Fish Sci
DOI 10.1007/s12562-015-0888-1

ORIGINAL ARTICLE

Fisheries

Effectiveness of single-pass backpack electrofishing to estimate juvenile coho salmon abundance in Alaskan headwater streams

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Received: 22 November 2014 / Accepted: 18 March 2015

Abstract The use of techniques with low or inconsistent sampling efficiency may lead to erroneous estimates of abundance. Although an increase in sampling intensity can improve sampling efficiency and precision, its cost can limit a study's spatial extent. A low-effort approach may be preferred for landscape-scale studies of fish distribution and abundance; however, this requires information on whether the low-effort sampling is vulnerable to habitat-mediated bias and imprecision of the estimator. To determine how habitat features affected sampling efficiency of juvenile coho salmon *Oncorhynchus kisutch* in headwater streams of the Little Susitna drainage, Alaska, we validated single-pass backpack electrofishing methods with closed population mark–recapture sampling. We found that habitat features, such as stream size and density of wood debris, had no measurable or consistent effect on sampling efficiency within the range of conditions present in these headwater systems, and single-pass catch explained 94.8 % of the observed variation in log-transformed mark–recapture estimates. This suggests that low-effort methods in headwater streams of the Little Susitna River can approximate actual fish numbers without accounting for habitat covariates that may influence sampling efficiency, and the advantage of sampling a greater spatial extent may sufficiently offset any concerns over low estimator precision.

Keywords Sampling efficiency · Validation methods · Salmonids · Headwater streams

Introduction

Biologists and fisheries resource managers require reliable methods to assess the abundance of stream fishes. One method of capture commonly used to sample wadeable, cold-water stream fishes is the backpack electrofisher [1, 2]. However, backpack electrofisher sampling efficiency can be affected by physical habitat characteristics and species or individual characters of the target organism [2–4]. Environmental characteristics affecting electrofisher sampling efficiency include water conductivity, substrate type [4], in-stream cover [3, 5], and stream size [6]. Further, factors that decrease sampling efficiency can also exacerbate the negative bias in commonly used abundance estimation techniques (i.e., the removal model using depletion electrofishing; [6]). For a study relying on reliable estimates of fish abundance, validation of electrofishing methods over the range of anticipated conditions is crucial.

High-effort approaches for sampling fish (e.g., 4-pass electrofishing, mark–recapture estimates) generally involve higher sampling efficiency and decreased, or more predictable, bias when compared to low-effort approaches [6]. However, these methods are costly and time-intensive, limiting the spatial extent of investigation. For researchers and managers aiming to investigate whole-watershed patterns of fish distribution and abundance, this requires trading high-effort, site-specific sampling with low-effort, extensive sampling of entire stream lengths (e.g., [7, 8]).

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Published online: 22 May 2015

Unfortunately, extensive sampling methods may be most vulnerable to sources of estimation bias (e.g., habitat-mediated sampling efficiency) and imprecision [6].

Single-pass sampling in the context of backpack electrofishing typically consists of moving upstream through all accessible areas within a site on a single sampling occasion. This technique is used for covering great distances of stream length and is often performed in a continuous manner, sampling every meter of stream between predetermined points. Although labor intensive, it is ideal for sampling fish in headwater streams, where fish presence may be limited to a few kilometers of stream and where representative reach approaches fail to capture variability in fish distribution or the importance of habitat features present throughout entire riverscapes [8–10].

In this study, we validate single-pass backpack electrofisher sampling methods to provide information on low-effort sampling efficiency of juvenile coho salmon *Oncorhynchus kisutch* in headwater streams and ascertain potential sources of estimation bias. This study will determine how accurately single-pass estimates reflect fish abundance over the range of habitat conditions available in Little Susitna headwater systems. Catch data from similar habitats can then be calibrated to confidently estimate juvenile salmon abundance, which will dramatically increase available information on those populations and reduce the likelihood of erroneous conclusions as a result of sampling bias. Specifically, our objectives were to: (1) conduct closed-population mark–recapture techniques to estimate the abundance of juvenile coho salmon in 50- or 100-m stream reaches of mainstem tributaries; (2) measure habitat features of mark–recapture sample reaches that may have affected sampling efficiency (e.g., habitat area, woody debris, undercut banks); (3) develop linear regression models to estimate single-pass sampling efficiency based on habitat features; and (4) create models that approximate mark–recapture population estimates based on single-pass catch and habitat covariates.

Materials and methods

Study region

The Little Susitna watershed drains over 160 km^2 in the Cook Inlet region of southcentral Alaska (Fig. 1). Small headwater streams (e.g., Nurse's, Swiftwater, Colter, and Mary's Creeks) within the upper Little Susitna drainage are high gradient (channel slope greater than 2 %) streams known to contain juvenile coho salmon [11]; however, the extent to which these headwater streams are used by fish in this life stage is unknown.

