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Imputing recreational angling effort from time-lapse cameras using an hierarchical Bayesian model

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ABSTRACT

Digital time-lapse cameras (cameras) are increasingly used for monitoring recreational angling effort on water bodies such as lakes and rivers. Cameras are an attractive alternative to traditional methods for monitoring angling effort such as aerial counts and on-water creel surveys because of their relatively low running costs. However, cameras take photographs intermittently and it is not possible for the camera field of view to cover the entire water body in most applications. It is therefore necessary to bias correct (uprate) the camera observations of angling effort to obtain estimates of total angling effort including those out of the camera field of view. We developed a hierarchical Bayesian model to predict total angling effort from camera observations of angling effort. The model was fitted to creel effort survey data and then used to impute ('fill-in') total angling effort data for a larger dataset of camera observations where there were no creel survey data. The model accounted for three issues encountered when uprating camera observations of angling effort to total angling effort: (1) camera observations of zero angler effort when anglers were outside the field-of-view; (2) incomplete creel survey data; and (3) occasional data gaps caused by equipment malfunction. We applied the model to camera data from a number of small lakes in British Columbia, Canada using it to predict total angling effort that accounts for observation error. We explore the various model assumptions and discuss the limitations of the approach.

1. Introduction

Inland recreational fisheries are typically made up of many discrete water bodies (lakes, rivers), angling types (e.g., consumptive-oriented, trophy-oriented, etc.; Johnston et al., 2010) and fish species (Post et al., 2002). Managing these fisheries is challenging due to the complex inter-dependence of management options, population dynamics and the distribution of anglers (Cox et al., 2003; Parkinson et al., 2004; Post et al., 2002, 2008; Ward et al., 2013b). The quantity of angling effort is often used by managers to evaluate the success of various management options (Lester et al., 2003; Parkinson et al., 1988; Shuter et al., 1998). However, reliably quantifying angling effort over large and varied landscapes can be costly and logistically challenging (Lester et al., 2003; Post et al., 2002).

Creel and aerial surveys of fishing effort are often too costly for all but the highest priority, most accessible water bodies, and are generally not intended to cover the entire fishing day or season (Smallwood et al., 2012). Time-lapse digital cameras or digital video cameras (cameras) are increasingly being adopted as an alternative method to monitor angling effort in a range of settings, including small lakes (Patterson and Sullivan, 2013; van Poorten, 2010; Ward et al., 2013a) and coastal marine fisheries (Parnell et al., 2010; Smallwood et al., 2012). Cameras have proven particularly useful in quantifying temporal and spatial trends in angling effort (Parnell et al., 2010; Smallwood et al., 2012) that were previously obtained using creel surveys[1]. Moreover, the frequency of observations obtained with cameras should permit them greater power to detect shifts in effort that may be difficult to achieve with other methods, such as creel and aerial surveys (Parkinson et al., 1988).

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[1] Creel surveys refer to on-site interviews to collect fishery-dependent information from recreational anglers.

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Cameras monitor a fixed fishing area and anglers are counted from images (either video, time-lapse or motion-activated). Limitations with both the camera field of view and the shape of a lake or stream shoreline mean that cameras often cannot capture the entire waterbody. It is therefore necessary to uprate (bias correct) camera observations of angling effort (camera effort) to provide estimates of total angling effort (total effort). This uprating is not as simple as dividing by the proportion of fishing area seen by the camera, because angler density on lakes is rarely homogeneous (Smallwood et al., 2012). Given that the degree of bias correction varies among lakes and also potentially due to other factors such as time of day, it is necessary to calibrate the uprating model on a lake-by-lake basis. This calibration requires camera effort data paired with data of total effort from an independent method such as a creel survey. Once calibrated, the uprating model can be used to impute ('fill-in') total effort in instances where creel survey data are missing.

There were three types of missing data: (1) zero camera effort when total effort is positive (e.g., anglers outside of the camera field of view), (2) positive camera effort when total effort is positive, (3) missing camera effort (e.g. due to malfunction, theft or damage). In many instances there is likely to be very low effort and uprated estimates of total effort are likely to be highly uncertain. It is therefore important that the uprating model can properly account for observation uncertainty.

The objective of this paper was to develop a statistically rigorous uprating model for the probabilistic imputation of total effort from camera effort and other explanatory covariates. The model employed a delta mixture method, allowing zero observations to be appropriately interpreted (Martin et al., 2005), which was particularly important in low-effort situations. We used a Bayesian multiple imputation approach (Rubin, 1987) to provide probabilistic estimates of missing total effort in instances where only camera effort was available. The model was applied to camera effort data collected from rural lakes distributed across central British Columbia (BC), Canada. We evaluated the predictive capacity of multiple uprating models that relied on different covariate data. The sensitivity of angler effort predictions to core model assumptions was also explored. Finally we used the evaluation of the BC dataset to discuss the limitations of the method and suggest improvements to camera use and data interpretation in future applications.

2. Methods

2.1. Data collection and processing

From 2009 to 2011, cameras were installed on 49 small lakes (surface area less than 250 hectares) throughout the interior of BC (Table 1; Fig. 1). Two models of camera were used: Cuddeback Digital Scouting Cameras that include their own weatherproof camouflage housing, and Pentax Optio W30 cameras that were placed in camouflaged weatherproof cases. Across 91 lake-years of camera monitoring, 152,029 images were taken, resulting in a total of 47,597 angler counts. Creel surveys were conducted over 30 lake-years, with number of hourly counts per lake-year ranging from 1 to 386 (median 81).

