Predicting fish weight using photographic image analysis: a case study of broad whitefish in the lower Mackenzie River watershed

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Abstract

Many small-scale fisheries are remote in nature, making data collection logistically difficult. Thus, there is a need for accessible solutions that address the data gaps present in these fisheries. One possible solution is to incorporate photography into community- or harvest-based monitoring frameworks and employ these images to estimate biological data. Here, we test this approach using łuk dagaii, or broad whitefish, *Coregonus nasus* (Pallus, 1776) in the Gwich'in Settlement Area, a remote region in the Mackenzie River system in Canada's Northwest Territories. We used photographs taken by Gwich'in collaborators using a simple, standardized set-up to ask the question: how accurately can weight be estimated from a photo? Using random forest models based on morphometric photograph measurements as well as season and location of harvest, we predicted broad whitefish weight to within 13% of true weight (257 g, for fish weighing an average of 2036 g). The model predictions were well distributed in their residuals for most fish, though we discuss biases at low and high weights. Image analysis is a simple, low cost, and accessible method that may contribute to ongoing, community/harvest-based fishery data collection where fish length (measured) and weight (predicted) can be tracked through time.

Key words: image analysis, community-based monitoring, broad whitefish, random forest analysis, fisheries monitoring

Résumé

De nombreuses petites pêcheries sont éloignées dans la nature, ce qui rend la collecte de données difficile sur le plan logistique. Il est donc nécessaire de trouver des solutions accessibles pour combler le manque de données dans ces pêcheries. Une solution possible est d'intégrer la photographie dans les cadres de surveillance fondés sur la communauté ou sur la récolte et d'utiliser ces images pour estimer des données biologiques. Les auteurs testent ici cette approche en utilisant le łuk dagaii, ou corégone tschir, *Coregonus nasus* (Pallus, 1776), dans la zone d'établissement des Gwich'in, une région éloignée du système du fleuve Mackenzie dans les Territoires du Nord-Ouest au Canada. Ils ont utilisé des photographies prises par des collaborateurs Gwich'in à l'aide d'une installation simple et standardisée pour poser la question suivante : avec quelle précision peut-on estimer le poids à partir d'une photo ? En utilisant des modèles forestiers aléatoires fondés sur les mesures de photographies morphométriques ainsi que sur la saison et le lieu de récolte, ils ont prédit le poids du corégone à 13 % près du poids réel (257 g, pour des poissons pesant en moyenne 2036 g). Les prédictions du modèle étaient bien distribuées dans leurs résidus pour la plupart des poissons, mais les auteurs abordent la question des biais pour les poids faibles et élevés. L'analyse d'images est une méthode simple, peu coûteuse et accessible qui peut contribuer à la collecte continue de données de pêcheries fondées sur la communauté ou sur la récolte où la longueur (mesurée) et le poids (prédit) des poissons peuvent être suivis dans le temps. [Traduit par la Rédaction]

Mots-clés : analyse d'image, surveillance fondée sur la communauté, corégone tschir, analyse forestière aléatoire, surveillance des pêches

Introduction

Collecting fisheries data can be difficult for small-scale fisheries in remote regions because of financial and logistical constraints. For instance, in northern Canada, there has been very limited effort to document small-scale fishery catches (Zeller et al. 2011); yet, it is a system where basic biological data are considerably lacking for many species (Dey et al. 2018). One method of collecting data in these situations

is harvest- or community-based monitoring, where trained fishers gather information (e.g., record measurements) from their catch, creating the opportunity for long-term biological data sets while a species is harvested, often for subsistence (Bell and Harwood 2012).

Innovative and accessible solutions that are suitable for widespread use could address some of the data gaps present in small-scale fisheries (Pita et al. 2019), and technology is becoming increasingly available to do so (Bradley et al. 2019). For example, cameras have been trialed in small-scale fisheries to identify species (Bartholomew et al. 2018), to monitor regulation compliance (Pitcher et al. 2009), and as a means for trained community members to report shark landings (Jeffers et al. 2019). Image analysis has also been used to discern fish morphometrics in large-scale fishing and aquaculture industries (Balaban et al. 2010).