Sampling design

Stream segments were selected within previously established 200-m stream reaches to conduct mark–recapture events. Stream segments were delineated beginning at discrete habitat unit breaks or at hydraulic control points favorable for block net deployment (i.e., no undercut banks and woody debris) and proceeded upstream to a similarly favorable net deployment site in close proximity to the designated site length. To collect fish for the marked baseline population, 6.5-mm mesh stainless steel minnow traps (a roughly cylindrical wire mesh enclosure, 44 cm length × 22 cm diameter, with a funnel located at either end leading into the trap) were placed in slow water habitats (e.g., pools, stream margins, undercut banks) within the chosen stream segment before block nets were in place. Traps were soaked for 12–24 h. We used minnow traps rather than electrofishing to capture fish for marking to minimize post-marking recovery time and prevent potential capture effects from electrofishing that would create bias in our mark–recapture estimates. All captured juvenile coho salmon were anaesthetized in a 1:10 clove oil–ethanol solution [12] at a 25–50 mg of clove oil solution/L water concentration [13] and measured to the nearest mm fork length. All captured juvenile coho salmon were marked by soaking them in Bismark brown dye at a concentration of 21 mg Bismark brown/L water for 50 min [14]. Battery operated portable aerators were used to maintain oxygen levels during the dye bath. Non-target species were kept in perforated live wells outside of the stream segment until in-stream sampling was complete.

Six and a half-mm square mesh netting was used to block fish movement within the stream segments and establish a closed population, a fundamental assumption of mark–recapture population estimates [15, 16]. Block nets secured with T-post fencing and sand bags were regularly cleared of organic materials to prevent bed scouring and net failure. Sampled stream segments were approximately 100 m in length unless block net failure from organic material accumulation or bed scour was frequent. If this practice did not prevent failure, reaches were shortened to about 50 m, reducing the time needed to sample the reach and, thus, the duration that block-nets were in the water. All marked fish were returned to the closed stream segment. A 2-h recovery period prior to recapture sampling was set to maximize recovery while minimizing escape potential and net failure [17, 18].

Electrofishing was used for recapture sampling. Prior to sampling with a backpack electrofisher (LR-24 electrofisher, Smith Root, Vancouver, WA), water temperature and conductivity were recorded using a water quality sensor (YSI 85, YSI Inc., Yellow Springs, OH) to calibrate electrofisher settings. Moving upstream, one electrofisher