The lakes on which cameras were installed were managed as recreational fisheries for rainbow trout and had little or no shoreline development (e.g., campsites, cabins, lodges). Camera effort data were generally collected throughout the open-water season (May to October). Cameras were attached to trees or other stable permanent structures such as fence posts. Care was taken to avoid any deciduous growth immediately in front of the camera that could obscure the camera field of view. The cameras were placed as high above the surface of the water as possible to maximize viewing distance and to minimize glare from the water surface. Cameras were also placed discretely to minimize damage or theft. No attempt was made to focus on high or low use areas; instead, cameras were generally placed in a position that would maximize the observable area of the lake. Cameras were programmed to take one picture per hour and were typically serviced every month to download data and change batteries.

Of the lakes with cameras, 24 were also subject to surveys of total effort (Table 1). Total counts of anglers on the lake were taken during creel surveys and when cameras were being serviced. Counts were conducted hourly and coincided with the time when cameras took pictures. Total effort on a lake is expressed in units of anglers per hour. Although we assumed that total effort was observed without error, these data were really independent observations with associated error. Care was taken to obtain a complete census of fishing effort, but errors may have occurred.

Camera images were analyzed using the Timelapse Image Analysis software (http://saul.cpsc.ucalgary.ca/timelapse/pmwiki.php?n=Main.HomePage; Greenberg and Godin, 2015), which facilitates manual counting of anglers, but is not an automated system. Analyzing a full fishing season of images (6 months) for one lake using this software took approximately 3.3 h (Greenberg and Godin, 2015). When quantifying camera effort from the images, it was assumed that each angler in an image equated to a single angler-hour of fishing. Although care was taken to distinguish fishing from non-fishing activities most lakes were relatively remote with limited shoreline development and hence most activity was related to fishing. There were instances where it was possible to observe a boat without being able to discern the number of anglers in the boat when conducting creel surveys and analyzing camera images. In these situations it was assumed that each boat held two anglers.

2.2. model for uprating camera effort to total effort

We developed a model that predicts total effort from camera effort. The model was then fitted to observations of total effort from creel surveys and used to estimate total effort in situations where camera data were available, but no surveys were carried out.

The model needed to operate under three data conditions: (1: true zero) zero total effort and zero camera effort; (2: false zero) positive total effort and zero camera effort; and (3: true positive) positive total effort and positive camera effort. The data were separated according to these three conditions (Fletcher et al., 2005), describing three corresponding sub-models for predicting: (1) the probability of a true-zero observation by a camera (δ); (2) the mean number of anglers present when zero anglers are observed by a camera (λ); and (3) the mean proportion of anglers seen when one or more anglers are observed by a camera (α). The first two sub-models are analogous to a delta mixture model or hurdle model (Carlson et al., 2007; Lo et al., 1992; Martin et al., 2005). We chose to describe separate sub-models for the prediction of zero and positive real effort as covariates could influence each process (Fletcher et al., 2005) differently.

The probability of a true zero observation ($p_{l,i}$) was modeled as a Bernoulli distribution,

$$p_{l,i} \sim \mathrm{Bern}(\delta_c) \quad (1)$$

where $p_{\mathrm{l,i}}$ is the binary observation of true presence (=0) or absence (=1) of anglers on lake-l at observation-i and δ_{c} is the camera-specific probability of a true-zero observation. This sub-model was fit to binary data representing a positive or zero true effort observation for each paired camera and true angler effort observation. The index c represents independent factors associated with each camera (multiple cameras may be present on a

Table 1
Characteristics of lakes monitored for recreational angling effort. Proportion of lake viewed indicates the proportion of surface area in view of a camera. Years sampled indicates if a lake was sampled using cameras alone (C) or cameras and independent counts (C,I).

Lake	Surface area (ha)	Elevation (m)	Proportion of lake viewed	Years sampled		
				2009	2010	2011
Alleyne	45	994	0.44			C,I
Amphitheatre	8	1070	0.88	C	C	C
Barnes	44	682	0.61	C	C	C
Billy	27	1410	0.70	C,I	C	C
Black	19	1163	0.53	C	C	
Burnell	14	730	0.50			C,I
Clear	11	907	0.82	C	C	
Cobb	223	771	0.60		C	
Crown	8	807	0.63	C,I	C,I	C
Crystal	40	721	0.80		C	
Dennis	9	1193	0.22	C	C	C
Dominic	33	1543	0.52	C	C	C
Doreen	44	1358	0.59			C,I
Dot	40	1423	0.88	C,I	C	C
Eena	54	762	0.73		C	
Emerald	14	727	0.43	C	C	
Ernest	24	1195	0.63		C	C
Flyfish2	29	1354	0.31			C,I
Grizzly East	71	962	0.48	C,I	C	
Grizzly West	137	992	0.77		C	
Gypsum	14	1458	0.43	C	C,I	C
Hart	54	715	0.54		C	
Hobson	66	906	0.55		C	
Idleback	13	1440	0.54			C,I
Jackpine	43	1311	0.70			C,I
Kentucky	37	1000	0.27			C,I
Kidd	18	1058	0.61			C,I
Leonard	12	1344	0.33			C,I
Lintz	218	952	0.31		C	
Loon	9	1355	0.33			C,I
McConnell	32	1285	0.28	C,I	C	C,I
McKenzie East	26	854	0.54	C	C	
Opatcho	40	833	0.63	C	C	
Pat	14	602	0.57	C,I	C	C,I
Peter Hope	108	1095	0.38	C	C	C
Pratt	18	1302	0.78	C	C	C
Ripley	7	923	0.86			C,I
Square	13	710	0.31	C,I	C	
Stake	24	1320	0.33	C	C	C,I
Surrey	52	1390	0.42	C	C	C
Teardrop	39	798	0.59		C	
Todd	17	1298	0.94	C	C	
Tory	19	730	0.53	C,I	C	
Tureen	58	784	0.49		C	
Turquoise	8	808	0.75	C,I	C,I	C
Tyner	20	1332	0.30	C	C,I	C
Vinson	22	1374	0.73			C,I
Vivian	47	779	0.66		C	

