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Estimating fishing effort from remote traffic counters: Opportunities and challenges

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ABSTRACT

This paper introduces traffic counters paired with infrequent observations of total fishing effort and relative fishing and non-fishing traffic to estimate daily and seasonal fishing effort. Fishing effort is an important metric in recreational fisheries, used as an index of fishing attractiveness and fishing mortality. There are several options for monitoring fishing effort, but for high-precision effort on a particular fishery, creel surveys and time-lapse cameras have been the only options. However, time-lapse cameras have high costs associated with reviewing images and technology failure requires imputing missing observations. To translate this index of counts of boats or shore anglers derived from time-lapse images into absolute fishing effort, this method requires independent measures of total fishing effort as well as observations of fishing and non-fishing traffic. We use remote traffic counters coupled with periodic on-site creel surveys to estimate daily and seasonal fishing effort. Fishing effort is estimated using a state-space Bayesian hierarchical model, which incorporates all of these data to provide a measure of daily or seasonal fishing effort. We further show that for our case study, fishing effort estimates require a high number of independent observations of effort and proportional distribution of fishing and non-fishing traffic. Comparing effort estimates from traffic counters with estimates derived from just a stratified random creel survey shows traffic counters provide more precise estimates of effort, though an absolute comparison is not possible with the data available. Our mixed-use lake necessitates a high number of independent observations of traffic and angling to produce reliable fishing effort estimates; we recommend traffic counters for lakes where most traffic is devoted to angling. We conclude traffic counters are a useful tool for estimating fishing effort, but should be used concurrently with other methods such as creel surveys or motion-detecting cameras that can estimate fishing and non-fishing traffic.

1. Introduction

Monitoring fishing effort is an important task in recreational fisheries management, since it can be a measure of attractiveness of the fishery and is correlated with fishing mortality (van Poorten et al., 2015). However, catch and effort reporting is not mandatory at most water bodies in North America and monitoring every fishery is impractical given their dispersed nature (Cooke et al., 2016; Lorenzen et al., 2016). Therefore decisions must be made about where to monitor fishing effort and with what frequency. It is therefore important to have a range of monitoring options available that allow you to achieve precision at the appropriate spatial scale needed to address a given management question.

Several methods currently exist for monitoring and measuring fishing effort on individual fisheries or across landscapes (Malvestuto, 1996; McCluskey and Lewison, 2008). Creel surveys (where individual anglers are intercepted on-site and interviewed) are an important part of effort estimation in their own right or can be used to validate data captured by cameras and other methods, though they are subject to their own set of biases (van Poorten et al., 2015). However, full creel surveys are expensive and labor intensive; surveying times are often subsampled and stratified to reduce costs, increasing variance in estimates. Even with fewer observations, creel surveys may be impractical for many situations, especially small, remote fisheries where effort at an individual lake is less important than effort distributed across a broader landscape. Off-site surveys through internet, telephone, or mail have a broad reach and are relatively inexpensive, but are prone to a variety of biases and additional follow-up surveys to correct biases add to the cost of the survey (Barrett et al., 2017). Aerial surveys using periodic flights over fishing sites are another method commonly used to estimate fishing effort and this method is useful for capturing a number of fishing locations simultaneously in the same flight (Malvestuto, 1996).

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However, because each flight is expensive, the number of flights per year is limited and precision of effort estimates may be poor (Parkinson et al., 1988). Cameras are increasingly being used to monitor effort at particular sites (Parnell et al., 2010; Smallwood et al., 2012; Patterson and Sullivan, 2013; Ward et al., 2013; Hartill et al., 2016), which can be cost effective, but these methods still have high data collection and entry costs due to the time necessary to manually count anglers from thousands of images per lake (Greenberg and Godin, 2015).

Several jurisdictions have investigated using traffic counters on access roads and boat ramps as an index of recreational use (Hunt and Hosegood, 2008; Hunt et al., 2008; Fay et al., 2010; Hunt and Dyck, 2011), but few have used them to estimate fishing effort (Steffe et al., 2008). Traffic counters are low cost, low maintenance, easily hidden or buried to protect against theft, and can be customized to capture most vehicles entering and exiting a recreation area. They also internally record all traffic data, removing the need for later data entry. However, their use presupposes traffic to waterbodies is confined to a limited number of access routes. The largest drawback of traffic counters are their inability to distinguish between fishing and non-fishing vehicles and not accounting for variation in trip length. To date, traffic counters have not been a reliable tool for estimation of total fishing effort.