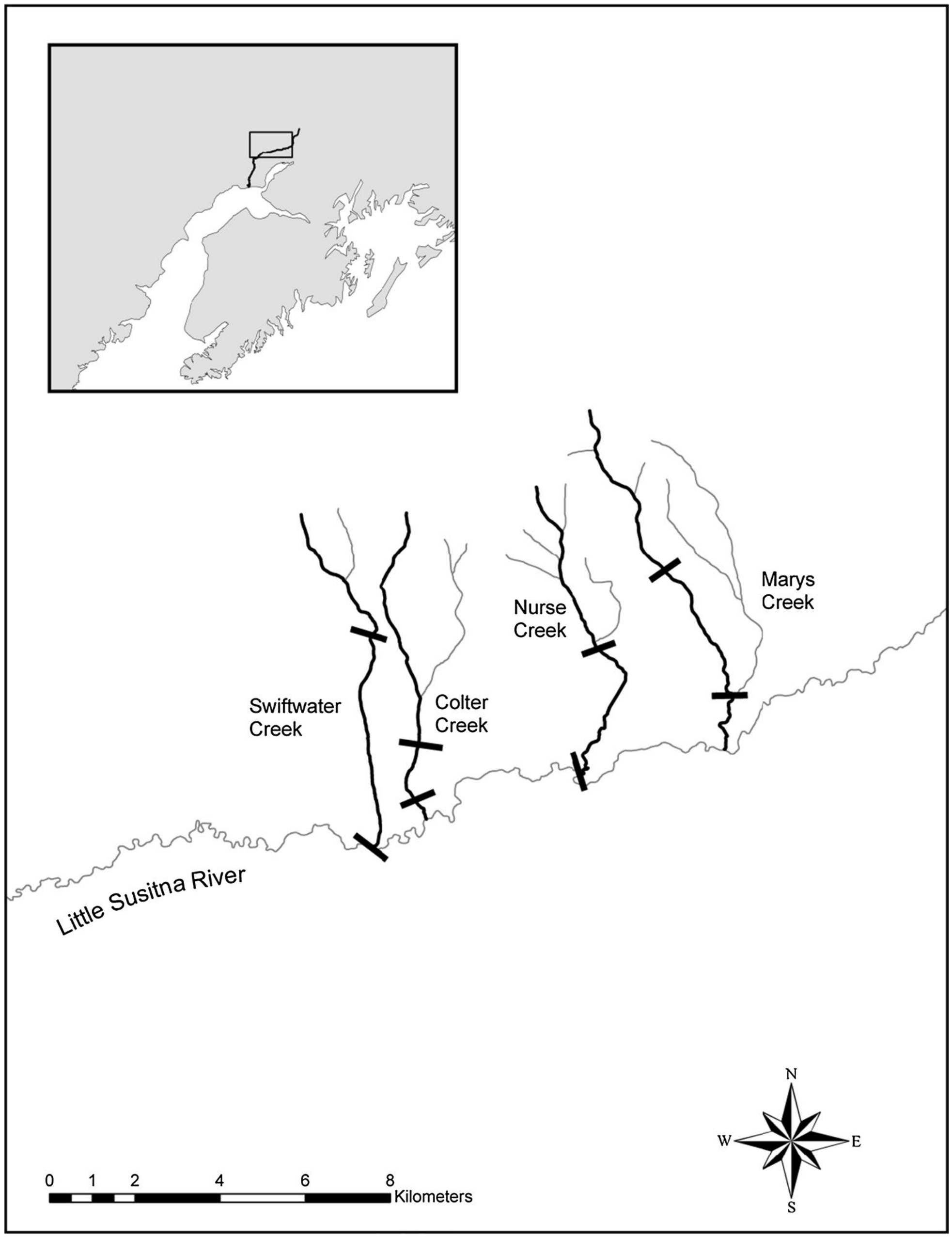

Fig. 1 Study area map. Headwater streams of the Little Susitna River, Alaska, selected for mark–recapture study during the summer of 2011. *Line markers* on the *streams* indicate the upper and lower boundaries of the study areas

operator, two dip netters, and a bucket carrier sampled for marked coho salmon from within each closed stream segment by exposing all areas within the channel to electricity [1, 2]. Voltage, pulse, and frequency were adjusted to optimize catch, beginning with a 30-Hz DC pulse at a 12-% duty cycle (4 ms) and 220–280 V [1, 2]. Once a single-pass of a reach was complete, coho salmon were anaesthetized, measured to fork length and visually inspected for Bismark brown coloration.

For each stream segment, habitat unit type was recorded (pools, riffles, rapids, or cascades; [19–21]), as was information for each habitat unit, including length, mean bank-full width, maximum depth, mean depth, length of undercut banks, dominant and subdominant substrate, and wood debris characteristics. The bank-full width measurements of each habitat unit were visually estimated based on actual measurements recorded on one out of every five or ten units [7]. Substrate particles were assigned to an eight-category Wentworth [22] scale as modified by Cummins [23]. Dominant substrate was recorded as particles of a given size class occupying more than half of the total substrate area, determined through visual observation (Table 1). For each stream segment, woody debris greater than 10 cm in diameter and 1 m in length within the wetted channel was counted, classified, and assigned class values along a six-category scale following Flebbe [24].

Table 1 Size classification for substrate and wood pieces

Size classification	Diameter (mm)	Length (m)
Substrate		
9—Bedrock	Uniform	
8—Boulder	>256	
7—Cobble	64–256	
6—Large gravel	10–64	
5—Small gravel	1.0–10	
4—Sand	0.061–1.0	
3—Silt	0.0039–0.061	
2—Clay	<0.0039	
1—Organics	Various	
Wood		
A	100–500	1–5
B	>500	1–5
C	100–500	>5
D	>500	>5
E	Rootwads[a]	Variable
F	Clusters[b]	<1

Size classifications for categorizing substrate and wood pieces within stream reaches of headwater streams, Alaska

[a] Rootwad not defined by diameter but by presence of root structures

[b] Small pieces of wood not as described above, but contributing to habitat complexity

Statistical analysis

Models of sampling efficiency included environmental factors identified as important in efficiencies of fish capture using electrofishing techniques [1, 4, 6]. The response variable was single-pass sampling efficiency and was determined as

$$n_2/\hat{N} \tag{1}$$

where $\hat{N}$ = Chapman mark–recapture estimator; n_2 = the number of fish captured in the second sampling period; a single-pass through the reach with the backpack electrofisher, which provides the baseline estimate of fish abundance [6, 16]

$$\hat{N} = \{[(n_1 + 1)(n_2 + 1)]/(m_2 + 1)\} \tag{2}$$

where n_1 = the number of marked fish; m_2 = the number of marked fish recaptured.