single lake). Integrating information across cameras within a lake is detailed in Section 2.3.

In false zero situations, the mean true angling effort when a camera observes zero effort was modeled by a Poisson distribution,

$$E0_{l,i} \sim \mathrm{Pois}(\lambda_c) \tag{2}$$

where $E0_{\mathrm{l,i}}$ is the true number of anglers on lake-l at observation-i and λ_c is the mean predicted number of anglers on the lake in instances where camera-c observes zero effort. This sub-model was fit to true effort data where no angling effort was detected by cameras.

True positive angling effort was predicted from positive camera effort by a Poisson model:

$$E1_{l,i} \sim \mathrm{Pois}\left(\alpha_c C_{c,i}\right) \tag{3}$$

where $E1_{l,i}$ and $C_{c,i}$ are the true number of anglers on lake-l and the camera index from camera-c at observation-i, respectively and α_c is the multiplier for anglers on lake-l detected by camera-c. This sub-model was fit to true angling effort and camera effort data where both are positive.

Recreational angling effort often varies temporally due to activity patterns of fish and anglers (Hunt et al., 2007; McCluskey and Lewison, 2008; Steffe et al., 2008). Additionally, the probability of cameras detecting anglers will vary with various environmental factors (Sunger et al., 2012). Two temporal covariates were investigated to determine whether they improved the predictive capacity of the models: daylight phase (dawn/dusk vs. daytime) as a categorical factor on δ_c and day-type (weekend and holidays or weekday) as a categorical factor on λ_c and α_c. All combinations of lake-specific parameters and factors were evaluated, leading to a total of eight uprating models (Table 2). The proportion of lake surface area viewed by a camera was also used as a camera-specific covariate on δ_c to represent an improved probability of true-zero observation when the camera field of view included a greater proportion of the lake.

After establishing cameras and conducting creel surveys over multiple lakes and years, hierarchical models were then used to