We present a state-space model using traffic counters to estimate seasonal fishing effort. Unlike Steffe et al. (2008), we present traffic counters as a primary means of estimating effort, rather than as supplemental information for a full creel survey. In our model, total hourly traffic patterns (arrivals and departures) are assumed to be normally distributed, as in the popular salmon escapement likelihood model (Hilborn et al., 1999). Predicted hourly traffic is fit to traffic counter data, supplemented with independent data on trip length, and hourly summaries of fishing and non-fishing boats, and non-boater traffic. The model is also fit to these supplemental data to separate anglers from non-angling traffic. We evaluate the model using a high-traffic lake with many anglers, non-angling boaters, and non-boaters, and evaluate various hypotheses of how fishing effort varies throughout the season.

2. Methods

2.1. Study site

Kawkawa Lake is a 72 ha coastal montane lake less than 90 min from Vancouver, British Columbia (BC). The lake is used by anglers fishing for wild kokanee salmon (*Oncorhynchus nerka*), coho salmon (*O. kisutch*), rainbow trout (*O. mykiss*) and cutthroat trout (*O. clarkii*), and by non-angling boaters throughout most of the year (the fishery is closed December to February due to occasional thin ice cover). Kokanee are the main focus of the fishery, primarily because they grow to uncharacteristically large sizes (asymptotic length > 400 mm). Fishing regulations limit kokanee harvest to four per day. The large body size of kokanee in this population, combined with the relatively close proximity to a large metropolitan area (Metro Vancouver) may cause stress on the fish population due to high fishing pressure and harvest. It is important to accurately monitor fishing pressure on the lake to appropriately regulate the fishery.

Kawkawa Lake is surrounded on two sides by residential development, including many privately owned docks, though the majority of boating activity originates from a single public boat launch. The launch is located in a regional park with other recreational opportunities (e.g. swimming, picnicking). The launch is accessed by a short road leading to a parking area away from the lake; there is no parking permitted near the launch, nor is there any place to moor a boat overnight. Therefore, all boats must be launched and retrieved the same day.

Two TrafX G3 traffic counters were installed along the short road accessing the boat ramp; one at either end. The traffic counter at the top of the road was buried just alongside of the road, the other at the bottom of the road in the base of a tree alongside the road near the turnaround at the ramp. Both counters were buried less than 10 cm deep. Both were set to detect car-sized or larger objects 24 h a day. Data were downloaded approximately monthly during the study period between May and December, 2016.

A creel survey was conducted throughout the 2016 fishing season to assess angler activity, demography and catch statistics. The survey was stratified by day-type (weekday, weekend/holiday) and time-period (morning, afternoon), with creel generally occurring four times per week. A total of 91 days were surveyed for approximately 7 h per day. The creel survey permitted the collection of ancillary data necessary for estimating total seasonal fishing effort on Kawkawa Lake. These data included hourly counts of the total number of boats fishing and not fishing on the lake, as well as hourly summaries of the number of vehicles coming to the boat launch with and without a boat. Since kokanee and coho are the primary fished species on the lake and are exclusively pelagic, virtually all anglers on Kawkawa Lake require a boat.

2.2. Model description

The total number of vehicles (V_t) passing the traffic counters each day *t* must have an angling boat (F_t), have a non-angling boat (B_t) or be a non-boater (NB_t):

$$F_t = V_t p_f, \tag{1}$$

$$B_t = V_t(1 - p_f)p_b, \tag{2}$$

$$NB_t = V_t(1 - p_f)(1 - p_b), \tag{3}$$

where p_f is the proportion of all traffic that are fishing and p_b is the proportion of non-fishing vehicles that have boats. Cumulative arrivals on day-*t* to hour-*h* for anglers ($A_{(F),h}$), non-angling boaters ($A_{(B),h}$) and non-boaters ($A_{(NB),h}$) are assumed to follow a cumulative normal distribution:

$$A_{(F)t,h} = F_t \int_{i=0}^{h} \left[\sqrt{\frac{\tau_{(F)t}}{2\pi}} exp\left(-\frac{\tau_{(F)t}}{2}(i - \mu_{(F)t})^2\right)\right] di, \tag{4}$$