Variances of the population estimates were approximated as in Seber [16]. Confidence levels (CLs) for population estimates with large sample sizes (e.g., m_2 greater than 50) were determined using the normal approximation [16]:

$$\hat{N} \pm \left\{Z_{(\alpha/2)}\left[\sqrt{\left(V\hat{N}\right)}\right]\right\} \tag{3}$$

where $z_{\alpha/2}$ is the $(1 - \alpha/2)$ quantile of a standard normal distribution and a 95 % CL is given by $\alpha = 0.05$. CLs for population estimates with small sample sizes (e.g., m_2 less than 50) were determined using values provided by Chapman [25], reproduced in [16] based upon values of m_2.

Explanatory variables consisted of environmental factors known to affect sampling efficiency, standardized to site length. The weighted average of dominant substrate was calculated by multiplying the substrate category numerical value by the length of each habitat unit within a given reach, summed and divided by the total reach length and rounded to the nearest whole number. Wood pieces of similar diameter (i.e., size classes A and B, and C and D, respectively), were summed and divided by the total reach length to determine an average number of wood pieces per meter of stream reach for each grouped size class (Table 2). Lengths of undercut banks were determined as the total length of right- and left-undercut streambank as measured within a given reach. Mean cross sectional areas of each reach were determined by multiplying estimated widths, calibrated with actual measurements of stream width, and an average depth for each habitat unit within a given reach. Calibrations to estimate width measurements were determined using the basin-wide visual estimation technique [7]. The cross sectional value for all habitat units within a given reach were summed and divided by the total number of habitat units within that reach. Mean fish length was determined by averaging fork lengths among all juvenile coho salmon captured in a given reach.

Evaluation of site-scale correlates of sampling efficiency

A general linear modeling approach was used to explore relationships between environmental variables and single-pass sampling efficiency. The variables that best explained variability in sampling efficiency were selected using an information-theoretic approach [26] as follows. First, a global model was constructed based on information from previous studies to select site-scale features that were most likely to have an effect on sampling efficiency (Table 2). Second, subsets of the global model were constructed as alternative candidate models. Variables known to affect sampling efficiency were distributed into three groups; mean cross-sectional area as a measure of stream size, in-stream cover, and fish size [6]. In-stream cover included counts of in-stream wood and undercut bank length, and mean fish size was used as a metric of fish size. It was anticipated that sampling efficiency would decrease with stream size and cover and increase with average fish size. The global model was examined for goodness-of-fit and violations of model assumptions (e.g., residual patterns, homoscedasticity, normality, outliers). If the global model was found to be significant, the best approximating model (among candidate models) most consistent with the data was selected using Akaike's information criterion (AIC;

Table 2 Characteristics of study sites

Variable	Abbreviation	Mean	Standard deviation (SD)	Range
Mean cross section (m^2)	CS	0.78	0.21	0.38–1.12
Site length (m)		83.2	25.4	51.8–134.8
Stream width		3.38	0.57	2.4–4.8
Weighted avg. dominant substrate	DS	5.26	1.06	3.0–7.0
Total length undercut banks (m)	UB	31.69	14.67	5.0–68.0
Wood AB (#/m)	WAB	0.85	0.43	0.31–1.8
Wood CD (#/m)	WCD	0.08	0.06	0.00–0.19
Wood E (#/m)	WE	0.00	0.01	0.00–0.02
Wood F (#/m)	WF	0.06	0.03	0.02–0.13
Total coho salmon (#/reach)		180	211	11–788
Mean fish size (mm)	MnFS	46.21	5.82	37.59–65.09
Fish (#/m)		2.11	2.76	0.11–11.04

Characteristics of ($n = 27$) study sites located within four separate headwater streams of the Little Susitna River, Alaska, sampled to estimate juvenile coho salmon abundances in 2010–2011

Wood classes A–F represent size classes: (A) 1–5 m in length; (B) 10–50 cm diameter; (C) greater than 50 cm diameter, and greater than 5 m in length; (D) 10–50 cm diameter; (E) greater than 50 cm diameter, rootwads; and (F) snags clusters of wood pieces not of size class A–E

[27]), corrected for small-sample bias (AIC_c; [27]). All statistical analyses were performed in R version 2.13.1 statistical programming language [28].

Formal diagnostics and tests for violation of model assumptions included the Spearman's rank correlation coefficient matrix, the Durbin–Watson test for autocorrelation, the Breusch–Pagan test for equal variance, the RESET test for linear model assumption, a variance inflation factor (VIF) for variable covariance, and the Shapiro–Wilk test for normality. These tests were implemented using the R packages 'lmtest' [29], 'car' [30], and 'Hmisc' v3.8-3 [31].

