is mainly controlled by the duration of the recording, resolution, and frame rate. One sonar typically collects between 0.2 GB and 1.6 GB per hour (Burwen *et al.*, 2014; Enzenhofer *et al.*, 2010; this study), and therefore substantial amounts of storage is needed for a full monitoring season. The number of sonars, the length of the monitoring project, and the number of backups will have to be considered when calculating the storage need. As an example, in our monitoring in the Miramichi River, one sonar (10.1 fps, range 1.5 m – 11.1 m) collected 80 GB every day; with the backup of each day, approximately 4.8 TB were generated monthly.

In a fish monitoring program where the number of fish is the result of interest, the raw sonar footage could be deleted after it has been analysed for fish count. However, one advantage of a computer-based fish monitoring over other methods of population estimation, is the possibility of saving the raw data to be revisited in the future for reanalysis (*e.g.*, reanalysis using improved analysing methods, analysis of other research questions, population estimate of other fish species). Storing sonar monitoring data has specific requirements due to the large volume of data collected over a long monitoring period.

In the Miramichi River, three different storage types were tested for storing and analysing the data: 1) large external hard drives, 2) a Network Attached Storage (NAS), and 3) Cloud-based storage. Although it is possible to store all data into multiple small units (*e.g.*, external hard drives 1-2 TB), organizing data over a long monitoring period becomes very complicated and easily leads to lost data and/or unorganized archives. Therefore, we searched for the largest external hard drives with still a reasonable price (8TB for ~ $200 USD in 2019); the optimal price-storage ratio is evolving quickly (Gupta *et al.*, 2015), but the 8 TB hard drives were found as the most suitable in our use due to their low price but large enough storage capacity to store sonar data. Larger storage can also be achieved using a NAS that combines multiple hard drives into one storage unit, and it has been used in other projects (Burwen *et al.*, 2014; Enzenhofer *et al.*, 2010). NAS has the advantage that when connected to a network (either local or internet), the data can be reached from multiple locations. In practice, however, we found that accessing large files over a network in NAS was slow compared to a hard drive with USB 3.0 connection. Overall, the NAS was mainly found suitable as the final storage for the data after all the analysis was done, and because the price was higher (~ 1400 USD / 32 TB) compared to 8TB external hard drives, we discontinued its use. Additionally, a cloud storage (Microsoft OneDrive for Business) was briefly tested, and it provided an overall easy-to-use solution: the physical copy of data can be stored on a computer in the office during analysis while it is also backed up into a cloud. However, downloading the files back from the cloud can be very slow depending on the speed of the internet connection.

Cloud technology also provides another option for data transfer and storage directly from the study site. We briefly tested this in the Miramichi monitoring project using Microsoft OneDrive but due to the slow speed of the internet connection at the study site, it was not used for daily analysis. Where faster connection is available, transfer over internet is an interesting option; however, storing the files in a cloud-based storage in a large scale such as multiple terabytes of imaging sonar files in a long monitoring project is currently too expensive. Technological advances will likely change the situation in the future. Future technological advances could also provide cloud-based sonar file processing, where physical copies of data would not be needed in users' computers and the files could be uploaded directly from the sonar site to cloud-based computers for analysis. As an example, cloud processing is already being used in processing sonar data for mapping purposes (Helminen *et al.*, 2019).

At least one backup copy of all data should be saved because hard drives can fail over time, even when not used (Li *et al.*, 2016). With external hard drives, a duplicate can be created automatically, *e.g.*, overnight, using additional software. Similarly, NAS can create duplicates automatically by itself. A cloud has advantages in backups, as it automatically creates several copies that are spread into multiple physical locations (Hu *et al.*, 2010).

Data analysis

The data collected in the field are brought to an office location where the footage is analysed. Three methods, or their variations, for counting migrating fish from the sonar footage are described in literature: 1) "tally whacking", 2) finding fish by watching the footage and selecting them using the software provided by sonar manufacturer, and 3) computer-automated counting.

Watching the sonar footage and using hand held counters (*i.e.*, tally whacking) is most commonly used in rivers with high fish passage rates, and it provides accurate counts in short time, although observer error can be high during periods of high fish passage (Enzenhofer *et al.*, 2010; Faulkner and Maxwell, 2020). The DIDSON and ARIS sonars include a software targeted for fish counting, and when more accurate information about *e.g.*, the fish size is needed, the fish are selected and measured in the software with a mouse (Pipal *et al.*, 2012). Additional software-adjusted methods are available and used in both tally whacking and software-based methods. A common method is to use the Contiguous Samples Over Threshold (CSOT) that selects frames where movement is detected and therefore, shortens the files and thus results in smaller file size and saves reviewer time (Pipal *et al.*, 2010; Sound Metrics Corp., 2019b). The CSOT settings can have a significant effect on the final fish counts and it is necessary to test the settings at each study (Pipal *et al.*, 2010). Instructions for manual counting using DIDSON software (Faulkner and

Maxwell, 2015) and for selecting the optimal frame for measuring the fish have been developed to reduce the bias (see *e.g.*, Burwen *et al.*, 2014) and are recommended especially when multiple users analyse the data, because multi-user analysis has been shown to result in deviations in fish counts and length measurements (Helminen *et al.*, 2020; Helminen and Linnansaari, 2021).

Automated methods have been discussed and used in several studies but to our knowledge, no salmon population monitoring project currently fully utilises automated fish tracking from sonar footage. However, with additional post-processing, the automation can provide similar results as manual counting (Eggleston *et al.*, 2020; Helminen and Linnansaari, 2021). Automation can also provide counts with a consistent error compared to projects with multiple observers, where the user-related bias can be high (Eggleston *et al.*, 2020; Helminen and Linnansaari, 2021). Currently, software cost is higher when using automated fish tracking, as specific commercially-licenced software such as MatLab (The MathWorks Inc.; www.mathworks.com) or Echoview (Echoview Software Pty Ltd; www.echoview.com) are used (Eggleston *et al.*, 2020; Han *et al.*, 2009; Handegard and Williams, 2008; Kang, 2011). On the contrary, cost of labor is lower as the counting process is mainly automated; however, in our experience, automated methods will need higher level of analytical skills and interest in computers than what is typically associated with staff affiliated with biological field of study. Manual counting does not need as much training and can be tasked to *e.g.*, a seasonal technician.

Sub-sampling is commonly used when the target population is large as it is not cost-effective to analyse all data (Cronkite *et al.*, 2006; Enzenhofer *et al.*, 2010; Maxwell and Gove, 2007), but in instances when the number of fish is low during the fish run, it may be necessary to record the entire run (Pipal *et al.*, 2010). Because fish escapement usually exhibits positive autocorrelation and nonlinear patterns (e.g., diurnal and seasonal patterns), a poor choice of variance estimator can increase the uncertainty in the estimate (Reynolds *et al.*, 2007). Even if sub-sampling is used and if data storage is not an issue, 24-h data can be collected and sampling datasets divided for analysis, and the uncounted proportions can be revisited at a later time (Enzenhofer *et al.*, 2010). Different methods for sub-sampling have been tested and they can include different parameters such as timing of migration, different sections of the river, or use of automated fish tracking for selecting the files to be analysed manually (Petreman *et al.*, 2014). Different sampling protocols can be used during times of varying fish densities; as an example, a standard sampling protocol can include measuring all fish of certain size but a "fast track" sampling protocol may be implemented during the peak of the run where only a sample of the fish are measured (Burwen *et al.*, 2014).

Overall, it is advisable to collect full datasets especially at the beginning of the project to fully understand and test the feasibility of different data subsampling methods. The full datasets and previously tested sampling protocols (Reynolds *et al.*, 2007) can be used when choosing a sampling method.