Here, we investigated the potential application of data collection through photography and image analysis for a łuk dagaii or broad whitefish (*Coregonus nasus* (Pallus, 1776)) fishery in the Gwich'in Settlement Area (GSA) in the western Canadian Arctic (Fig. 1). To evaluate an accessible data collection tool that could be utilized by a community-based monitoring program, we explored the feasibility of predicting broad whitefish weight from fish measurements (e.g., length) derived from photographs. Monitoring fish weight is of interest because from fish length and weight one can understand fish body condition, and potentially fecundity, where changes in these characteristics through time can indicate stress on a population (Pope et al. 2010). In the GSA, healthy, robust fish populations are intertwined with the well-being of Gwich'in peoples as fishing is integral to Gwich'in identity and culture (Proverbs 2019) and provides an important source of recreation and food (Kuhnlein et al. 2009). Moreover, fish weight is directly related to the amount of food obtained from a fishery. Using the methods presented herein, fisheries data could be collected through the ongoing submission and measurement of appropriately collected photographs of broad whitefish harvested for subsistence. Hence, these methods can allow for long-term data collection that is not constrained to a field season, schedule, or budget.

We used random forest (RF) analysis in a model selection process to discern prediction accuracy and which set of measurements best predicted broad whitefish weight. Specifically, we addressed the question: how accurately can weight be estimated from a photo? To do this, we investigated (1) what was the best set of morphometric measurements to predict fish weight without any additional knowledge (such as location or season of capture)? and (2) when location and season of capture are known, do these variables improve predictive ability?

Methods

Study system

This study was a part of a research program that began in 2017 between Gwich'in community members, renewable resources organizations within the GSA, and university scientists (Hovel et al. 2020). The monitoring and sample collection of broad whitefish (herein, whitefish as is the common name in the GSA) used in this study was done by Gwich'in community collaborators (herein, monitors) (Hodgson et al. 2020). As part of the ongoing collaborative structure of this research, the results from this study were shared with the three Gwich'in communities involved in the monitoring program through a plain language summary and community presentations.

The Mackenzie River ends in the largest Arctic delta in North America (Burn and Kokelj 2009). In this region, whitefish have diverse life-history strategies (Harris et al. 2012a) with at least four described migratory patterns (Harris et al. 2012b). While whitefish are not considered to be under immediate threat (Committee on the Status of Endangered Wildlife in Canada 2019), this species is susceptible to the impacts of a changing environment as it inhabits one of the most rapidly warming areas on the planet (Bush and Lemmen 2019). Whitefish have been harvested since time immemorial by Gwich'in peoples in the lower Mackenzie River watershed (Thompson and Millar 2007). Fishing occurs on the lower Mackenzie River (Nagwichoonjik), Arctic Red River (Tsiigehnjik), and Peel River (Teetł'it Gwinjik) (Gwich'in Social and Cultural Institute 2016).

Data collection

Community monitors collected photographs of fish captured as part of the subsistence fishery along the Peel Channel in the Mackenzie Delta and the Peel River (Fig. S1) between July and October in 2017 and 2018. Thus, this study utilized opportunistic sampling of fish that were being harvested already. Fish were caught in gillnets (5–25 m in length; ~10 or 13 cm mesh size). Monitors measured fish length (using a measuring tape) and weight (using a Brecknell ElectroSamson digital hanging scale, 10.00 ± 0.01 kg), and took a photograph (using a Nikon COOLPIX W100 13.2MP waterproof digital camera). Photographs were taken from directly above and included the entire fish. At the start of each season, monitors were trained in all fish measurement methods, including how to photograph the fish consistently. Photograph methods included ensuring that the fish was laid straight and flat, and the entire body was in the image (Fig. 1). The photograph set-up was intentionally kept simple (e.g., no copy stand was used) to increase accessibility among users. Research was conducted under Aurora Research Institute Scientific Research License No. 16225, Simon Fraser University Animal Care Protocol #1248B-17, and Fisheries and Oceans Canada (DFO) permit DFO LFSP S-18/19 3015-YK.

We used ImageJ (Schindelin et al. 2012) to take 15 measurements from each photograph. Measurements were selected based on (1) a modified Truss measurement method (Strauss and Bookstein 1982; modified based on Beddow and Ross 1996 and Hockaday et al. 2000) giving lines 1–2, 1–3, 1–4, 2–3, 2–4, 3–4, 3–5, 3–6, 4–5, 4–6, and 5–6; (2) traditional methods of predicting weight from fish length and body depth (as in Jones, Petrell and Pauly 1999) giving lines A–F and 3–E; and (3) monitor knowledge identifying differing belly size between fish, which is captured in the region of the body measured by lines 3–D and B–C (Fig. 1; see Fig. S2 for details).