Direct calibration of single-pass catches

Single-pass catches were used to predict mark–recapture population estimates for calibration. Mark–recapture estimates ($\hat{N}$) were assumed to be proportional to the single-pass estimates (n_2). Because variability in the mark–recapture estimates increases with population size, we assumed a multiplicative error structure, resulting in the following model:

$$\hat{N} = a{\cdot}(n_2)^{\beta}{\cdot}e^{\varepsilon} \tag{4}$$

where a and β are proportionality parameters that allow the mark–recapture estimates to increase more slowly ($\beta < 1$) or faster ($\beta > 1$) than the single-pass estimates and ε are normally distributed errors with a mean of zero and variance σ^2. The model can be log-transformed by taking the natural logarithm of both sides of the equation to yield a simple linear regression model of the form:

$$\ln \hat{N} = \alpha + \beta{\cdot}\ln(n_2) + \varepsilon \tag{5}$$

where $\alpha = \ln(a)$ and the errors are additive and normally distributed ($\varepsilon \sim N\{0, \sigma^2\}$). The model was fit using least-squares regression and the fit was examined for residual patterns, homoscedasticity, normality, and outliers to check model assumptions.

To evaluate how well the single-pass estimates predict the mark–recapture estimates, we computed the mean relative error (MRE) between the back-transformed abundances predicted from the calibration model ($\hat{\hat{N}}$) and the mark–recapture estimates ($\hat{N}$) using leave-five-out cross-validation:

$$\mathrm{MRE} = \frac{1}{R{\cdot}5}{\cdot}\sum_{i=1}^{R}\sum_{j=1}^{5}\left|\hat{\hat{N}}_{i,j} - \hat{N}_{i,j}\right|/\hat{N}_{i,j} \tag{6}$$

where the model (Eq. 5) was fit $R = 1000$ times to 22 randomly selected reaches ("training set") to predict abundances for the remaining 5 reaches ($j = 1, 2, \ldots, 5$) and back-transformed predicted abundances ($\hat{\hat{N}}$) were computed from the predicted log-abundances ($\widehat{\ln \hat{N}}$) using a bias correction for the mean of a log-normal distribution (e.g., Sprugel [32]):

$$\hat{\hat{N}} = e^{\widehat{\ln(\hat{N})} + \hat{\sigma}^2/2} \tag{7}$$

$$\widehat{\ln \hat{N}} = \hat{\alpha} + \hat{\beta}{\cdot}\ln(n_2) \tag{8}$$

where $\hat{\alpha}, \hat{\beta}$, and $\hat{\sigma}^2$ are the estimated parameters and residual variance from the fitted regression model (Eq. 5). The choice of 22 reaches for the training set was arbitrary

Table 3 Population estimates from closed population marking periods

Site	n_1	n_2	m_2	$\hat{N}$	SD	95 % LCL	95 % UCL	Efficiency
1	98	100	20	475	80	294	758	0.21
2	52	40	14	144	24	79	252	0.28
3	136	133	40	447	48	320	614	0.30
4	47	377	15	1133	220	647	1967	0.33
5	62	235	30	479	56	324	692	0.49
6	33	97	15	207	34	117	355	0.47
7	36	788	16	1716	294	993	2894	0.46
8	43	81	9	360	90	172	756	0.23
9	25	441	11	957	192	488	1819	0.46
10	27	78	7	276	74	118	651	0.28
11	31	31	9	101	21	48	209	0.31
12	30	19	8	68	14	30	146	0.28
13	51	23	12	95	15	49	172	0.24
14	22	37	9	86	17	40	177	0.43
15	21	30	10	61	10	29	118	0.49
16	62	481	20	1445	246	896	2305	0.33
17	37	196	7	935	271	407	2241	0.21
18	32	81	12	207	40	109	381	0.39
19	22	54	8	140	32	62	304	0.39
20	17	39	6	102	26	40	257	0.38
21	16	23	4	81	25	25	272	0.29
22	41	61	11	216	46	111	413	0.28
23	31	46	14	99	15	54	173	0.46
24	183	645	81	1449	111	1232	1666	0.45
25	84	252	35	596	69	417	838	0.42
26	155	446	49	1394	152	1036	1860	0.32
27	18	11	4	45	12	14	146	0.25

Juvenile coho salmon population estimates from a closed population, single marking period and single recapture period from 27 sites located within headwater streams of the Little Susitna River, Alaska, sampled in 2011 (n_1 = number of caught and marked using minnow traps, n_2 = number of caught in the second sample period using a backpack electrofisher, m_2 = number of marked juvenile coho caught in the second sampling period, $\hat{N}$ = population estimator, SD = standard deviation of population estimator, LCL and UCL = lower and upper confidence level, respectively, and efficiency is single-pass sampling efficiency determined as $n_2/\hat{N}$)

and was used here to illustrate the magnitude of the MRE when 22 reaches are available for calibration. The MRE is expected to be smaller if more reaches are used for calibration. The relationship between relative error and absolute abundance was evaluated to determine if the magnitude of the error depended on abundance.