Finally, because multiple datasheets (*i.e.*, the information from each sonar file) are created in both manual and automatic counting methods, they need to be combined before producing the timely fish escapement estimate. To avoid large human errors in *e.g.*, copy + pasting the data, computer can be used to merge multiple sheets. The process can be implemented in the software or programming language used in the final analysis (*e.g.*, R or Python), or the data can be copied to one sheet before starting the analysis. As an example, two lines of code can be used in Microsoft Windows Command Prompt to copy the information from multiple datasheets to one:

(1) $cd\ C\text{:}\backslash Users\backslash FolderPathHere$ || selects the folder where all the files are located

(2) $copy *. csv\ all. csv$ || copies all .csv files in the folder to one file named "all.csv"

Collecting environmental information

Additional data collected will depend on the study site-specific needs and the study questions. The ARIS has an internal sensor for water temperature that is used for calculating the sound velocity. The temperature data are not currently provided in a user-friendly format for continuous monitoring, and additional data loggers are recommended. Water level and tide are also commonly measured or referenced, and collection of such data is highly recommended unless otherwise available from a local monitoring site operated by other organizations.

Public online updates

Because the imaging sonar data can be analysed daily, frequent updates are possible. The data can be published online in different formats (*e.g.*, daily run numbers, hourly migration patterns). Online updates were tested in the Miramichi River, and the experience was positive overall. In our application, it was difficult to keep the daily frequency of the updates as the technicians were usually also working on multiple other tasks and producing the updates to general public was an additional skillset to learn, however, updating the numbers on a weekly basis was typically successful. Dozens of daily page views (based on website provider data) were recorded and both local people and tourists were highly interested in the fish counts. Other examples of such timely fish counts are provided by

Alaska Department of Fish and Game (https://www.adfg.alaska.gov/sf/FishCounts/; visited June 15, 2021) and the Natural Resources Institute Finland (https://www.luke.fi/en/natural-resources/fish-and-the-fishing-industry/fish-resources/salmon-2/monitoring-of-salmon-runs-in-river-tornionjoki-and-simojoki/; visited June 15, 2021) that also garner significant attention especially among the recreational fisheries tourism industry.

6.6 Costs

Operational requirements are broken down to two general types: 1) one-time only (start-up) costs and 2) running (recurring) seasonal costs (Enzenhofer *et al.*, 2010). One-time costs include infrastructure development, possible modifications to banks, and equipment purchases, while the running seasonal costs are related to personnel, transporting equipment, utility charges, rental agreements, routine maintenance, equipment break-downs (and associated shipping and insurance costs), data storage, and possible species apportion method such as underwater cameras or a fishing program (Enzenhofer *et al.*, 2010; Faulkner and Maxwell, 2020; Pipal *et al.*, 2010; this study).

One-time cost

The one-time purchase costs listed previously in Pipal *et al.* (2010) were mostly similar to the costs in the Miramichi River and also in other studies (Enzenhofer *et al.*, 2010) (Table 14). The largest differences were found in fencing material (longer fence and different material used in the Miramichi), software license, and data storage (longer monitoring period) costs (Table 14). As stated by Pipal *et al.* (2010), the power installation costs can vary drastically depending on the installment complexity and local rates.

Table 14. One-time approximate costs of starting an imaging sonar monitoring program by Pipal *et al.* (2010) in 2006 and in the Little Southwest Miramichi River in 2016-2019. Prices in USD and for one sonar system.

	2006	**2016-2019**
DIDSON/ARIS and Cables (one unit)	75,000	85,000
Mount	3,800	1,000
Pan and Tilt Rotator	13,000	24,000
Laptop Computer (for recording and analysis, one each)	3,500	3,500
Data storage (on site)	400	350
Data Storage (archival)	2,500	1,000
Power Installation	5,000	250
On-Site Storage Box	500	1,500
Misc. Hardware (bolts, cables, locks, *etc*.)	200	500
Fencing materials	100	40,000
Echoview software licence (for automated counting)	-	19,500
Total	**104,000**	**176,600**

Recurring costs

The staff requirement reported in different projects has been similar (Burwen *et al.*, 2014; Campbell, 2015; Enzenhofer *et al.*, 2010): a senior scientist/project manager (responsible for the overall operation), a senior technician with acoustics experience (can assume the responsibilities and oversee the operation), and several junior (seasonal) technicians (responsible for counts and maintenance). The costs of operation is reported in multiple studies (Burwen *et al.*, 2014; Campbell, 2015; Enzenhofer *et al.*, 2010) and it varies greatly depending on the number of sonars, personnel wages, travel distance to and from the site, and the length of the program. Following the estimates in other studies and based on the experience in the Miramichi River, the need for personnel and cost using either the automated or manual counting is estimated in Table 15.

As a rule of thumb, 3-4 seasonal technicians and one project leader are needed to run a two-bank sonar operation (Maxwell, 2007). This translates roughly to 1.5-2 seasonal technicians per sonar unit, which is similar to other projects (Burwen *et al.*, 2014; Faulkner and Maxwell, 2020) and in the Miramichi River (Table 15). The daily tasks of the personnel vary over the season, and the technicians will operate the software, distinguish fish in the acoustic images, aim the sonar, and perform troubleshooting. Project leaders may be needed to visit the site to solve major problems or switch broken equipment (Faulkner and Maxwell, 2020). The study phase, study site distance from staff base, and environmental conditions all influence the staffing requirements (Pipal *et al.*, 2010).

A large portion of the technicians' time is analysing the fish count footage, and a smaller number of staff is required if the sonar data are analysed automatically (Helminen and Linnansaari, 2021). However, automated analysis requires a specialised technician/researcher and it may not be feasible to train new personnel every year. Additionally, if the technicians are hired for the study site maintenance work, it may be more cost-effective to analyse the data manually by the same technicians, if other types of work are not available to complete the daily hours. The greatest saving using automation can be achieved in large programs with multiple sonars, as one person can automate multiple datasets at the same time (Table 15).

While not required, the manufacturer recommends sending the sonar units for an annual factory maintenance. The annual maintenance costs in the Miramichi River have been approximately $1350.00 USD (for a sonar and a rotator), but they can be higher if parts are replaced outside of the regular maintenance (Table 15). Additional issues (*i.e.*, frequent equipment breakdowns) with the sonars or rotators have required maintenance mid-season, which can also cause major gaps in the monitoring data and add to the maintenance costs. Because the manufacturer is in the United States, the shipping and customs fees are also included when sending from other countries. The shipping, insurance, and customs brokerage cost from Canada and back has been approximately $1,700.00 USD for a sonar and a rotator (Table 15).

Table 15. Cost estimate for running an imaging sonar monitoring project using either manual or automated fish counting. The cost for personnel is estimated as monthly involvement, where 1 is full-time equivalent (FTE).

	Manual counting (FTE)	**Automated counting (FTE)**
Senior scientist	0.25	0.25
Senior technician	1	1.5 (with strong computer knowledge)
Seasonal junior technician	$1.5 * n_{sonar}$	1
Annual maintenance + shipping from Canada	$\$3,050 * n_{sonar\ \&\ rotator}$	
Other costs	Per Diem, Vehicle + mileage, Misc. supplies, permits, species apportion method	

6.7 Conclusions

The imaging sonar system is a useful tool for Atlantic salmon population monitoring but troubleshooting and site setup is a time-involving task that is easily overlooked. In hindsight, in the Miramichi River, we would have taken a different approach for installing and monitoring the study site that would have resulted in more efficient use of time and improved data quality overall. We want to address the importance of careful site selection, followed by installation of a strong structure that allows for easy and safe installation of equipment at the site annually even in high water levels. The ensonified range should be kept as short as possible for the highest frame rate and resolution; when longer ranges (*i.e.*, > 15 m) are used, detail is lost and *e.g.*, length measurements or tail-beat calculations become less reliable, if not unreliable. We also want to address the difficulty of species apportion method: rivers with single migratory species remain the safest and simplest option where counts are unequivocal by default. However, as multiple migratory species often exist in rivers that require monitoring, we provide several options that can be used for species apportioning, depending on the site and cost-efficiency. While we believe automated methods for producing a fish count are a useful tool and will produce fiscal savings in a long term, we also want to address that automation requires enhanced understanding of the sonar systems and analysis from the personnel in comparison to "simply" manually counting the fish from the footage where minimum training will suffice. High costs are associated with starting an imaging sonar project due to the expensive equipment. Additionally, several costs are also associated with continued operation of a program, including personnel costs and significant equipment maintenance. The information and insights provided in this paper should make starting of an imaging sonar monitoring program easier and more cost-effective and will hopefully avoid the proverbial "*re-invention of the wheel*".