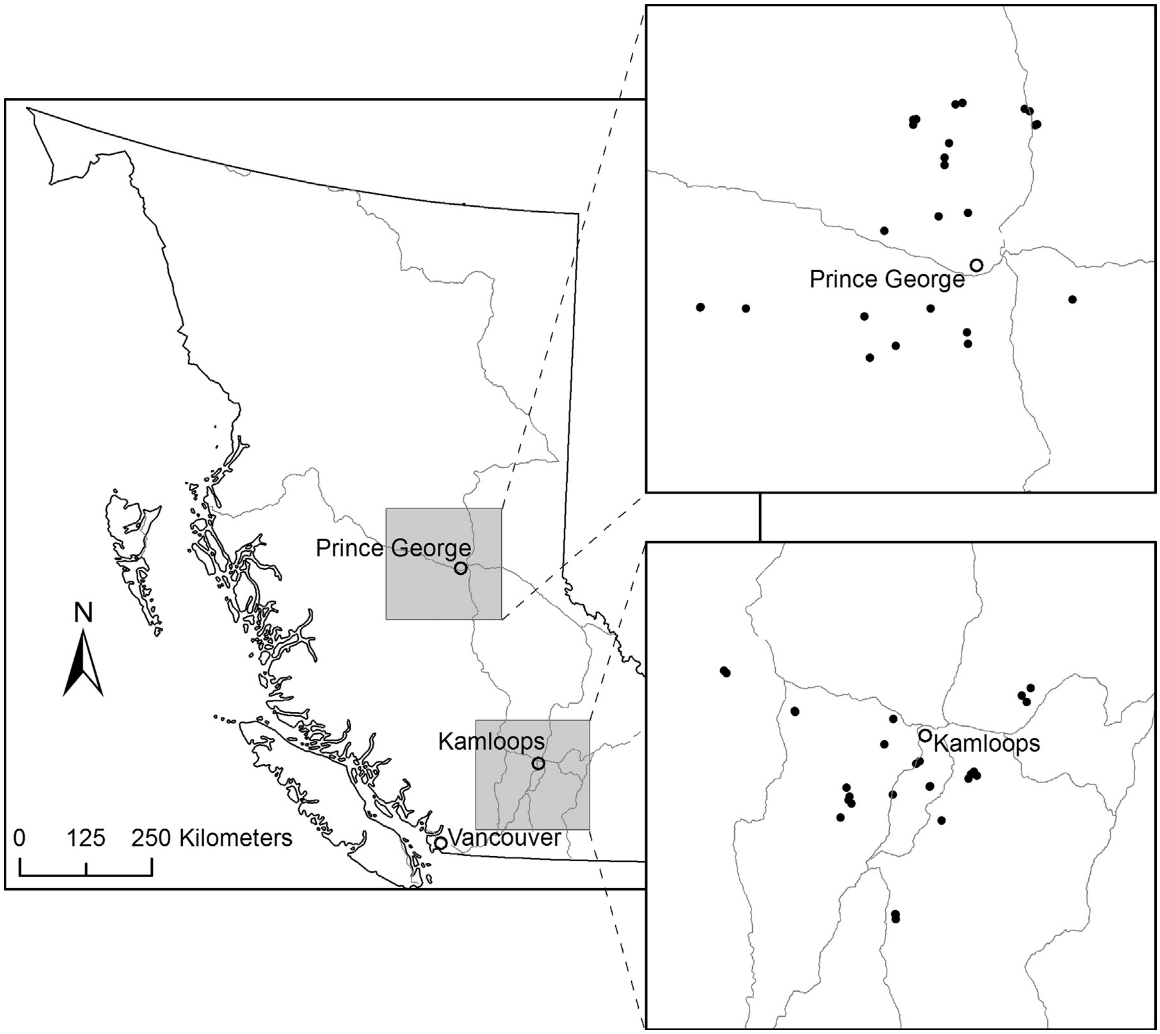

Fig. 1. Map of British Columbia with the location of lakes with cameras installed for estimating annual fishing effort.

Table 2
Structure of the eight evaluated mixed models. Covariates include a weekend effect (wk) and a dusk/dawn effect (t). Each model is reported with the effective number of parameters (p_D), the deviance information criterion (DIC) and the relative difference between model DIC and the minimum DIC among models (ΔDIC). Mean squared error and proportional error of a randomly selected validation data representing 20% of the full dataset are reported for each model with median predictions and 80% credible intervals for each.

	Transformed model structures							
Model	Delta	Lambda	Alpha	p_D	DIC	ΔDIC	Mean squared error	Proportional error
1	δ_{0i}	λ_{0i}	α_{0i}	73.0	7889.7	95.3	13.6 (12.3,15)	0.05 (0,0.1)
2	δ_{0i}	λ_{0i}	$\alpha_{0i}+\alpha_{1i}\mathrm{wk}_i$	89.2	7860.2	65.8	13.7 (12.4,15.2)	0.05 (0,0.1)
3	δ_{0i}	$\lambda_{0i}+\lambda_{1i}\mathrm{wk}_i$	α_{0i}	84.6	7824.1	29.7	13.4 (12.1,14.8)	0.04 (−0.01,0.09)
4	$\delta_{0i}+\delta_{1i}t_i$	λ_{0i}	α_{0i}	75.2	7891.0	96.6	13.5 (12.3,15)	0.04 (−0.01,0.09)
5	δ_{0i}	$\lambda_{0i}+\lambda_{1i}\mathrm{wk}_i$	$\alpha_{0i}+\alpha_{1i}\mathrm{wk}_i$	100.9	7794.4	0.0	13.6 (12.2,15.1)	0.04 (−0.01,0.1)
6	$\delta_{0i}+\delta_{1i}t_i$	λ_{0i}	$\alpha_{0i}+\alpha_{1i}\mathrm{wk}_i$	90.8	7860.9	66.5	13.7 (12.4,15.2)	0.04 (−0.01,0.1)
7	$\delta_{0i}+\delta_{1i}t_i$	$\lambda_{0i}+\lambda_{1i}\mathrm{wk}_i$	α_{0i}	89.7	7828.4	34.0	13.4 (12.1,14.8)	0.04 (−0.01,0.09)
8	$\delta_{0i}+\delta_{1i}t_i$	$\lambda_{0i}+\lambda_{1i}\mathrm{wk}_i$	$\alpha_{0i}+\alpha_{1i}\mathrm{wk}_i$	106.1	7799.4	5.0	13.5 (12.2,15.1)	0.04 (−0.01,0.09)

estimate hyper-parameters shared across lakes. Bayesian hierarchical models assume parameters are exchangeable across lakes, such that lake-specific prior distributions may be independently drawn from a common population distribution across lakes, referred to as hyperprior probability distributions (Askey et al., 2007; Gelman and Hill, 2007). The posterior predictive distributions of hyper-parameters were then used to impute total effort using Bayesian multiple imputation for a lakes with fewer or no sampling data (Wyatt, 2002; in our case, lakes where few or no independent effort counts were conducted). The uninformative hyperprior and prior probability distributions used in the eight models evaluated are presented in Table 3.

We used JAGS 3.4.0 (Plummer, 2003) to numerically approximate the posterior probability distributions of true effort predictions using Markov Chain Monte Carlo (MCMC) simulation. Posterior distributions were calculated from 20,000 iterations after an initial burn-in of 2000 iterations and further thinned to provide a final sample of 10,000 iterations from each of two MCMC chains.

Table 3
Prior and hyperprior probability distributions used for each model evaluated. Prior probability distributions include uniform (*U*), gamma (*G*) and normal (*N*).