Fig. 1. Top left: all 15 photograph measurements where bold lines indicate measurements used in weight-IV-SL (see Fig. S2 for details on measurement landmarks). Top right: location in Canada of the Gwich'in Settlement Area. Bottom: weight-IV-SL true versus predicted broad whitefish weights (see Results section for more details). Dashed black line is the 1:1 line. Black, solid line is the trendline of the plotted testing data. Grey shaded area is 95% confidence interval. Tick marks denote the distribution of the training data true weights.
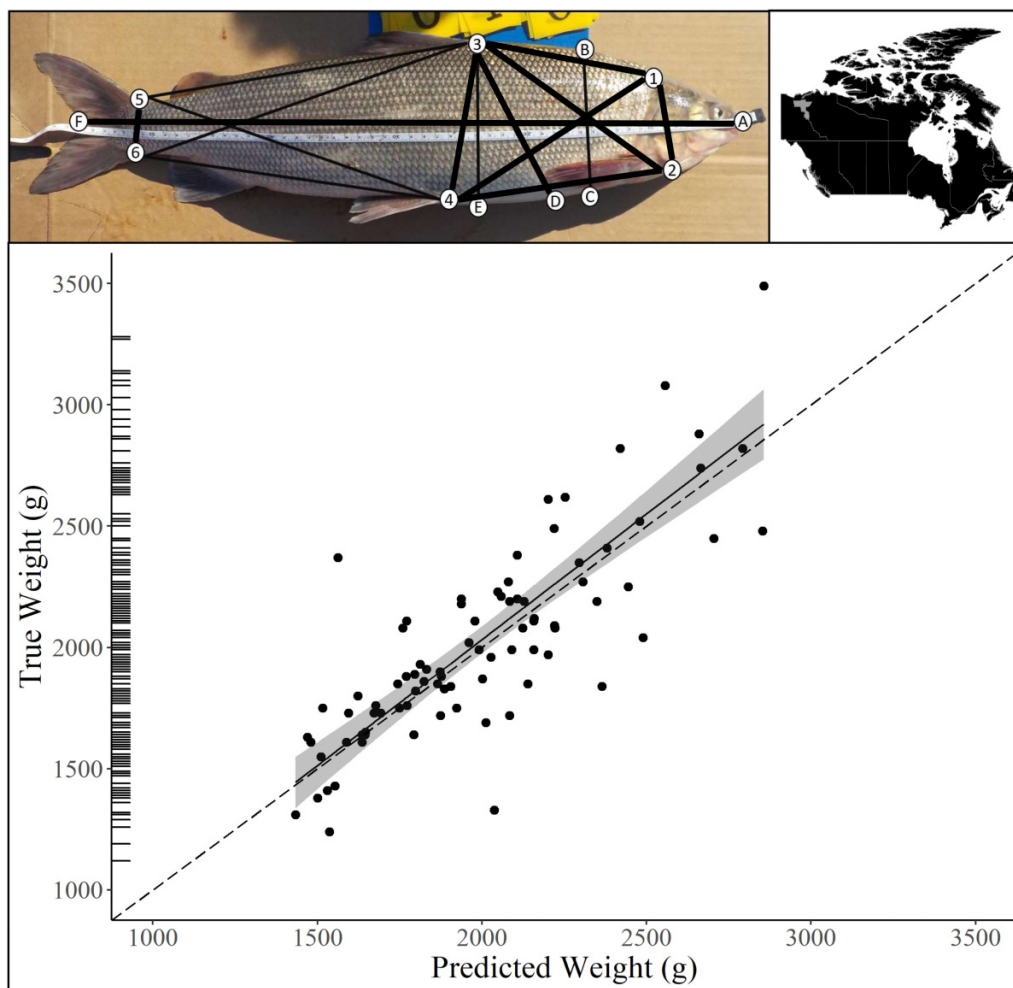
Photograph analysis includes measurement error. Inherent to the act of photography, the conversion of a 3D item into a 2D image may distort distances, making photograph-based measurements shorter than they would be on the real fish (Petrtýl et al. 2014). Error due to different operators is also possible (Fruciano 2016). We took steps to mitigate both sources of error and provide the details in Section S1 (error mitigation) in the Supplementary material.

