



# 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.

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## 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<sup>1</sup>. 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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<sup>1</sup> Creel surveys refer to on-site interviews to collect fishery-dependent information from recreational anglers.

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 ( $\delta$ ); (2) the mean number of anglers present when zero anglers are observed by a camera ( $\lambda$ ); and (3) the mean proportion of anglers seen when one or more anglers are observed by a camera ( $\alpha$ ). 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,

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

where  $p_{l,i}$  is the binary observation of true presence (=0) or absence (=1) of anglers on lake- $l$  at observation- $i$  and  $\delta_c$  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

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