Results

Site-scale correlates of sampling efficiency

Population estimates and sampling efficiencies based upon $n = 27$ mark–recapture stream segments are listed in Table 3. Spearman's rank correlation coefficient revealed strong covariance among habitat variables (i.e., coefficient values greater than 0.6); redundant variables, weighted average dominant substrate and wood size class *F* were then removed from the global model. The resultant global model met all formal tests for violation of model assumptions, including tests for autocorrelation, equal variance, linearity, normality, and variance inflation. The global model was not significant at the 95 % CL ($R^2 = -0.0018$, p value: 0.447), and all parameter estimates other than the intercept contained zero in their 95 % confidence intervals (Table 4). Given the poor performance of the global model, we concluded we could directly calibrate our single-pass catches to reflect high-effort estimates of fish abundance without considering habitat covariates of sampling efficiency.

Table 4 Sampling efficiency of global model parameter estimates

Parameter	Estimate	Std. error	95 % LCL	95 % UCL
Mean cross section	-1.14×10^{-1}	1.13×10^{-1}	-3.36×10^{-1}	1.08×10^{-1}
Length undercut bank	8.82×10^{-5}	1.25×10^{-3}	-2.36×10^{-3}	2.54×10^{-3}
Wood size class AB	-3.36×10^{-2}	4.87×10^{-2}	-1.29×10^{-1}	6.19×10^{-2}
Wood size class CD	-1.84×10^{-1}	3.68×10^{-1}	-9.05×10^{-1}	5.38×10^{-1}
Mean fish size	-6.89×10^{-3}	4.15×10^{-3}	-1.50×10^{-2}	1.25×10^{-3}

Parameter estimates and 95 % CLs for predictor variables of the global model for determining sampling efficiency based on (n = 27) mark–recapture sites within headwater streams of the Little Susitna River, Alaska sampled during 2011 (*LCL* lower confidence limit, *UCL* upper confidence limit). The global model was not significant at the 95 % CL ($R^2 = -0.0018$, p value: 0.447)

Direct calibration of single-pass catches

A linear model of a log-transformed first-pass catch of juvenile coho salmon performed well as a predictor of log-transformed mark–recapture abundance estimates ($R^2 = 0.95$, $p < 0.001$; Fig. 2; Table 5). Estimates for intercept and natural log-transformed parameters of the best fitting linear regression model were 1.42 and 0.93, (UCLs and LCLs of 1.00 and 1.84, and 0.84 and 1.02, respectively). The 95 % variability explained in the mark–recapture estimates pertains to the log-scale only, and does not reflect back-transformed abundance estimates. The MRE for predicting abundances was estimated to be 24.4 %; therefore, with a 'training data set' of 22 reaches, the single-pass estimator produces an estimate that is about 24 % lower or higher than the mark–recapture estimate on average, while the mean absolute error was approximately 111 fish (Fig. 3). No relationship was observed between the relative abundance and absolute abundance (Fig. 4a). Of the 27 stream segments, 13 mark–recapture estimates fell within the 95 % confidence intervals of the single-pass model predictions (Fig. 4b).

Discussion

Our validation exercise revealed that catch per unit effort from single-pass electrofisher sampling may be used as an index of abundance in headwater streams of the Little Susitna. Using sampling efficiency and mark–recapture abundance baselines, we developed a predictive model of relative abundance based upon single-pass catch of juvenile coho salmon (Fig. 2). These findings are similar to other studies that used electrofishing methods to determine abundance estimates. For example, Kruse et al. [3] and Riley and Fausch [33] determined that complex in-stream habitat (e.g., undercut banks or woody debris) or variance in measures of stream size had a negligible effect on estimates. Riley and Fausch [33] attributed this to thorough, non-time constrained sampling, rather than a constant unit of time as a measure of sampling effort. Because of our varied stream lengths, we could not standardize to time, and, similar to Riley and Fausch [33], a thorough sampling technique was used. Similar to Kruse et al. [3], low variance in habitat conditions throughout our sites may have concentrated fish