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6.9 Literature

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7. General discussion

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The main objective of this dissertation was to test and develop the imaging sonar method for monitoring the Atlantic salmon (*Salmo salar*) runs in rivers in Atlantic Canada, using the Miramichi River as a case study. To answer my overarching objective, multiple research needs were identified in Chapter 1, and the information from this research is synthesized below, answering the chapter-specific objectives in full.

The full discussion regarding the specific objectives is presented in Chapters 2-5, and is not repeated herein in detail. Rather, the following discussion re-iterates the main findings, and conclusions from each research chapter, including the practical advice from Chapter 6, and is pulled together for overall discussion regarding the major considerations in applying the imaging sonar method in Atlantic Canada.

Overall, I conclude that the imaging sonar method, when combined with underwater cameras, can be used to provide a reliable count of returning Atlantic salmon in Atlantic Canadian rivers. However, there are some caveats and limitations that are discussed below. I also present recommendations for future research, to further improve the accuracy and cost-efficiency of the sonar method.

7.1 Conclusions from the individual research chapters

In Chapter 2, the accuracy of the length measurements derived from ARIS sonar using a long range (~30 m) and 1.1 MHz frequency was tested. The measurements by four users and a semi-automated computer algorithm were very variable and on average 7.8 cm to 20 cm different compared to the true lengths. Therefore, a size class and length prediction model was implemented to group salmon into two size categories: One-Sea-Winter (<63 cm) and Multi-Sea-Winter (≥63 cm) groups, and the model correctly predicted the size category in 83% of the fish in the computer-generated dataset and ranged from 68% to 74% in the human-generated datasets. Thus, the long-range sonar data can be used to count fish of different size-classes. However, when an accurate length measurement is needed, the users should use higher frequencies (*e.g.*, 1.8 MHz) and shorter ranges.

In Chapter 3, an automated data analysis workflow was developed and tested for datasets collected in the Miramichi River. Echoview software was used to automatically produce fish counts from long-range (up to 30 m) imaging sonar data and postprocessing steps were developed to address sources of error that have been reported in previous studies. The computer-generated counts were compared to multiple human-generated counts, and although there were differences in the number of fish, all the counts were in a good agreement between each other (ICC=0.79) in the upstream counts. There were larger differences in the downstream counts where there was no agreement between the datasets (ICC=0.03); because multiple computer-generated downstream moving fish-tracks were confirmed as true fish tracks when generating the model, it is suspected that the number of downstream-moving fish was underestimated in the human-generated datasets. The computer analysed the 24-hour datasets in 500 to 600 minutes and was slower than human-generated counts that required 200 to 600 minutes, however, computer generated-counts can be derived in the background without the presence of a technician and may produce significant savings in personnel cost.

In Chapter 4, the tail-beat frequencies of three commonly sympatric anadromous fish species of eastern North America, namely striped bass (*Morone saxatilis*), Atlantic salmon, and American shad (*Alosa sapidissima*), were measured using a previously developed method (Mueller *et al.*, 2010) and were found significantly different. Building on this, an automated tailbeat calculation method was developed and tested as a potential species identification tool. When compared to manually identified number of beats the error was large (on average, 1.1 (Atlantic salmon), 4.8 (striped bass), and -0.4 (American shad) beats in a fish track), especially in high fish densities. Therefore, the presented automated method can not be used as the only method for distinguishing between these three fish species. However, it has utility in fisheries management as part of a larger model that also uses other information for species prediction, or when the species of interest have tailbeat frequencies that are larger than the associated errors.

In Chapter 5, the daily and monthly species ratios were calculated from underwater video camera data and used to apportion the total short-range (11.1 m end range) sonar fish counts in the Little Southwest Miramichi River. The combined method estimated 358 Atlantic salmon and 255 striped bass ascended the river when using daily apportion method (species ratio applied every day), and 274 Atlantic salmon and 337 striped bass when using monthly apportion method in October 2019. The counts were compared to catches in a downstream index net using estimated values for catchability of the trap net and for proportion of fish ascending to the same tributary. As an example, the daily apportion method produced a count that was 1.01 times the trap net catch that was adjusted with values similar to previous knowledge (10 % catchability and 50 % proportion). For striped bass, the same catchability and proportion values produced a lower agreement (*e.g.*, sonar count was 13 – 16 % of the catch), and the comparison between the two methods was more difficult because unlike salmon, striped bass are not deterministically migrating up the tributary in the autumn but some bass may only visit the river opportunistically. Additionally, hourly and daily summaries were calculated from the sonar data and more specific information, such as external fish tag detections were recorded from underwater videos. In conclusion, the combined short-range sonar and underwater camera method can be used to provide more information of the salmon population in the Miramichi River in the tributaries that are currently unmonitored.

In Chapter 6, a guide was produced where international literature was reviewed and the multiple practical "lessons-learned" throughout this dissertation research is presented. The chapter gives insight into the factors that need to be considered before investing in a sonar-based monitoring program for fish population estimates in rivers, and the guide reviews the recommended practice and cost for selecting the study sites, designing and building the site equipment, choosing analysis methods, and daily operational tasks. Insights are added from the experience of running an imaging sonar monitoring project in the Miramichi River, NB, Canada, in 2016-2019. Recommendations for selecting the study site and careful *a priori* testing of the site are made, and the decision on whether to use an automated or manual data analysis method is discussed: while the use of automated methods need less personnel overall, the personnel need to be more experienced than those involved in manual methods.

7.2 Synthesis: How to monitor Atlantic salmon in the Miramichi River

The current population modeling of Atlantic salmon in the Miramichi River would benefit from the use of the sonar methods presented in this dissertation by adding tributary-based information that can then be used in management and conservation planning (Chapter 5). The research undertaken in this dissertation will allow development of sonar-based monitoring system of Atlantic salmon in rivers characteristic in Atlantic Canada, and I outline multiple recommendations to achieve success.

Study site selection

As described in Chapter 6, the study site selection is an important step when starting a monitoring study. Because of the large number of fish of other species and their non-unidirectional movements (*i.e.*, swimming back and forth instead of migrating upriver) in the estuary and lower stretches of the river, proportionally low number of Atlantic salmon overall, and the width of the river that would necessitate at least two long-range sonars in the lower stretches, it is recommended to find study sites in the small or medium-sized rivers/tributaries (*e.g.*, up to ~30-40 m in width during most of the monitoring season) rather than using one study site near the head of the tide. Similar study sites (river width, velocity) as used in the Little Southwest Miramichi River in Chapter 5 can be found in all the major tributaries such as the Sevogle River, the Northwest Miramichi River, the Renous River, the Dungarvon River, the Cains River, and upper stretches of the Main Southwest Miramichi River. Monitoring in these seven locations would cover the majority of the Atlantic salmon run in the Miramichi River, and if sonar monitoring would completely substitute the current mark-recapture modelling, a study site would be needed in all the mentioned tributaries, which would lead to increasing costs at the start of the program through building of study sites and buying the sonar equipment.

Following the recommendations in Chapter 6, the study sites can be chosen near the mouth of the tributary in other locations except the Main Southwest, where the river is wider, and suitable locations are further upstream. Even if the data transfer can be done remotely in the future, study site maintenance still requires crew visits especially during high water season. Therefore, operating study sites that are in close proximity to each other (*e.g.*, near the mouth of the tributaries in the Northwest Miramichi: the Little Southwest Miramichi, the Northwest Miramichi, and the Sevogle) is more efficient as they can be operated by one crew. The mouth of Cains, upper stretches of the Main Southwest Miramichi, and the mouth of Renous and Dungarvon are further apart from each other, and therefore the road access should also be considered in study site selection. As an example, selecting a study site near the roads that lead from the Main Southwest Miramichi in Doaktown or Upper Blackville to the Cains can allow easy access to the two rivers.

Species identification and sonar setup

For accurate fish counts in the Miramichi River, a species identification method is needed, and it is recommended to combine the sonar counts with underwater camera data (Chapter 5). When used at a same study site with a sonar, operating the underwater cameras can be done with relatively low cost (Chapter 6). When data are collected every day, the daily apportion method (Chapter 5) can be used as it will provide information on species on a daily basis. However, because the monthly and daily species apportion methods provided similar results (Chapter 5), the monthly (or weekly) proportion can also produce comparable information in the event of *e.g.*, data losses.