$$A_{(B)t,h} = B_t \int_{i=0}^{h} \left[\sqrt{\frac{\tau_{(B)t}}{2\pi}} exp\left(-\frac{\tau_{(B)t}}{2}(i - \mu_{(B)t})^2\right)\right] di, \tag{5}$$

$$A_{(NB)t,h} = NB_t \int_{i=0}^{h} \left[\sqrt{\frac{\tau_{(NB)t}}{2\pi}} exp\left(-\frac{\tau_{(NB)t}}{2}(i - \mu_{(NB)t})^2\right)\right] di, \tag{6}$$

where $\mu_{(F)t}$ and $\tau_{(F)t}$ is mean and precision in arrival timing for anglers on day-*t*; the same nomenclature was used for non-angling boaters and non-boaters. Similarly, cumulative departures for anglers and non-angling boaters are given by

$$D_{(F)t,h} = F_t \int_{i=0}^{h-L_F} \left[\sqrt{\frac{\tau_{(F)t}}{2\pi}} exp\left(-\frac{\tau_{(F)t}}{2}(i - \mu_{(F)t})^2\right)\right] di, \tag{7}$$

$$D_{(B)t,h} = B_t \int_{i=0}^{h-L_B} \left[\sqrt{\frac{\tau_{(B)t}}{2\pi}} exp\left(-\frac{\tau_{(B)t}}{2}(i - \mu_{(B)t})^2\right)\right] di. \tag{8}$$

Note that non-boaters are assumed to leave immediately (within the same hour of arrival) because there is no area for parking. The difference in arrivals and departures is simply the mean time spent fishing by anglers (L_F) and boating by non-anglers (L_B). In our application, L_F is freely estimated, while L_B is assumed fixed at 2 h. Early simulations where L_B was freely estimated resulted in a precise posterior estimate close to two hours, but resulted in high autocorrelation and longer burn-in. We therefore chose to fix L_B to improve model convergence. The total number of anglers and non-angling boaters present on the lake at day-*t* and hour-*h* is given respectively by

$$\hat{N}_{(F)t,h} = (A_{(F)t,h} - D_{(F)t,h})e^{\omega_t}, \tag{9}$$

$$\hat{N}_{(B)t,h} = (A_{(B)t,h} - D_{(B)t,h})e^{\omega_t}, \tag{10}$$

where ω_t is a normally distributed random process error with precision

τ_{Ac}. Observations of angling and non-angling boaters counted over discrete hours were fit to Eqs. (9) and (10) assuming Poisson observation error.

The traffic to the lake each hour with ($\hat{I}_{(B)t,h}$) and without ($\hat{I}_{(NB)t,h}$) a boat is predicted as the sum of arrivals and departures occurring each hour:

$$\hat{I}_{(B)t,h} = [(A_{(F)t,h} + D_{(F)t,h} + A_{(B)t,h} + D_{(B)t,h}) - (A_{(F)t,h-1} + D_{(F)t,h-1} + A_{(B)t,h-1} + D_{(B)t,h-1})]e^{\psi_t}, \tag{11}$$

$$\hat{I}_{(NB)t,h} = [(A_{(NB)t,h}) - (A_{(NB)t,h-1})]e^{\psi_t}, \tag{12}$$

where ψ_t is a normally distributed random process error with precision τ_{Cc}. Observations of numbers of vehicles with and without boats arriving at the launch at discrete hours and days were fit to Eqs. (11) and (12) assuming Poisson observation error.

Finally, the number of observations recorded by each traffic counter (j) is predicted as the number of trips to the boat ramp (arrivals and departures) of all visitor types multiplied by the number of times a vehicle will pass by a traffic counter on a trip to the boat launch, n_c. At the Kawkawa Lake launch, n_c is fixed at 2 accounting for no parking at the launch, so vehicles must pass the traffic counters once on their way to launch and again when leaving the launch to park their vehicle:

$$\hat{C}_{j,t,h} = n_c(\hat{I}_{(B)t,h} + \hat{I}_{(NB)t,h})e^{\chi_t}, \tag{13}$$

where χ_t is a normally distributed random process error with precision τ_{Tc}. Hourly observations by each of the two traffic counters were fit to Eq. (13) assuming Poisson observation error.