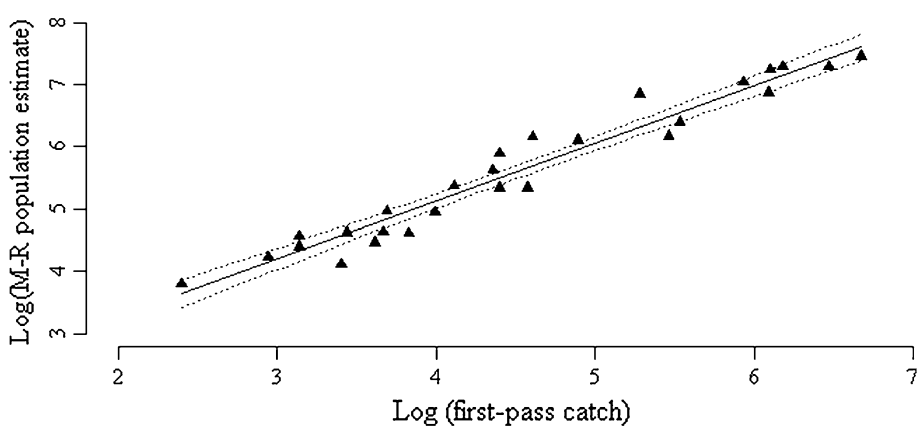

Fig. 2 Mark–recapture population estimates as a function of single-pass catch. Natural log of mark–recapture population estimates as a function of natural log single-pass catch of juvenile coho salmon ($R^2 = 0.95$, $p < 0.001$). Fish were sampled within headwater streams of the Little Susitna River, Alaska in 2011 at 27 study sites. *Dashed lines* represent 95 % confidence intervals for the mean. The 95 % variability explained in mark–recapture estimates pertains to the log-scale only, and does not reflect back-transformed abundance estimates

Table 5 Parameter estimate for best-fitting linear regression model of mark–recapture population estimates based on known numbers of marked coho salmon released into a site and single-pass catch of coho salmon

Parameter	Estimate	95 % LCL	95 % UCL
Intercept	1.42	1.00	1.84
ln (single-pass catch)	0.93	0.84	1.02

Coefficients correspond to those in Eq. 8. Sites were located in headwater streams of the Little Susitna River, Alaska, and sampled in 2011 (*LCL* lower confidence level, *UCL* upper confidence level)

in discrete areas of habitat complexity within the reach. Although Kruse et al. [3] included stream width in their model to account for additional variance in the relationship between single-pass electrofisher sampling and multiple-pass depletion population estimates ($R^2 = 0.94$ and 0.96, respectively), they concluded that no stream attributes were needed to strengthen the relationship. However, this is contrary to findings of other studies that have cited habitat complexity as factors that bias sampling efficiency [4, 6, 17, 34, 35].

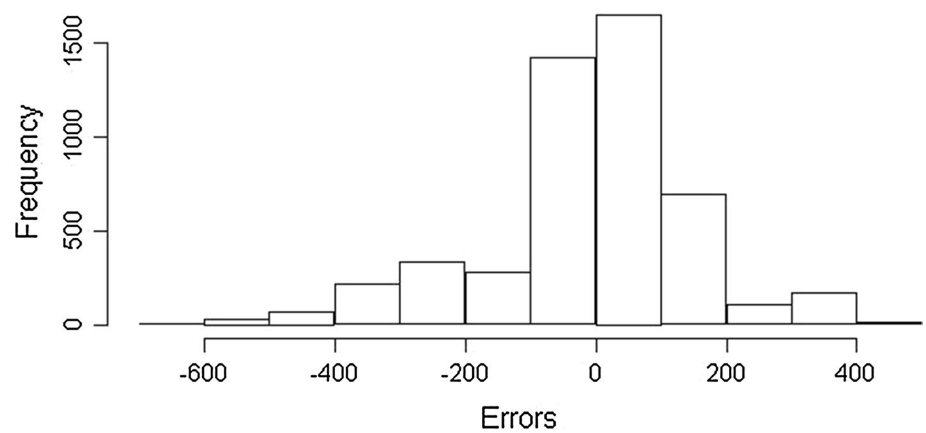

Fig. 3 Error rate of predicted juvenile coho salmon abundances. Error in the number of fish (mark–recapture estimate of abundance minus single-pass predicted abundance expressed as error terms) associated with a bias-corrected back-transformation of predicted juvenile coho salmon abundances. Predictive models are on average off by approximately 111 fish (mean of absolute errors = 111)