Only sampling part of the width of the river with a sonar is not recommended in the Miramichi River without additional structure that guides the fish to the sonar field, because the number of salmon is relatively low and each fish has a proportionally large value in the total count, *i.e.*, spatial or temporal sampling increases the error and can be easily avoided by fencing or longer sonar range. Therefore, even in these small- or medium-width tributaries, a decision will have to be made whether to use a barrier fence to narrow the opening of the river *(i.e.*, to <15 m) for a higher resolution sonar imaging or use a lower resolution sonar (Table 16). Operating a partial barrier is a task itself and an additional cost in both purchase and maintenance (Table 16). However, accurate length measurements (Chapter 2) or tailbeat frequency measurements (Chapter 4) can only be achieved when using high-frequencies and short (<15 m) sonar range (Table 16).

Because it is possible to count the fish automatically (Chapter 3) and get an idea of the size class of the fish (Chapter 2) using the long-range sonar, and the information on species can be collected using underwater cameras (Chapter 5), a barrier fence structure is not necessary for a relatively accurate fish count. The sonar data provides the total fish count, and underwater cameras are needed for sampling the species of fish – and providing additional data such as information on external fish tags (Chapter 5). Increasing the number of cameras in the river will also increase the accuracy of fish species identification, however, for efficiency, an assumption will have to be made that all species are sampled equally using a small number (*e.g.*, one to six) cameras (Table 16). During high water periods especially in the spring, installing the barrier fence is difficult, and using long-range sonar is the only option unless an easy fence installation method can be developed.

More accurate information can be collected when a barrier and short-range sonar are used (Table 16), and the accurate information (*e.g*., length) itself is valuable in long-term datasets and can provide fisheries management more information about individual fish. Currently, underwater camera sampling is needed for species identification, but the barrier allows for increased sampling rate with fewer underwater cameras, and thus higher accuracy in total counts. Short-range is also the only option if a truly automatic method that also predicts the species is desired: a workflow can be built that automatically detects and measures the fish (Chapters 2 and 3), followed by a model that predicts the fish species using automatic tailbeat frequency measurements (Chapter 4), length (*e.g.*, Daroux *et al.*, 2019; see also Chapter 4 length measurements), timing (Chapter 5), and schooling behavior (Chapter 5; same fish species were more likely to be seen in a given day). Using such automation would reduce the monitoring costs significantly, but it can be challenging to collect high-quality sonar data that are required for this approach (*e.g.*, Chapter 4) through a full season, and research is needed in testing the accuracy and comparing the counts to fish species (*e.g.*, in video camera) data. In rivers that are turbid and underwater camera sampling is not possible, this (*i.e.*, short-range sonar) is the recommended approach.

Table 16. The advantages and disadvantages of building a barrier to guide fish.

	No barrier, lower sonar resolution	**Barrier, higher sonar resolution**
Advantage	Lower cost monitoring option	More accurate information for fisheries management. More potential for future research
Length measurements	Not accurate, size class can be modeled	Accurate
Species Identification using underwater cameras	Large number of cameras needed to cover the river width. Optionally, underwater cameras that only sample parts of the river: easier operation, potentially lower accuracy	Species identification currently rely on underwater cameras. Possible to cover the whole width of the open channel with cameras
Species identification using sonar imaging only	Only timing and fish size class available for modeling approach: very low accuracy	Modeling possible using length, timing of migration, and (automated) tailbeat measurements
Costs	Purchase and operational costs lower. Possibility to use other (low-cost) sonar devices	Purchase of barrier material needed. Barrier maintenance cost. Higher data storage costs due to larger data files

In the Miramichi River, due to a potentially large number of study sites (if a full return across the whole Miramichi River was the desired outcome), a recommended operation would consist of a combination of the two, with one or two study sites collecting higher resolution data and others using either lower resolution sonars or other methods. For cost-efficiency, some of the tributaries could be operated with a lower cost sonar device (Chapter 6; also see section 7.3 below), or with resistivity counters (Coyle and Reed, 2012), or solely using underwater cameras.

While the focus of this study was on imaging sonars, the underwater cameras showed potential as a counting device, as the water visibility was high enough and fish were frequently detected in the videos. This method could be used in many tributaries, and it would provide a very cost-effective option: simple underwater cameras were built from a set of CCTV cameras and self-made waterproof cases (Chapter 5). Research would be needed for careful aiming of the cameras and/or using fencing, to ensure that all fish are forced to swim through a camera field in every visibility conditions. Additional lights must be used at night (Laiho, 2019; Chapter 5), and a stereo-camera setup could be added for length measurements. The automated video analysing methods (*e.g.*, Ditria *et al.*, 2020) can streamline the species-specific fish count as well. A setup for easy automation can be achieved by forcing the fish into a tunnel or tunnels, however, based on a small dataset at a Jacquet River fish barrier, New Brunswick, Canada, most of the fish visiting the barrier do not enter the small opening of a fish counting barrier but turn back downriver, and therefore the counting fence is probably a factor slowing down the fish migration (Helminen, unpublished).

Sonar data analysis: automatic or manual?

As described in Chapter 6, manual sonar data analysis can be more cost-efficient than automation when the monitoring season is short and only one study site is used. In the Miramichi River where multiple study sites are needed and the monitoring season lasts from May to November, it is recommended to use an automated data analysing workflow (Chapter 3) for cost-efficiency and comparability between the study sites. For automated data analysis, cloud data transferring and analysis could speed up the process in the future (Chapter 6), and as an example, the newest version of Echoview already includes a real-time visualization and analysis that could possibly be used to process the data already in the recording computer.

Neither the imaging sonar nor the combination of imaging sonar and automated data analysis should be considered a data logger that can automatically provide the user with desired data. Several experienced personnel are needed for running the program and for troubleshooting, and to understand the data, regardless of if the data are analysed manually or automatically (Chapter 6). This is even more crucial when automation is used, and understanding and interest in fisheries biology, sonars, and even programming is required (Chapters 3 and 6).

Source of continued funding is also a critical consideration when choosing the data analysis method. As an example, if the funding is solely dedicated to hiring *e.g.*, seasonal technicians, manual counting of fish from the data may be the only way forward. A (semi-)permanent source of funding (*i.e.*, tendered multi-year contract agreement) would be desired when using automation, so that personnel (*e.g.*, local First Nations or non-government organisations) could get trained to take on annual sonar monitoring, and time could be allotted to more specialized skillset without personnel changing annually.

7.3 Future research

In addition to Atlantic salmon, the imaging sonar and underwater camera combination will allow the estimation of numbers of other fish species migrating up the river, namely American shad (*Alosa sapidissima*), blueback herring (*Alosa aestivalis*), and alewife (*Alosa pseudoharengus*). Using the underwater camera apportion (Chapter 5), the automatic counting workflow (Chapter 3) can be used also for these other species. American shad are large and can be separated from each other in the sonar image, although with large schools there is an increased risk of errors in fish tracking. For blueback herring and alewife, direct counts are likely not possible, and the population estimates could be based on estimating the school size / dimensions of the school (width of the school in river and total time of the school in image) using a school detection algorithm. Additionally, if such approach is used, those schools could be removed prior to producing the fish count (of other species) to speed up the fish counting procedure.

Because the underwater cameras need lights overnight, influence of artificial light on fish behaviour is also of interest. In our setup, either the lights or the change in the water current from the camera mounts attracted schools of small (10-20 cm) fish and complicated the sonar analysis until the lights were moved outside of the sonar field (Helminen, Unpublished). In an experiment conducted over six nights in October 2018 at the sonar study site, no difference was found in the numbers of fish that passed the study site when the lights were on or off (Laiho, 2019). Therefore, the influence is likely negligible but should be tested over a full monitoring season.

As mentioned in Chapter 6, building a permanent study site structure is recommended after initial tests at each study site. A clear opening without big rocks or other obstacles should be built at the sonar site. More importantly, designing and building a method for easily attaching and removing the barrier fence even in high water would ensure successful fish monitoring throughout the season.