The creel survey gathered a variety of information including trip length for anglers. Mean trip length in the model was estimated by fitting to these data assuming they are lognormally distributed with mean $\ln(L_F)$ and precision of 100.

We assume parameters of the model associated with arrival timing for anglers, boaters and non-boaters are exchangeable across days. Prior probability distributions for these parameters share common hyper-priors defined by estimated hyper-parameters (Gelman and Hill, 2007). Therefore, days with more data (e.g. independent vehicle and boat counts) help inform hyper-parameters, which in turn inform prior probability distributions for days with less data. Hyper-prior and prior distributions for all estimated parameters are shown in Table 1.

It is uncertain how the proportion of vehicles that fish (p_f) and the proportion of non-fishers with a boat (p_b) may change through the year. Four hypotheses were tested to evaluate sensitivity of the model fits and overall estimates of seasonal fishing effort. The simplest hypothesis (Model 1) is that both p_f and p_b vary randomly throughout the fishing season as beta-distributed random effects. Each is predicted daily as

$$p_{f,t} = B(\alpha_f, \beta_f) \tag{14}$$

and

$$p_{b,t} = B(\alpha_b, \beta_b) \tag{15}$$

The shape parameters in Eqs. (14) and (15) are assumed to be exchangeable across days and share common hyper-priors that themselves are transformed from the mean and precision of p_f and p_b across days. For example:

$$\alpha_b = \mu_{\alpha_b}\tau_{\alpha_b} \tag{16}$$

and

$$\beta_b = \tau_{\alpha_b} - \alpha_b, \tag{17}$$

where μ_{α_b} and μ_{α_b} are the mean and precision of daily p_b over the season.

The second hypothesis (Model 2) assumes the proportion of visitors fishing each day varies as a function of weekday/weekend and weather. We assume the proportion of visitors fishing is a logit-transformed linear function:

$$\text{logit}(p_{f,t}) = \delta^0_{(F),t} + \delta^D_{(F)}D_t + \delta^T_{(F)}T_t + \delta^P_{(F)}P_t + \delta^{TP}_{(F)}T_tP_t, \tag{18}$$

where D_t is a dummy variable indicating weekday (=0) or weekend/holiday (=1), T_t is air temperature (°C), P_t is precipitation (mm) and δ^x are estimated coefficients. As in Eqs. (14) and (15), $\delta^0_{(F),t}$ was assumed to vary randomly by day as a logit transformed normally distributed random variable with hyper-mean and hyper-precision described in Table 1. Under this assumption the proportion of non-fishers with a boat are assumed to vary randomly (e.g. Eq. (15)). Weather data were downloaded from Environment Canada (http://climate.weather.gc.ca/historical_data/search_historic_data_e.html). Weather data were normalized to vary around 0 to aid in model convergence.

The third hypothesis (Model 3) is to assume day of week and weather impact p_b using the same structure as Eq. (18) and p_f varies randomly as Eq. (14). The fourth hypothesis (Model 4) is to assume both p_b and p_f are influenced by day of week and weather.

Model selection for characterizing how p_f and p_b vary over days was evaluated in two ways. The first was by calculating the Deviance Information Criterion (DIC; Spiegelhalter et al., 2002), which balances posterior model fit against the effercive number of parameters (p_D) and is the preferred method for evaluating parsimony in hierarchical models. The second was to compare predictive performance of each model using k-fold cross validation (James et al., 2013). Days where independent observation data were collected were randomly separated (folded) into five sets of approximately equal number of days. Observations on those days form k data sets. Parameters were estimated k times, where each time, four of the folds were treated as a training dataset. The mean squared error (MSE_i) was calculated between held-out observations and the corresponding validation data. Posterior estimates of cross validation (CV) are calculated as the mean posterior MSE across all k folds (James et al., 2013).

The dataset is rich with independent observations (traffic and boat counts), and so we evaluated model sensitivity of the selected model to available independent data. This was conducted by randomly selecting 20, 40, 60 and 80% of independent observations to be excluded, grouped by creel days. The selected model was re-ran with all available traffic counter data and remaining independent data to explore how posterior estimates of seasonal fishing effort varied with sample size.