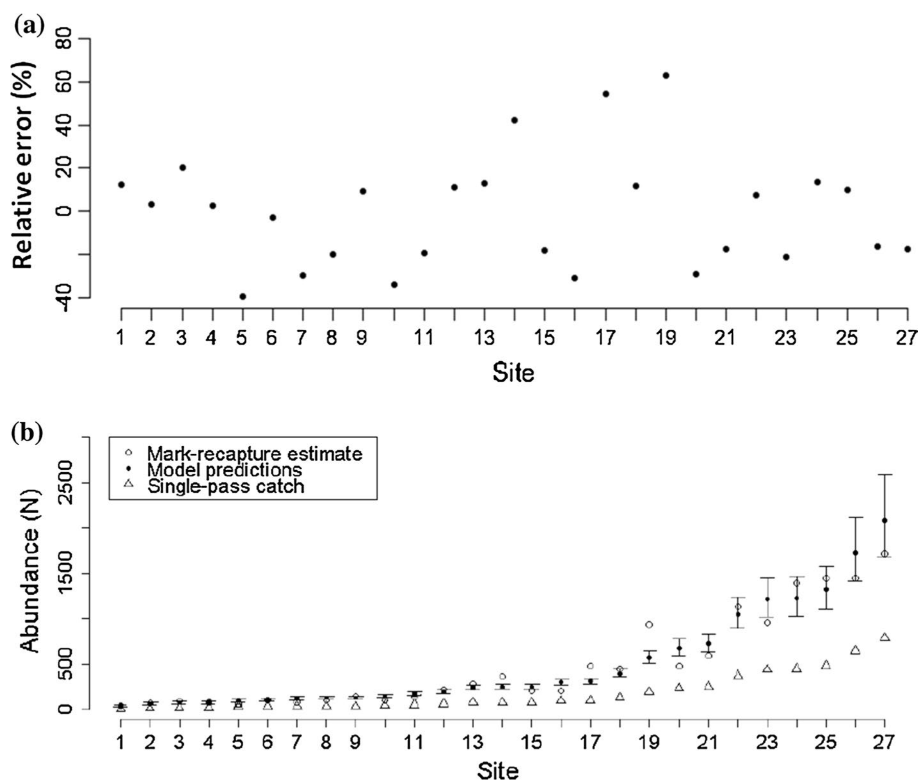

Fig. 4 **a** Relative errors for model-predicted abundance estimates. The relative error is the difference between the observed abundance and our model predictions divided by our model predictions expressed as a percent. **b** Model predictions of juvenile coho salmon. Abundance (*open circles*), first pass catch (*triangles*), and model predictions (*solid circles*) of juvenile coho salmon at 23 sites in headwater streams of the Little Susitna River, Alaska, sampled in 2011. Sites are ordered from lowest single-pass catch to highest. *Vertical lines* represent 95 % confidence intervals of cross-validated model prediction estimates

We determined that in streams with a narrow range of habitat conditions and low fish densities, single-pass electrofishing can produce accurate abundance estimates of fish assuming that our mark–recapture estimates are unbiased. This model may apply to similar high gradient streams or other watersheds or geographic areas within the Matanuska-Susitna Valley that contain equivalent habitat conditions. However, we must caution that managers remain aware of the hazards of applying this model to estimate fish abundances in streams with habitat conditions beyond the range for which the model was developed. We caution against directly using the parameter estimates from our calibration for other sites as it is likely to be specific to our study species and to the type of streams in our study region. This was not our intent and we provide this study as an example of how a relatively simple calibration experiment can be conducted and used to estimate population size based on single-pass electrofishing with reasonable accuracy and prediction. Failure to determine the effects of habitat-mediated biases may lead to inaccurate population estimates. Although labor intensive, validation is a useful tool for managers to assess population abundances of salmonids especially where entire stream extents are sampled in a continuous manner.

As shown with this study, low-effort sampling can approximate actual fish numbers without accounting for habitat covariates that could affect sampling efficiency; but the real advantage to this approach exists when addressing ecological processes operating on spatial scales equivalent to, or greater than, the stream segment level. For example, managers addressing longitudinal distributions of fish within headwater streams may wish to incorporate a low effort sampling approach, as it allows sampling over greater distances and in shorter time periods. This is in lieu of intensive sampling, which may yield more precise abundance estimates but is more costly in terms of time and effort. However, as no single scale is appropriate for investigating all ecological problems, special attention should be paid to the scale at which the process of interest occurs [36, 37]. Thus, it follows that a chosen sampling method must be commensurate with research goals, and logistical, financial, and temporal constraints.

Acknowledgments This project received Institutional Animal Care and Use Committee (IACUC) approval under IRBNet ID 157737-5. We thank Phillip Taylor, Casey Smith, Parke Loyd, Danielle McClain, Sydney Clark, Sarah Laske, Jonathon Gerken, and Doug McBride for assistance with field data collection. We also thank the many landowners throughout the study region who granted access across their property to our study sites, most notably Scott and Linda Schwald. We also thank Justin Carney and Nicholas Smith for their assistance in data analyses. We thank Sarah Laske and Trevor Haynes for their assistance and helpful comments on previous versions of this manuscript. Funding for this work was provided by the U.S. Fish and Wildlife Service, Anchorage Field Office. Use of trade names does not imply endorsement of any product or service by the U.S. Government.

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