When long sonar range sonar is used, other manufacturers' products may provide a more cost-effective option compared to DIDSON or ARIS with a similar data quality (Braun *et al.*, 2016). In the multiple branches and study sites of the Miramichi River, a cost-efficient option can provide significant savings and additionally, extra devices could be purchased as replacement devices in case of equipment failures and that way, continuous data collection can be ensured. Furthermore, the future research should take advantage on the consumer-grade fishfinders' multibeam 'live'-view that could be modified to monitoring use, and potentially provide a very low-cost option for monitoring (Chapter 6). Tests in different environments and using different end-ranges would allow for a very cost-efficient method for monitoring fish in small rivers. The same methods that were presented for automation in Chapter 3 can be modified to the video-files collected using a consumer-grade sonar with minor modifications. The price-range would make monitoring possible by many other user groups, such as First Nations and non-governmental organisations, and therefore, standardizing the data collection and analysis is recommended.

7.4 Regarding the accuracy and errors

Throughout this dissertation, many sources of error in the sonar method have been tested, presented, and in some cases the error was shown to be large. An error is always associated with the accuracy of the data, and it will likely vary over time depending on the environmental conditions and user-defined settings such as aiming the transducer and data analysis. That said, an advantage of the combined sonar and underwater camera method over traditional methods such as fishing is that the accuracy and precision can be measured rather than estimated in each step of the processing. As an example, the length measurement error in a certain setup is known (Chapter 2) and the accuracy of the automation for finding fish can be tested (Chapter 3). With “traditional methods” measurements are often made only in a small sample of the population, *i.e.*, fewer measurements are made, and the sample is then assumed to represent the whole population. The non-invasiveness of the sonar method is also an advantage itself that supports choosing it over methods that need fish handling, even if a higher accuracy could be achieved with another method.

These errors are important to consider when making management decisions using imaging sonar (or any other) data. In small populations these errors can be crucial for the population, because an inaccuracy in the population estimate can lead to poor management decisions. Therefore, ultimately, it is most important to ensure that the fish population is in good health so that the errors in the population estimate would have a negligible effect on the population.

7.5 Literature

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Appendixes

A1. Contribution of Authors in Chapters 2 – 6

Chapter 2 [*Length measurement accuracy of Adaptive Resolution Imaging Sonar (ARIS) and a predictive model to assess adult Atlantic salmon (Salmo salar) into two size categories with long-range data in a river*]

The three authors planned the study concept together. The data collection was a group effort in which J. Helminen and G.J.R. Dauphin were part of the team. J. Helminen conducted the statistical analysis for the accuracy testing; the idea for the predictive Bayesian model was G.J.R. Dauphin's. J. Helminen was responsible for writing the article, and G.J.R. Dauphin and T. Linnansaari were the primary editors.

Chapter 3 [*Object and behavior differentiation for improved automated counts of migrating river fish using imaging sonar data*]

J. Helminen designed the study, carried out the field work and data collection with a team of multiple technicians, created the automation workflow, performed all the analysis, and wrote the article. T. Linnansaari was the primary editor.

Chapter 4 [*Measuring tailbeat frequencies of three fish species from Adaptive Resolution Imaging Sonar (ARIS) data*]

All authors contributed to the design of the study. J. Helminen collected the field data with a team of multiple technicians, performed the analysis, and wrote the manuscript. The automated method was conceptualized together with A.M. O'Sullivan. T. Linnansaari and A.M. O'Sullivan were the primary editors.

Chapter 5 [*Combining imaging sonar counting and underwater camera species apportioning to estimate the number of Atlantic salmon (Salmo salar) in the Miramichi River, New Brunswick, Canada*]

J. Helminen collected the field data with a team of multiple technicians, performed all the analysis and wrote the manuscript. T. Linnansaari was the primary editor. Both authors contributed to the design of the study.

Chapter 6 [*Monitoring adult Atlantic salmon run in rivers using imaging sonars – A practitioner's guide*]

All authors contributed to the design of the study. J. Helminen conducted the literature review and writing. C. MacIntyre, C. DeCoste, and T. Linnansaari were the primary editors.

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I am incredibly excited for your defense.