We were interested in evaluating whether traffic counters combined with creel observations would improve precision of fishing effort estimates over what would be gained simply from creel alone. We therefore estimated fishing effort from instantaneous counts of fishing boats using a hierarchical model based on methods of Pollock et al. (1994) and. Mean hourly fishing effort ($\overline{E_t}$) was calculated from

$$\log(\overline{E_t}) = \rho_{(S)W,t}; \quad \rho_{(S)W,t} \sim N(\mu_{(S)W}, \tau_{(S)W}) \tag{19}$$

where $\mu_{(S)W}$ and $\tau_{(S)W}$ are hyper-mean and hyper-precision for weekdays (W = 1) or weekends and holidays (W = 2). Daily effort is estimated then calculated as

$$\hat{E}_t = \overline{E}_t S_t e^{\xi_t} \tag{20}$$

Where S_t is the number of daylight hours for day-t and ξ_t is a normally distributed random process error with precision τ_B. Days where no fishing effort observations were made are predicted from hyper-mean and hyper-precision for that day-type (weekend or weekday). Seasonal effort is predicted by summing across all days. Observations of angling boaters counted over discrete hours were fit to Eq. (20) assuming Poisson observation error.

All data manipulation was performed in R (R Core Development Team, 2016), with MCMC numerical approximation of the posterior distribution performed in JAGS 4.2.0 (Plummer, 2003). Posterior distributions were calculated from 10,000 iterations after an initial burn-in of 50,000 iterations and further thinned to provide a final sample of 1000 iterations from each of three MCMC chains. Convergence could not be rejected given visual inspection of MCMC chains and Gelman-Rubin convergence diagnostics. All R and JAGS code are available at

Table 1
Prior and hyper-prior distributions for all estimated parameters and random variables used the model. Note parameters $p_{f,t}$ and $p_{b,t}$ are estimated using either hyper-parameters or logit-transformed linear models. Prior distributions are defined as B:beta; G:gamma; and N:normal.

Parameter	Description	Prior	Hyper-prior	Model
V_t	Total visitors	$U(0,1000)$		
L_F	Length of fishing day	$U(0,12)$		
L_B	Length of non-fishing boat day	2		
$p_{f,t}$	Proportion of daily traffic that fishes	$B(\mu_f\tau_f, \tau_f(1-\mu_f))$	$\mu_f \sim B(1,1)$	1,3
		Eq. (18)	$\tau_f \sim G(0.001,0.001)$	2,4
$p_{b,t}$	Proportion of non-fishing traffic with a boat	$B(\mu_b\tau_b, \tau_b(1-\mu_b))$	$\mu_b \sim B(1,1)$	1,2
		Eq. (18)	$\tau_b \sim G(0.001,0.001)$	3,4
$\mu_{(F)t}$	Mean arrival hour for anglers	$N(\mu_{\mu(F)}, \tau_{\mu(F)})$	$\mu_{\mu(F)} \sim N(0,0.01)$	
			$\tau_{\mu(F)} \sim G(0.001,0.001)$	
$\tau_{(F)t}$	Precision in arrival time for anglers	$G(\alpha_{\tau(F)}, \beta_{\tau(F)})$	$\alpha_{\tau(F)} \sim G(0.001,0.001)$	
			$\beta_{\tau(F)} \sim G(0.001,0.001)$	
$\mu_{(B)t}$	Mean arrival hour for non-fishing boaters	$N(\mu_{\mu(B)}, \tau_{\mu(B)})$	$\mu_{\mu(B)} \sim N(0,0.01)$	
			$\tau_{\mu(B)} \sim G(0.001,0.001)$	
$\tau_{(B)t}$	Precision in arrival time for non-fishing boaters	$G(\alpha_{\tau(B)}, \beta_{\tau(B)})$	$\alpha_{\tau(B)} \sim G(0.001,0.001)$	
			$\beta_{\tau(B)} \sim G(0.001,0.001)$	
$\mu_{(NB)t}$	Mean arrival time for non-boaters	$N(\mu_{\mu(NB)}, \tau_{\mu(NB)})$	$\mu_{\mu(NB)} \sim N(0,0.01)$	
			$\tau_{\mu(NB)} \sim G(0.001,0.001)$	
$\tau_{(NB)t}$	Precision in arrival time for non-boaters	$G(\alpha_{\tau(NB)}, \beta_{\tau(NB)})$	$\alpha_{\tau(NB)} \sim G(0.001,0.001)$	
			$\beta_{\tau(NB)} \sim G(0.001,0.001)$	
$\delta^0_{(F),t}$	Proportion of visitors fishing	$N(\mu_{\mu(\delta F)}, \tau_{\mu(F\delta)})$	$\mu_{(\delta F)} \sim N(0,1.47)$	
			$\tau_{(\delta F)} \sim G(0.001,0.001)$	
$\delta^0_{(B),t}$	Proportion of non-fishing visitors with boats	$N(\mu_{\mu(\delta B)}, \tau_{\mu(\delta B)})$	$\mu_{(\delta B)} \sim N(0,1.47)$	
			$\tau_{(\delta B)} \sim G(0.001,0.001)$	
$\delta^D_{(F)}, \delta^D_{(B)}$	Weekend coefficient	$N(0,1.47)$		2,3,4
$\delta^T_{(F)}, \delta^T_{(B)}$	Temperature coefficient	$N(0,1.47)$		2,3,4
$\delta^P_{(F)}, \delta^P_{(B)}$	Precipitation coefficient	$N(0,1.47)$		2,3,4
$\delta^{TP}_{(F)}, \delta^{TP}_{(B)}$	Temperature-precipitation interaction coefficient	$N(0,0.1.47)$		2,3,4
$\rho_{(S)W=1,t}$	Mean hourly fishing effort for weekdays	$N(\mu_{(S)W=1}, \tau_{(S)W=1})$	$\mu_{(S)W=1} \sim N(0,0.35)$	
			$\tau_{(S)W=1} \sim G(0.001,0.001)$	
$\rho_{(S)W=2,t}$	Mean hourly fishing effort for weekdays	$N(\mu_{(S)W=2}, \tau_{(S)W=2})$	$\mu_{(S)W=2} \sim N(0,0.35)$	
			$\tau_{(S)W=2} \sim G(0.001,0.001)$	
ω_t	Fishing and boating process error	$G(0.001,0.001)$		
ψ_t	Traffic process error	$G(0.001,0.001)$		
χ_t	Launch use process error	$G(0.001,0.001)$		
ξ_t	Fishing process error for stratified counts	$G(0.001,0.001)$		