Parameter	Prior	Transformation	Models
μ_δ	$U(-5,5)$	NA	1, 2, 3, 4, 5, 6, 7, 8
μ_λ	$U(-5,5)$	NA	1, 2, 3, 4, 5, 6, 7, 8
μ_α	$U(-5,5)$	NA	1, 2, 3, 4, 5, 6, 7, 8
$\mu_{\delta t}$	$U(-5,5)$	NA	4, 6, 7, 8
$\mu_{\lambda t}$	$U(-5,5)$	NA	3, 5, 7, 8
$\mu_{\alpha w}$	$U(-5,5)$	NA	2, 5, 6, 8
τ_δ	$G(0.001,0.001)$	NA	1, 2, 3, 4, 5, 6, 7, 8
τ_λ	$G(0.001,0.001)$	NA	1, 2, 3, 4, 5, 6, 7, 8
t_α	$G(0.001,0.001)$	NA	1, 2, 3, 4, 5, 6, 7, 8
$\tau_{\delta w}$	$G(0.001,0.001)$	NA	4, 6, 7, 8
$\tau_{\lambda w}$	$G(0.001,0.001)$	NA	3, 5, 7, 8
$\mu_{\alpha w}$	$G(0.001,0.001)$	NA	2, 5, 6, 8
δ	$N(\mu_\delta, 1/\tau_\delta)$	logit	1, 2, 3, 4, 5, 6, 7, 8
δ_w	$N(\mu_{\delta t}, 1/\tau_{\delta t})$	logit	4, 6, 7, 8
λ	$N(\mu_\lambda, 1/\tau_\lambda)$	log	1, 2, 3, 4, 5, 6, 7, 8
λ_w	$N(\mu_{\lambda w}, 1/\tau_{\lambda w})$	log	3, 5, 7, 8
α	$N(\mu_\alpha, 1/t_\alpha)$	log	1, 2, 3, 4, 5, 6, 7, 8
α_w	$N(\mu_{\alpha w}, 1/t_{\alpha w})$	log	2, 5, 6, 8

Convergence could not be rejected given visual inspection of MCMC chains and Gelman-Rubin convergence diagnostics available in the CODA package in R (Plummer, 2010).

2.3. Imputing total angling effort

The uprating model combined the predictions of the three sub-models to impute missing total effort. The probability of a false zero observation for camera-*c* and observation-*j* on a lake-*l*, is distributed

$$\kappa_{c,j} \sim \text{Bern}(1-\delta_c) \tag{4}$$

and the expected true effort given a false zero observation is distributed:

$$\omega_{c,j} \sim \text{Pois}(\lambda_c) \tag{5}$$

The true effort given a positive camera observation is assumed distributed as:

$$\phi_{c,j} \sim \text{Pois}(\alpha_c C_{c,j}) \tag{6}$$

where *C* is the number of anglers observed by a camera. The number of anglers present on any lake and observation-*j* were then imputed by

$$\hat{E}_{i,l} = \frac{\sum_{c=1}^{nc_{i,j}} \kappa_{c,j}\omega_{c,j} + \phi_{c,j}}{nc_{l,j}} \tag{7}$$

where *nc* is the number of cameras, which allows angling effort predictions to become a mean across multiple cameras on the same lake. This summation improves effort predictions regardless of whether their fields of view overlap. Using this approach, the uncertainty in posterior parameter and hyperparameter estimates were propagated through to predictions of $\hat{E}_{l,j}$.

We used cross validation to evaluate the predictive ability of each model and the Deviance Information Criterion (DIC; Spiegelhalter et al., 2002) to evaluate model parsimony. The datasets were randomly split so that 80% of the data were used as training data to calculate posterior parameter distributions. The remaining data were used as validation data where observations were imputed and compared against independent observations taken at the same time. This procedure was used to evaluate mean squared error (MSE) across all imputed angling effort observation. Both the calculated MSE and DIC were used to choose the most appropriate model for imputing angling effort using cameras.

2.4. Filling missing camera effort

Camera effort data were missing in cases where cameras failed, were stolen, damaged or programmed incorrectly. Without these data, predictions of total effort would be incomplete and overall patterns of angling over time would be distorted. It was therefore necessary to fill gaps in the camera effort data prior to the calculation of total effort.

Camera effort gaps were filled using average camera effort imputed from nearby, similar comparison lakes, as suggested in Gelman and Hill (2007). Comparison lakes chosen were in the same fisheries management region and had the same access (trail; rough road; smooth road) and were closest to the lake missing camera effort. The average ratio of predicted total effort on a nearby lake to the lake to be filled *r*, was calculated:

$$r_{a,b} = \frac{\sum_t \hat{E}_{a,t}}{\sum_t \hat{E}_{b,t}} \tag{8}$$

where *a* is the lake to be filled and *b* is the comparison lake. The ratio *r* was calculated across all days (*t*) where both lakes had camera effort observations.

Gaps in imputed effort on any lake *a* and day *t* were then filled by averaging the camera effort inferred from the multiple comparison lakes weighted by the comparison lake-specific ratio calculated in Eq. (8):

$$\hat{E}_{a,t} = \frac{\sum_t r_{a,b}\hat{E}_{b,t}}{B} \tag{9}$$

where *B* is the number of comparison lakes. We arbitrarily decided to fill data using four comparison lakes, but evaluated the sensitivity of total effort estimates to 0 (no filling) and two comparison lakes.

3. Results

The model including the effect of weekend/weekday on the mean number of anglers present when none were detected by cameras (model 5) was the most parsimonious according to DIC (Table 2), indicating that day of the week was an important factor determining angling effort. Model 8, which included a covariate representing time of day (daytime vs. dawn/dusk) had a similar DIC value, highlighting the potential role of light level in determining the probability of detecting anglers. The ability to predict cross-validation data was approximately the same for all models, indicated by similar mean squared error values. Additionally, all models were relatively unbiased, with mean proportional error close to zero (Table 2). Based on these criteria, we chose model 5 to predict angling effort on BC lakes.