All the best,

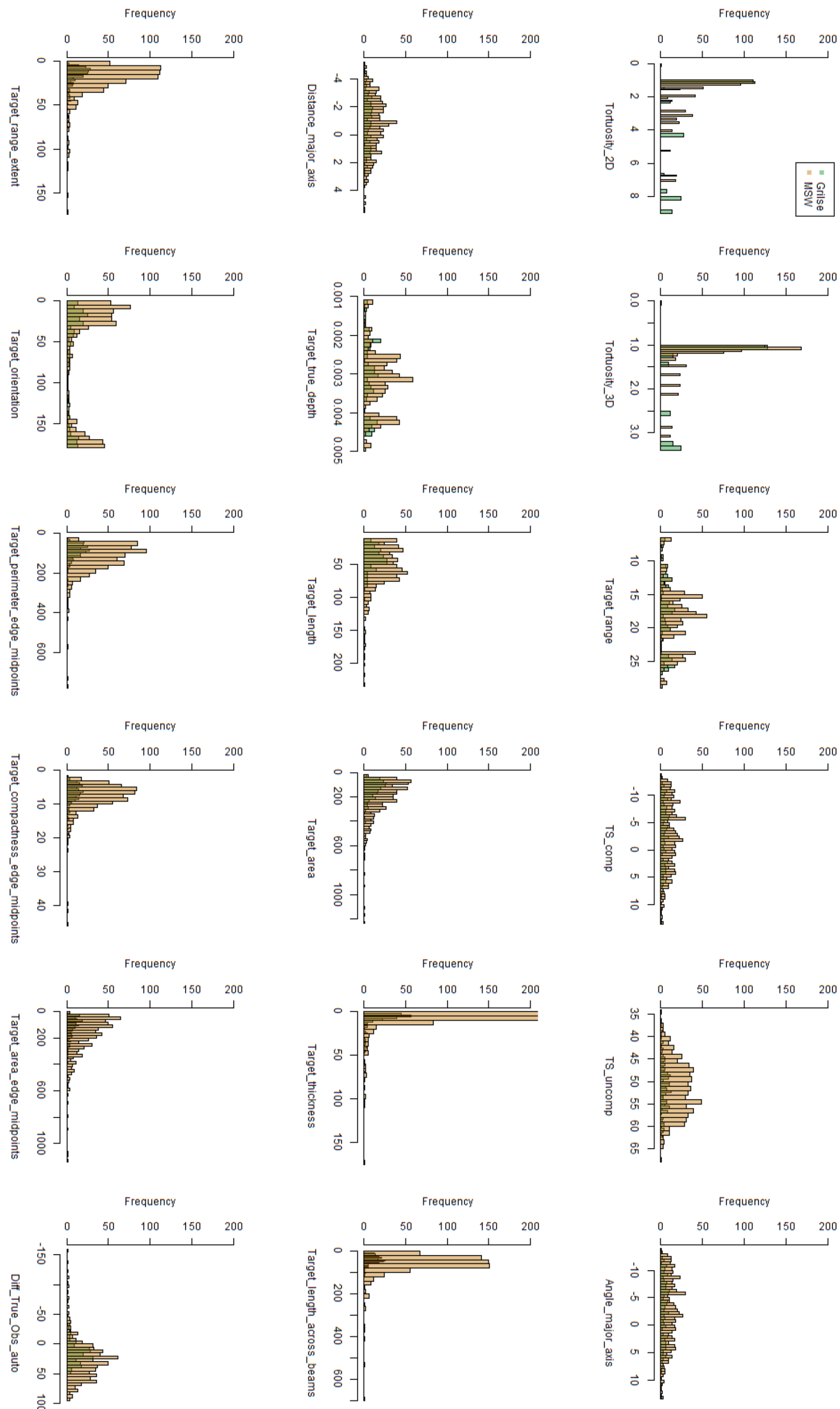
*antóin

A4. Chapter 2 supplementary material

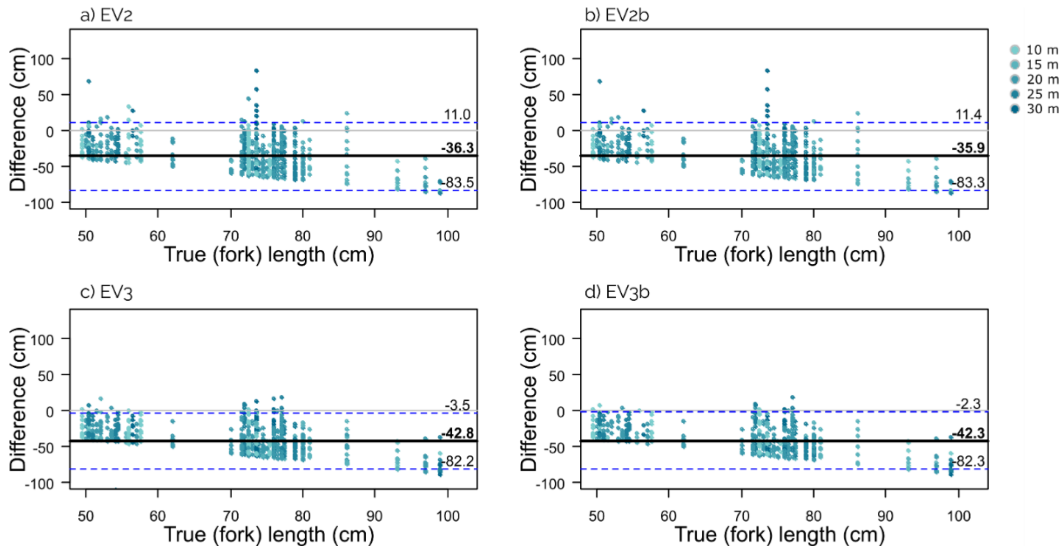
Supporting Information Table S1. List of Atlantic salmon in this study: girth, fork length, total length, release distance and if they were measured from the sonar footage (*i.e.*, swimming upriver and identified in the sonar image).

1SW/MSW	Girth	Fork length	Total length	Released at distance (m)	Measured from sonar footage
1SW	21.5	50	53	29	No
1SW	21.5	54	56	15	Yes
1SW	21	53	54	20	Yes
1SW	25.5	57	59.5	29	No
1SW	21.5	51	53	25	No
1SW	21	51	54	25	No
1SW	23	55	58	29	No
1SW	22	54	57.5	15	Yes
1SW	21.5	53.5	58	20	Yes
1SW	20	51	54	25	Yes
1SW	21.5	50.5	53.5	29	Yes
1SW	21	50	53.5	15	Yes
1SW	21	51.5	56	20	Yes
1SW	24	57.5	61.5	25	Yes
1SW	21.5	51.5	54.5	29	Yes
1SW	24	55.5	58.5	15	Yes
1SW	23.5	56	59	25	Yes
1SW	22	50.5	54	15	Yes
1SW	20	51	54	20	Yes
1SW	21	50.5	54.5	29	No
1SW	20.5	49	52.5	15	No
1SW	23	53	56.5	20	No
1SW	23.5	57	61	25	Yes
1SW	23	54	57.5	29	No
1SW	23	54.5	58	15	Yes
1SW	21.5	49.5	53	20	Yes
1SW	20.5	50.5	53.5	29	Yes
1SW	24.5	56.5	59.5	15	Yes
1SW	21	52	56.5	20	Yes
1SW	21	50.5	54.5	15	Yes
1SW	25.5	62	65	20	Yes
MSW	36.5	72	76	15	Yes
MSW	36	80	84	20	Yes
MSW	36	80	84.5	25	Yes
MSW	38	77.5	81.5	29	Yes
MSW	35	77.5	81	15	Yes
MSW	34	73	77	20	Yes
MSW	47	97	102	25	Yes
MSW	32.5	74	78	15	Yes
MSW	34	74.5	79.5	20	Yes
MSW	33	70	74	15	Yes
MSW	35	75	79.5	20	Yes
MSW	36	76	80.5	25	Yes
MSW	37	79	83	29	Yes
MSW	33	71.5	76	20	Yes
MSW	37	79	84	29	No
MSW	36.5	76.5	81.5	15	Yes
MSW	34.5	74.5	78	20	Yes
MSW	32.5	72.5	76.5	25	Yes
MSW	34	73.5	77.5	29	Yes
MSW	34	72.5	77	25	Yes
MSW	46	93	95	29	Yes
MSW	35.5	79	83	15	Yes
MSW	41.5	86	89.5	20	Yes

MSW	37	76	81	25	Yes
MSW	33	75	79.5	25	No
MSW	35.5	76	80.5	29	No
MSW	34	72.5	77	15	Yes
MSW	37.5	80	85.5	25	No
MSW	35	81	85.5	29	Yes
MSW	36	76	80.5	15	Yes
MSW	35	73.5	78	20	Yes
MSW	45	99	103	25	Yes
MSW	34	75.5	80	29	Yes
MSW	35	77	81.5	15	Yes
MSW	31	76	79	20	Yes
MSW	35	77	83	25	Yes
MSW	34	74.5	79	25	No
MSW	33	73.5	78	29	No



Supporting Information Figure S1 Variables available for modelling from computer-generated measurements.



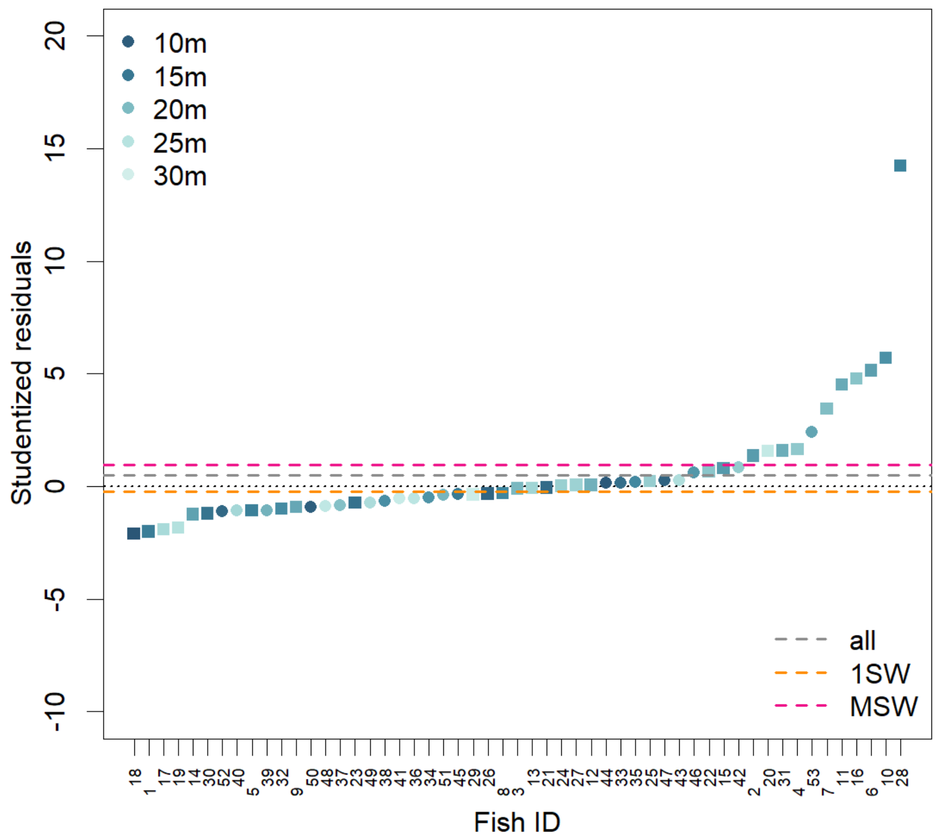
Supporting Information Figure S2 Bland–Altman difference plots for repeated measurements for computer-generated data EV2 (a), EV2b (b), EV3 (c) and EV3b (d). The *y*-axis represents the measurement difference (ARIS (estimated) length – observed (true) length) and the *x*-axis is the observed (true) length of adult Atlantic salmon. Colours indicate the distance of the observation from the ARIS transducer. The black line is the mean of differences, dashed lines show the limits of agreement and the grey line shows the no-bias (0) line for reference.