In addition to the photograph measurements, the categorical variables of location ("Peel" or "delta") and time of harvest (July, August, or September/October (which were combined due to the small sample size in October), herein collectively referred to as season) were included in our analysis to explore whether additional variation in weight could be explained. Sample location was used as a categorical variable because there is preliminary evidence that Peel River and Mackenzie Delta whitefish differ in weight (R. Hovel, J. Moore, E. Hodgson, and T. Lantz, personal communication, 2019). Season was used due to the potential for seasonal shifts in body shape

due to environmental or life-history factors. For example, female fish become increasingly gravid in the fall. We hypothesized that body size characteristics may change accordingly as eggs develop; however, fish sex was not differentiated as gonads were not checked for all fish in our data set. We explored time through the season rather than between years as we expected sizes to change from the beginning to end of summer but did not hypothesize that they would change substantially between years.

RF analysis

We used RF analysis to explore model predictions for whitefish weight. RFs are collections of decision trees where data are split into nonoverlapping categories by randomly sampling with replacement of two-thirds of the data (Liaw and Wiener 2002). RFs decorrelate their generated trees by randomly selecting a subset of all explanatory variables to consider at each split in the tree (Liaw and Wiener 2002). We generated RFs with the randomForest package (Liaw and Wiener

2002) in R (version 3.6.2; R Core Team 2019), retaining the default setting for the number of parameters (one-third) at each split (Liaw and Wiener 2002), but increasing the total number of trees in each model from default (500) to 100 000 (see Section 2 in the Supplementary material for RF rationale, including number of trees (Figs. S3–S8) and in comparison to linear models).

We split the full suite of data (281 fish) into two subsets: training and testing. The training subset was composed of 196 randomly selected fish (70% of the data) and was used to develop the prediction models. The testing subset consisted of the remaining 85 fish and was used for cross-validation (for details on data distribution, see Table S1).

In total, we tested 20 models to predict weight using a two-phased approach to investigate (1) what was the best set of morphometric measurements to predict fish weight and (2) whether including location and season as variables improved predictive ability. In the first phase, we selected suites of measurements to make five models. The first model was the most complex (weight-I; all 15 measurements). In the next three models, we dropped the most correlated variables (correlation > 0.9) as a model with fewer measurements would streamline the measurement process (weight-II = 10 measurements, weight-III = 9 measurements, and weight-IV = 9 measurements; Table S2). The final model, weight-V, used only one measurement to predict weight (A–F; length), based on traditional approaches (Spencer 1898 as referenced in Beddow and Ross 1996). In phase 2, the location and (or) season were added to each of the five phase 1 models (represented in the model name by "L" or "S", respectively) to see whether these parameters improved predictive accuracy. This created an additional 15 models (Table S2).

We identified the most statistically accurate model using the root mean squared error (RMSE) rounded to the nearest gram. When RMSE was the same, we used the intercept and slope of the "true weight" versus "predicted weight" (TP) regression line (Table S2). It was expected that the most accurate model would have the RMSE and TP intercept closest to 0, and TP slope closest to 1.

Results

The training and testing data (196 and 85 fish, respectively) both had similar characteristics (Fig. S9). Training data whitefish photo length (A–F) ranged from 398 to 606 mm (mean = 482 mm) and testing data fish length ranged from 392 to 615 mm (mean = 483 mm). Whitefish true weights ranged from 1120 to 3280 g (mean = 2038 g) in the training data and from 1240 to 3820 g (mean = 2036 g) in the testing data.

Photograph measures of fish length and body size contributed to the best prediction of weight (models weight-I through weight-IV) over a length-only model (weight-V). Based on performance metrics for accuracy and bias, weight-IV (measurements A–F, 1–2, 1–3, 1–4, 2–3, 2–4, 3–4, 5–6, and D–3) was selected as the best model from phase 1 (RMSE = 260 g, TP intercept = −31 g, and TP slope = 1.03; Table S2). Comparatively, weight-V performed the worst (RMSE = 358 g, TP = 534 g, and TP slope = 0.74; Table S2).