The probability of a false-zero camera effort observation varied greatly by lake-year, ranging from near zero to near one (Fig. 2A). This led to a posterior predictive distribution for δ that was imprecise, with a median of 0.47. In false zero cases, the mean angling effort for most lakes (λ_l) was generally between 1 and 4 anglers on weekdays (Fig. 2B) and between 1 and 6 anglers on weekends (Fig. 2C). This difference between weekdays and weekends was apparent from posterior estimates of total effort for individual lakes, which also showed that weekend estimates were often less precise (Fig. 2C). In true positive cases, the multiplier on effort observed by cameras (α_l) varied considerably across lake-years, but was generally between 1 and 3 on weekdays (Fig. 2D) and between 0.5 and 3.5 on weekends (Fig. 2E). The predictive posterior probability distribution of α_l had a median value of 1.83 on weekdays and 1.90 on weekends corroborating somewhat higher expected angling effort during weekends.

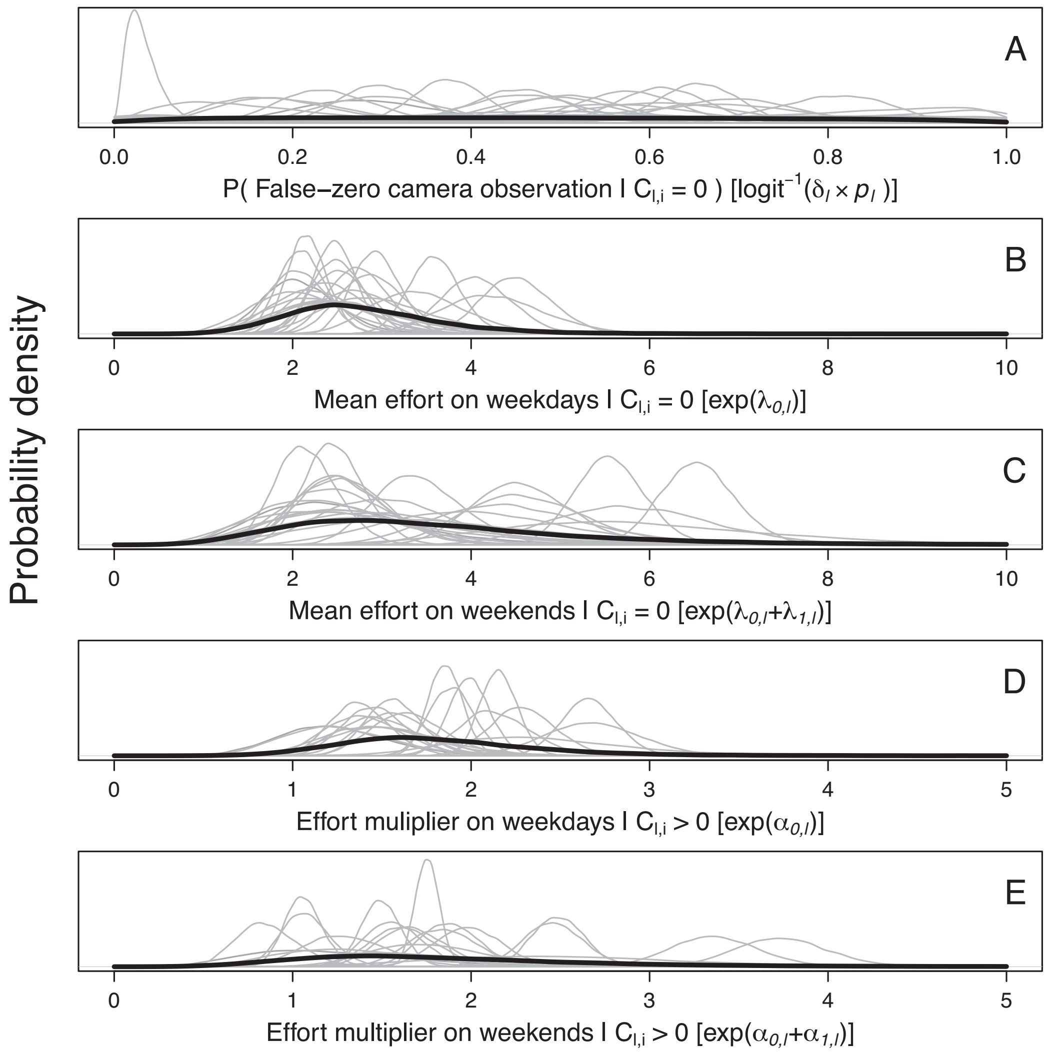

Fig. 2. Posterior predictive distributions for each of the five parameters assessed in the selected model (model 5): δ, λ_0, $\lambda_0+\lambda_1$, α_0, and $\alpha_0+\alpha_1$ when estimated with the hierarchical Bayesian model. Thin black lines represent posterior distributions for each camera; thick grey lines are posterior distributions for an unsampled camera.