Supporting Information Table S2 Summary statistics of the posterior distributions of the main parameters of the models obtained with the User 1, User 2 and User 3 datasets

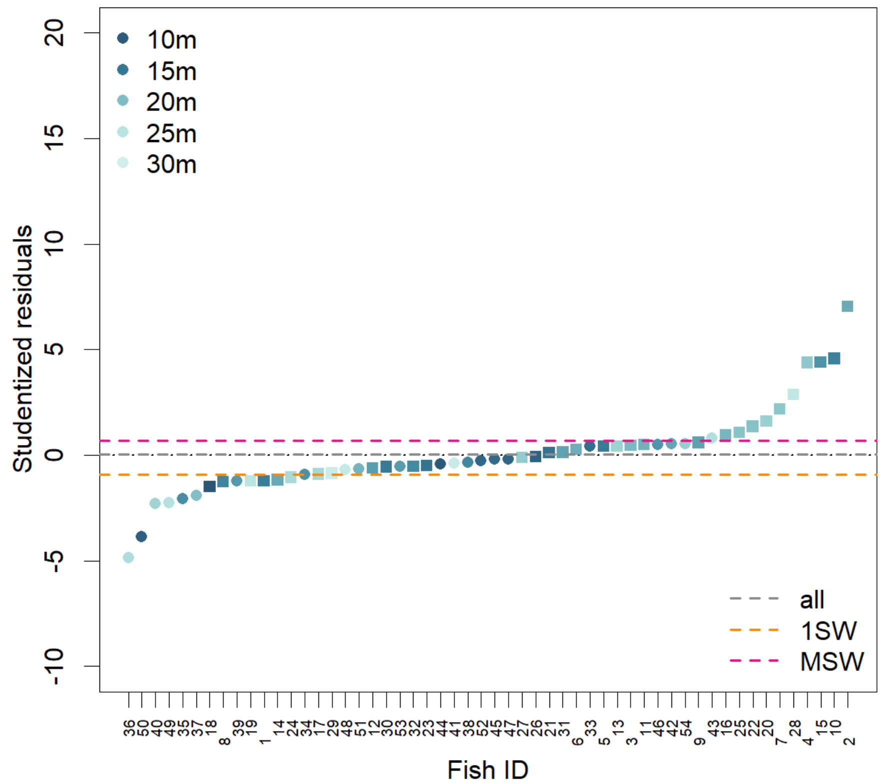
Dataset	Parameter	Mean	S.D.	2.5th	25th	Median	75th	97.5th
User 1	$\bar{L}^{\mathrm{1SW}}$	52.49	0.83	50.83	51.94	52.50	53.05	54.12
	$\bar{L}^{\mathrm{MSW}}$	78.18	1.02	76.24	77.49	78.16	78.85	80.24
	σ^{L}	0.08	0.01	0.06	0.07	0.08	0.08	0.09
	σ^{R}	0.22	0.01	0.20	0.21	0.22	0.22	0.24
	α_0	−0.86	0.34	−1.58	−1.08	−0.85	−0.63	−0.24
	α_1	−1.17	0.25	−1.68	−1.32	−1.15	−1.00	−0.72
	α_2	0.04	0.07	−0.08	0.00	0.04	0.08	0.18
	α_3	0.07	0.04	−0.01	0.04	0.07	0.10	0.16
	β_0	1.55	0.24	1.07	1.38	1.55	1.71	2.03
	β_1	0.60	0.06	0.49	0.56	0.60	0.64	0.71
	β_2	0.01	0.00	0.00	0.00	0.01	0.01	0.01
	β_3	0.00	0.00	0.00	0.00	0.00	0.00	0.01
User 2	$\bar{L}^{\mathrm{1SW}}$	52.99	0.84	51.34	52.43	52.98	53.54	54.65
	$\bar{L}^{MSW}$	77.79	1.04	75.79	77.09	77.77	78.48	79.87
	σ^{L}	0.08	0.01	0.06	0.07	0.07	0.08	0.09
	σ^{R}	0.30	0.02	0.27	0.29	0.30	0.31	0.34
	α_0	−2.00	0.91	−4.14	−2.51	−1.87	−1.34	−0.60
	α_1	−4.59	1.46	−8.03	−5.42	−4.39	−3.54	−2.33
	α_2	0.05	0.15	−0.22	−0.05	0.04	0.15	0.38
	α_3	0.13	0.24	−0.31	−0.03	0.12	0.28	0.64
	β_0	1.46	0.50	0.49	1.13	1.46	1.79	2.46
	β_1	0.62	0.12	0.38	0.54	0.62	0.70	0.85
	β_2	0.00	0.00	−0.01	−0.01	0.00	0.00	0.01
	β_3	0.00	0.00	−0.01	0.00	0.00	0.00	0.01
User 3	$\bar{L}^{\mathrm{1SW}}$	52.97	0.85	51.31	52.40	52.96	53.53	54.65
	$\bar{L}^{MSW}$	77.80	1.04	75.78	77.10	77.79	78.48	79.89
	σ^{L}	0.08	0.01	0.06	0.07	0.07	0.08	0.09
	σ^{R}	0.43	0.02	0.38	0.41	0.42	0.44	0.47
	α_0	−0.80	0.39	−1.61	−1.04	−0.78	−0.53	−0.10
	α_1	−1.99	0.53	−3.13	−2.33	−1.96	−1.62	−1.04
	α_2	0.00	0.07	−0.14	−0.05	0.00	0.05	0.15
	α_3	0.08	0.10	−0.10	0.01	0.07	0.14	0.28
	β_0	1.64	0.77	0.19	1.11	1.62	2.15	3.19
	β_1	0.64	0.18	0.28	0.52	0.65	0.77	0.98
	β_2	−0.02	0.01	−0.03	−0.02	−0.02	−0.01	0.00
	β_3	0.00	0.01	−0.01	0.00	0.00	0.00	0.01

Supporting Information Figure S3 Studentized residuals ($\left(L_n - \mathrm{mean}\left(L_n^{\mathrm{pred}}\right)\right)/sd\left(L_n^{\mathrm{pred}}\right)$) associated with the length predictions of each individual salmon (MSW salmon: square, 1SW salmon: circle) based on (a) EV1 and (b) User 4 datasets.

a



b


10m
15m
20m
25m
30m
Studentized residuals
all
1SW
MSW
Fish ID

A5. Chapter 3 supplementary material

Track detection properties. Changes between 1st and 2nd round highlighted.

	1st Round	2nd Round
Algorithm (4D)		
Major Axis Alpha	1	1
Major Axis Beta	1	1
Range Alpha	1	1
Range Beta	1	1
Major Axis Exclusion Distance (m)	1	2
Major Axis Missed Ping Expansion (%)	20	20
Range Exclusion Distance (m)	1	1
Range Missed Ping Expansion (%)	20	20
Weights		
Major Axis	2.0	2.0
Range	1.5	1.5
TS	0.0	0.0
Ping Gap	2.0	2.0
Track Acceptance		
Minimum number of single targets in a track	5	5
Minimum number of pings in track	5	5
Maximum gap between single target (pings)	8	15

A6. Chapter 5 supplementary material

The Bonferroni corrected p-values for pairwise Fisher's exact test. Values < 0.05 are highlighted