In phase 2, season and sampling location improved model predictions. Weight-IV-SL was the best phase 2 model (RMSE = 257 g, TP intercept = −43 g, and TP slope = 1.04; Table S2), and had the lowest RMSE out of both phases; therefore, it was selected as the best model overall (weight-IV-SL also predicts whitefish weight more accurately than a simple linear model; see Section S3 (linear model) and Fig. S10 in the Supplementary material). Comparing the true weights of test data whitefish with their predicted weights (Fig. 1), weight-IV-SL predicted within 13.22% of true fish weight on average.

Weight-IV-SL performed consistently for the majority of fish sizes evaluated. We assessed model bias using residual density (Fig. S11) and by comparing residuals to predicted (Fig. S12) and true (Fig. S13) fish weight. We note that, when plotted against true weight, there is a bias in model predictions where the weight of lighter fish is overestimated and that of heavier fish is underestimated; this is discussed further below.

Discussion

We found that whitefish weight can be estimated from photographs using morphometric measurements paired with information on sampling location and season of capture. For an average whitefish that weighed 2036 g, the selected model (weight-IV-SL) predicted weight within an average of 257 g (13.22% different) from true weight. While the best model included measurements, season, and location of capture, similar RMSE values show that a measurement-only model may perform sufficiently well (i.e., weight-IV; RMSE = 260 g; 13.38% different) in cases where a simpler approach is of value (e.g., when season and location are not recorded, the model could still be applied). This research suggests that photography and image analysis provide an opportunity for collection and verification of basic biological data in remote regions that may be data poor.

This study aimed to test methods that would be accessible to community-based monitoring programs in remote regions. Community- or volunteer-based projects have been shown to be valuable sources of data (Pattengill-Semmens and Semmens 2003). In this case, fish length (measured) and weight (predicted) could be used to track changes in these parameters as well as fish condition through time, where photographs of both future and historical catches can be analyzed. Gwich'in monitors took photographs using a simple set-up, and all computation was done using free software. Photograph-based methods such as these may help avoid the need to distribute multiple pieces of potentially expensive and (or) cumbersome equipment to participants and reduce in-field time requirements. Moreover, a photographic record could be used for other applications such as checking for/documenting external parasites or lesions, which can indict stress on a population (Pope et al. 2010).

A remaining challenge from this study is that weights were overestimated for light fish and underestimated for heavy fish (Fig. 1; Figs. S12 and S13). Because RFs predict new observations using the averages of a known data set, these two trends may in part be due to limited data at the extremes of observed fish size (see Section S4 in Supplementary material

(limited data) for details). Regardless, there are inherent limitations of measuring a laterally oriented photograph. For example, if weight is at some point accumulated (or lost) not in lateral body size (e.g., length or depth) but in girth, it would not be captured in a photograph. This is consistent with our findings in that weight-IV-SL was not biased for the majority of whitefish conditions but tended to overpredict at the low and high extremes (Fig. S14). For this, further work would benefit from testing the addition of a photograph and corresponding measurement(s) of the ventral side of each fish. Future work may also investigate alternative measures of size to predict weight (e.g., centroid size or lateral area) and (or) ways to automate the prediction process through mobile computation (e.g., a smart phone application; Bradley et al. 2019). Finally, should this approach be implemented, it could benefit from exploring a bias correction approach for those heavier and lighter weight fish.

Globally, there is a need to improve small-scale fisheries management. The data-poor nature of these fisheries can severely impact the food security, culture, and economies of the communities that depend on them (Chuenpagdee et al. 2019). Accessible solutions are needed to tackle these complex systems, particularly in remote regions like the GSA. Whitefish are a priority for monitoring as they are the most important fish to Gwich'in communities in Canada and inhabit a region of the Arctic that is rapidly changing. New technologies like camera-based monitoring are becoming increasingly available to fill data gaps (Bradley et al. 2019), and the tool presented here to estimate whitefish weight from a photograph advances one accessible method of remote fisheries data collection.

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Article information

Data availability

All data used in this manuscript are available through Zenodo, doi:10.5281/zenodo.4677774.

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Competing interests

The authors declare there are no competing interests.

Supplementary material

Supplementary data are available with the article at https://doi.org/10.1139/AS-2021-0017.

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