Several of the cameras used in the analysis had substantial data gaps. Of the 91 lake-years included in the analysis, only 81 had more than 30% of the season captured by cameras. Filling camera data gaps using information from nearby, similar lakes increased the proportion of the fishing season predicted by using the weighted average of predicted effort on these lakes. The number of comparison lakes used to fill camera effort gaps influenced the final prediction of seasonal angling effort for any particular lake because it increased the proportion of the total season for which effort was estimated (Table S1). However, as the proportion of the season included approached 1, additional comparison lakes had little effect on seasonal effort estimates, indicating that results were relatively insensitive to the number of comparison lakes so long as most gaps were filled (Table S1).

Annual seasonal effort estimates varied across lakes, but were often quite consistent within lakes over years (Fig. 3). This was expected since management of these lakes (stocking rate or fishing regulations) had not varied over the course of study. Predictions of seasonal angling effort ranged from 17 to 785 angler-hours/ha. Lakes without surveys of total effort generally exhibited angling effort predictions with wider credible intervals. The relative uncertainty in predictions was a combination of the fraction of zero camera observations, the amount of total effort data available for a particular lake and the number of camera effort gaps. Though some lakes had relatively tight credible limits despite having no creel survey data simply due to the combination of zero and positive camera observations, others had a higher level of uncertainty.

4. Discussion

The use of cameras as tool for quantifying angling effort is an emerging method and subject to ongoing development. In this paper we advance the approach by developing statistically rigorous models for uprating camera effort to total effort. These models address three critical issues associated with using cameras to quantify total effort: camera observations of zero effort, patchy creel surveys of total effort and gaps in camera effort data. Additional sources of uncertainty could be incorporated into these models, such as the mean proportion of total boats fishing or the mean number of anglers per fishing boat. The choice of which factors to admit into the model will depend on the questions being addressed by the model. The models evaluated here resulted in total effort predictions on many lakes being quite precise, though the model also identified lakes where there was still a fair level of uncertainty due to the combination of zero and positive camera observations. These findings may be used to prioritize surveys of true effort in future years to help improve precision in predictions of total effort.

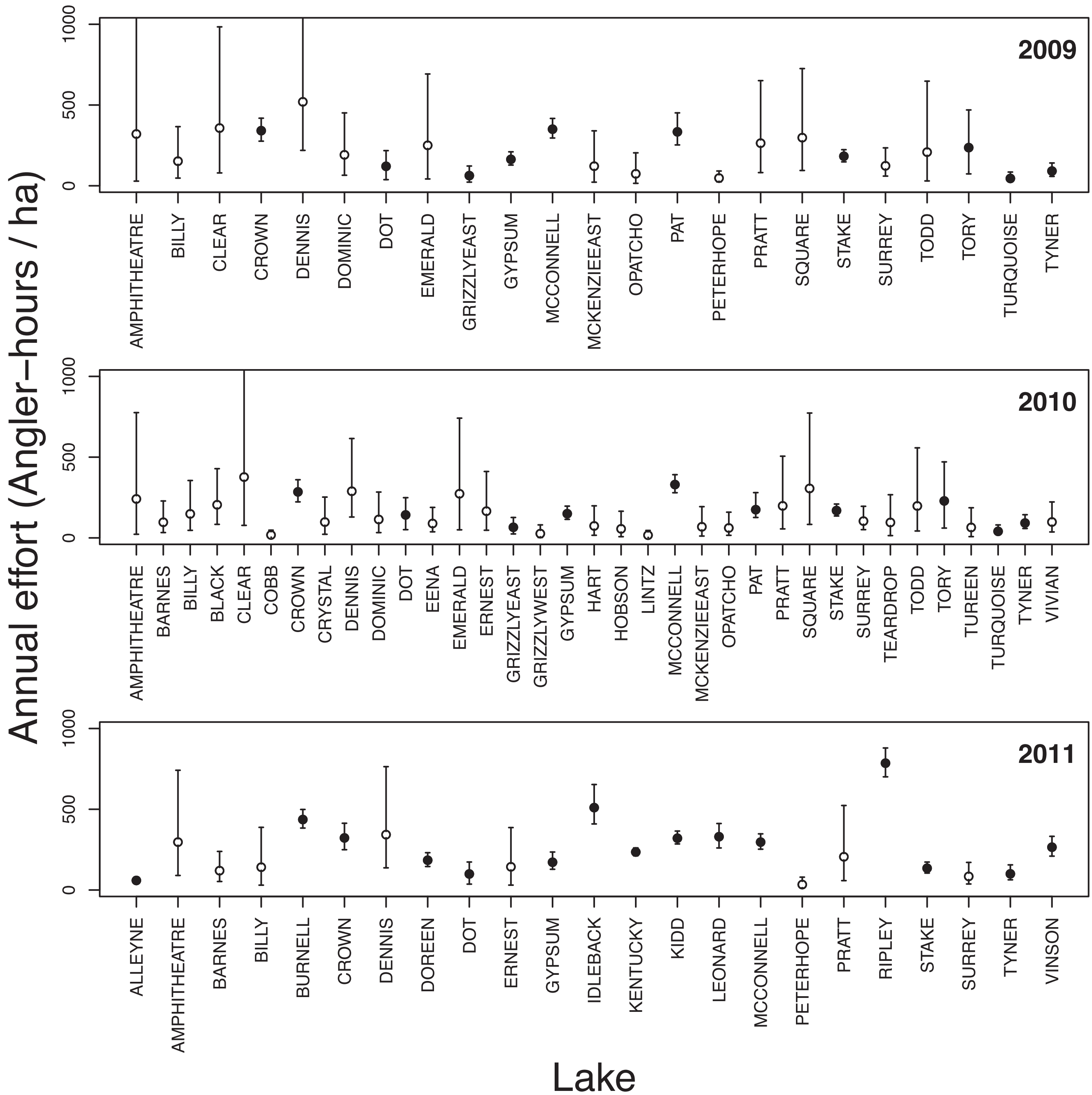

Fig. 3. Total annual recreational fishing effort (medians with 95% credible intervals) on all lakes evaluated in A) 2009; B) 2010; and C) 2011. Filled circles represent lakes where creel effort observations were used to inform the model; open circles represent lakes with no creel survey data.