Time (hour)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	NA	1	1	1	1	1	1	1	0.069	**0.003**	**0.017**	**0.017**	**0.000**	**0.003**	**0.017**	**0.003**	**0.000**	0.232	0.630	1	1	1	1	1
1	1	NA	1	1	1	1	1	1	0.069	**0.003**	**0.017**	**0.017**	**0.000**	**0.003**	**0.017**	**0.003**	**0.000**	0.232	0.630	1	1	1	1	1
2	1	1	NA	1	1	1	1	1	0.175	**0.008**	**0.046**	**0.046**	**0.001**	**0.008**	**0.046**	**0.008**	**0.001**	0.531	1	1	1	1	1	1
3	1	1	1	NA	1	1	1	1	0.408	**0.024**	0.119	0.119	**0.002**	**0.024**	0.119	**0.024**	**0.002**	1	1	1	1	1	1	1
4	1	1	1	1	NA	1	1	1	0.408	**0.024**	0.119	0.119	**0.002**	**0.024**	0.119	**0.024**	**0.002**	1	1	1	1	1	1	1
5	1	1	1	1	1	NA	1	1	**0.025**	**0.001**	**0.006**	**0.006**	**0.000**	**0.001**	**0.006**	**0.001**	**0.000**	0.091	0.274	1	1	1	1	1
6	1	1	1	1	1	1	NA	1	0.408	**0.024**	0.119	0.119	**0.002**	**0.024**	0.119	**0.024**	**0.002**	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	NA	1	0.359	1	1	0.051	0.359	1	0.359	0.051	1	1	1	1	1	1	1
8	0.069	0.069	0.175	0.408	0.408	**0.025**	0.408	1	NA	1	1	1	1	1	1	1	1	1	1	0.175	1	0.408	1	1
9	**0.003**	**0.003**	**0.008**	**0.024**	**0.024**	**0.001**	**0.024**	0.359	1	NA	1	1	1	1	1	1	1	1	1	**0.008**	0.359	**0.024**	0.359	1
10	**0.017**	**0.017**	**0.046**	0.119	0.119	**0.006**	0.119	1	1	1	NA	1	1	1	1	1	1	1	1	**0.046**	1	0.119	1	1
11	**0.017**	**0.017**	**0.046**	0.119	0.119	**0.006**	0.119	1	1	1	1	NA	1	1	1	1	1	1	1	**0.046**	1	0.119	1	1
12	**0.000**	**0.000**	**0.001**	**0.002**	**0.002**	**0.000**	**0.002**	0.051	1	1	1	1	NA	1	1	1	1	1	1	**0.001**	0.051	**0.002**	0.051	0.308
13	**0.003**	**0.003**	**0.008**	**0.024**	**0.024**	**0.001**	**0.024**	0.359	1	1	1	1	1	NA	1	1	1	1	1	**0.008**	0.359	**0.024**	0.359	1
14	**0.017**	**0.017**	**0.046**	0.119	0.119	**0.006**	0.119	1	1	1	1	1	1	1	NA	1	1	1	1	**0.046**	1	0.119	1	1
15	**0.003**	**0.003**	**0.008**	**0.024**	**0.024**	**0.001**	**0.024**	0.359	1	1	1	1	1	1	1	NA	1	1	1	**0.008**	0.359	**0.024**	0.359	1
16	**0.000**	**0.000**	**0.001**	**0.002**	**0.002**	**0.000**	**0.002**	0.051	1	1	1	1	1	1	1	1	NA	1	1	**0.001**	0.051	**0.002**	0.051	0.308
17	0.232	0.232	0.531	1	1	0.091	1	1	1	1	1	1	1	1	1	1	1	NA	1	0.530886	1	1	1	1
18	0.630	0.630	1	1	1	0.274	1	1	1	1	1	1	1	1	1	1	1	1	NA	1	1	1	1	1
19	1	1	1	1	1	1	1	1	0.175	**0.008**	**0.046**	**0.046**	**0.001**	**0.008**	**0.046**	**0.008**	**0.001**	0.530886	1	NA	1	1	1	1
20	1	1	1	1	1	1	1	1	1	0.359	1	1	0.051	0.359	1	0.359	0.051	1	1	1	NA	1	1	1
21	1	1	1	1	1	1	1	1	0.408	**0.024**	0.119	0.119	**0.002**	**0.024**	0.119	**0.024**	**0.002**	1	1	1	1	NA	1	1
22	1	1	1	1	1	1	1	1	1	0.359	1	1	0.051	0.359	1	0.359	0.051	1	1	1	1	1	NA	1
23	1	1	1	1	1	1	1	1	1	1	1	1	0.308	1	1	1	0.308	1	1	1	1	1	1	NA

Curriculum Vitae

Candidate's full name: Jani Helminen

Universities attended (with dates and degrees obtained):

- University of Helsinki (Helsinki, Finland), 17 June 2016, Master of Science (Aquatic Sciences – Specialisation in Fish and Fishery Biology)
- University of Helsinki (Helsinki, Finland), 12 May 2016, Bachelor of Science (Biological and Environmental Sciences)
- Aalto University (Espoo, Finland), 11 January 2013**,** Minor Degree for BSc studies (Water and Environmental Engineering)

Publications in peer-reviewed journals:

- **Helminen, J.,** O'Sullivan, A.M. & Linnansaari, T. (2021). Measuring tailbeat frequencies of three fish species from Adaptive Resolution Imaging Sonar (ARIS) data. Transactions of the American Fisheries Society. DOI: 10.1002/tafs.10318
- **Helminen, J.** & Linnansaari, T. (2021). Object and behavior differentiation for improved automated counts of migrating river fish using imaging sonar data. Fisheries Research, 237. DOI: 10.1016/j.fishres.2021.105883
- **Helminen, J.,** Dauphin, G. J.R. & Linnansaari, T. (2020). Length measurement accuracy of Adaptive Resolution Imaging Sonar (ARIS) and a predictive model to assess adult Atlantic salmon (*Salmo salar*) into two size categories with long-range data in a river. Journal of Fish Biology. DOI: 10.1111/jfb.14456

- O'Sullivan, A., Wegscheider, B., **Helminen, J.,** Cormier, J. G., Linnansaari, T., & Curry, R. A. (2020). Catchment-scale, high-resolution, hydraulic habitat models. Journal of Ecohydraulics. DOI: 10.1080/24705357.2020.1768600
- Andrews, S., O'Sullivan, A. M., **Helminen, J.,** Arluison, D., Samways, K.M., Linnansaari, T. & Curry, R.A. (2020). Development of Active Numerating Side Scan for a High-density Overwintering Location for Endemic Shortnose Sturgeon (*Acipenser brevirostrum*) in the Saint John River, New Brunswick. Diversity 12(1):23. DOI: 10.3390/d12010023
- **Helminen, J.,** Linnansaari, T., Bruce, M., Dolson-Edge, R. & Curry, R.A. (2019). Accuracy and Precision of Low-Cost Echosounder and Automated Data Processing Software for Habitat Mapping in a Large River. Diversity 11(7):116. DOI: 10.3390/d11070116

Selected Conference Presentations:

- **Helminen, J.**, Linnansaari, T. & Dauphin, G.J.R (2019). Estimating Atlantic Salmon (*Salmo salar*) Population Size in a Multispecies River Using Adaptive Resolution Imaging Sonars (ARIS) and Underwater Cameras. American Fisheries Society & The Wildlife Society 2019 Joint Annual Conference. 29 September - 3 October. Reno, Nevada, USA.
- **Helminen, J.**, Linnansaari, T. & MacIntyre, C. (2019). Counting fish with ARIS imaging sonars. How to tell if it is a salmon? Atlantic Salmon Ecosystems Forum. 12-13 March. Quebec City, Quebec, Canada. [Poster Presentation]
- Curry, R.A., Andrews, S., Babin, A., Carrow, R., Corey, E., Cunjak, R., Gautreau, M., Gray, M., **Helminen, J.**, Linnansaari, T., Roth, D., Samways, K. & Yamazaki,

G. (2018). Tracking Fish From Freshwater to the Sea. Technologies and Issues Across Spatial Scales and Ecological Considerations. Asian Fisheries Acoustics Society, AFAS meeting 2018. 13-15 November 2018. Jeju, South Korea.

- **Helminen, J.** & Linnansaari, T. (2018). Monitoring Atlantic Salmon run in the Miramichi River using imaging sonars. Nowpas, salmonid research network – 2018 Workshop. 13-17 March. Oulanka, Finland.
- **Helminen, J.** & Linnansaari, T. (2018). Monitoring the Atlantic Salmon (*Salmo salar*) run in the Miramichi River using imaging sonar – first full monitoring season 2017. The Atlantic Salmon Ecosystems Forum (ASEF) - Are we moving the needle? 17-18 January 2018. Orono, ME, USA.
- **Helminen, J.**, Linnansaari, T. & Smith, C. (2017). Development of Population Assessment Methods for Atlantic Salmon (*Salmo salar*) in the Miramichi River Using Adaptive Resolution Imaging Sonar (ARIS). Canadian Conference for Fisheries Research (CCFFR). 5-8 January 2017, Montreal, QC.