When our uprating model was applied to rural lakes in BC, we often found a high rate of false zeros in which camera effort was zero but total effort was positive. Simple extrapolation of camera observations (i.e., ignoring zero camera observations) to absolute effort estimates would ignore these anglers, and lead to underestimation of angling effort (Fletcher et al., 2005). Similarly, more complicated data transformations to normalize positive observations do not affect zeros, leading to bias in total angler effort predictions (Fletcher et al., 2005; Martin et al., 2005). Additionally, this bias increases as either total effort declines or the proportion of total effort seen by cameras declines due to an increased frequency of zero camera observations (Sunger et al., 2012) and could therefore lead to bias in trends in estimated total effort. Estimates of total effort were the least precise in false zero situations further emphasizing the need for careful consideration of camera placement (Smallwood et al., 2012). This may be addressed by targeting high-use areas, ensuring the view is clear of obstructions or by using multiple cameras to cover a higher proportion of the total fishing area.

Models that included weekend/weekday effects were among the most parsimonious, indicating that angling effort differs between weekdays and weekends. There may be a shift in the types of anglers who fish on weekends and weekdays, which have different preferences for fishing areas (Ward et al., 2013a). Capturing these temporal phenomena in more detailed uprating models would require additional surveys of total effort across a wider temporal range including various times of day and period of the fishing season. Ignoring finer-scale temporal phenomena may contribute to inaccuracy in effort predictions, especially when summarizing total angling effort across shorter time-scales (e.g., weeks).

A central assumption of Bayesian hierarchical models is that sampling units are exchangeable (Gelman and Hill, 2007). To meet this assumption, it is important to ensure that experimental lakes are similar in characteristics. Large lakes and reservoirs, for example, may attract a different type of fishing behavior than smaller lakes. Likewise, lakes with notably higher productivity may create more abundant or diverse fish populations and communities, attracting different angler types with different fishing behaviors (Beardmore et al., 2015). In a wider application of our models, it may be necessary to separate classes of lakes or include additional parameters to account for important differences in lake characteristics (Leon-Novelo et al., 2012). How exactly to separate lakes into classes will be context-specific but should be formally evaluated using a model-selection criteria such as DIC (Burnham and Anderson, 2002; Spiegelhalter et al., 2002).

Our method for uprated camera effort relies on Bayesian multiple imputation which assumes that data are 'missing at random' (Rubin, 1987). This is a condition where the mechanism by which data are missing is unrelated to the magnitude of the missing data. This assumption would be violated in this analysis if observations of total effort (creel surveys) were most likely on lakes with the highest total effort. Since by definition the total effort was not known for those lakes where it was imputed we cannot know for certain whether this assumption was violated. However creel surveys were deliberately conducted on lakes with a wide range of historical effort levels and choice of lake was not biased in favor of those of higher historical effort levels.

Cameras represent a novel means of estimating total effort in a variety of situations. The small, remote lakes of the BC case study may be the most benefitted since these lakes are often overlooked by other effort monitoring methods that are deemed too expensive for the monitoring of relatively low value lakes. In our BC case study, infrequent but long-lasting equipment failure was a primary concern. A small number of cameras failed to collect data over the entire fishing season, a problem alleviated in our analysis by post-hoc imputation of camera effort (Gelman and Hill 2007).

The most appropriate use of cameras for fisheries management and monitoring may come when combining this technology with other monitoring methods, such as creel surveys and aerial surveys (Parnell et al., 2010; Smallwood et al., 2012; Steffe et al., 2008). Smallwood et al. (2012) demonstrated how cameras can be used to compliment other methods to capture times (e.g., night) when other methods are not feasible. The analysis presented here could expand complimentary methods more formally by imputing total effort using a wider range of available covariate data rather than simply uprating only camera effort as in Smallwood et al. (2012) and Parnell et al. (2010).

The models we present can be extended to a wide range of other effort imputation problems. Indeed early applications of such models have been successfully applied in the prediction of pelagic fishing effort (Carruthers, 2007). Our application to camera data on remote lakes is particularly appropriate in other recreational fisheries management settings because sampling using other methods (e.g., aerial surveys) are likely to be costly and produce insufficient power to detect changes in response to management actions (Parkinson et al., 1988). However, the use of cameras and these models need not be restricted to small lakes: they are well suited to a variety of situations such as along coastlines (Parnell et al., 2010; Smallwood et al., 2012), on coastal reefs or at ports or access points. By identifying and addressing the central issues inherent with using cameras to estimate total angling effort we have taken a step toward unlocking this new technology. The methods described may help to improve our understanding of angler dynamics and contribute to more effective management of this economically and socially important resource (Post et al., 2002).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishres.2015.07.032

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