https://github.com/bvanpoor/Traffic-counter-effort-model.git. We include our datasets in the posting for use by others as a template for future analyses.

3. Results

Two traffic counters operated continuously at Kawkawa Lake from May 1 to December 1, 2016. The counter at the top of the road recorded 3491 vehicles and the counter near the boat ramp recorded 3511 vehicles. As part of the stratified-design creel survey, independent counts of boats and traffic occurred for 91 days over the same date range. A total of 633 hourly counts of fishing and non-fishing boats were recorded, observing 1934 angling hours and 1104 non-angling boat hours. A total of 173 hourly counts of traffic to the boat launch were also recorded, with 241 vehicles with boats and 700 vehicles with no boats.

Each of the models successfully fit to data from traffic counters when supplemented with data on hourly summaries of fishing/non-fishing boats on the water, hourly summaries of vehicles with and without boats approaching the boat ramp and data on trip length of anglers. Posterior estimates of seasonal fishing effort from the four models overlapped with medians ranging from 6600 to 7158 angler-hours (Fig. 1).

Model selection was evaluated using both DIC and k-fold cross validation. Model 3 was the most parsimonious model based on DIC and had the lowest mean MSE when performing k-fold cross validation, although Model 1 was approximately equivalent (Table 2). Models 2 and 4 had higher mean MSE suggesting weather is a poor predictor of the proportion of traffic that is boating but not fishing. We chose Model 3 as the best model evaluated, due to its superior parsimony and predictive ability.

Model 3 was used to predict daily estimates in fishing effort over the season (Fig. 2). The model predicted strong daily variation in fishing effort, which does not necessarily follow a weekday-weekend pattern. There was a marked decline in fishing effort in September, coinciding with the end of the holiday season and the beginning of kokanee staging for spawning, where angler success declines.

Model results were sensitive to the number of days of independent data (Fig. 3). Reducing the available independent data to 80% (72 days of data) did not change the estimate of seasonal effort, but further reductions led to variation in effort estimates, though the precision of posterior seasonal effort estimates did not change appreciably. With only 18 days of independent data the seasonal effort estimate was significantly different, with median estimate nearly 50% of the estimate obtained with 100% of independent data.

Fishing effort was also estimated with only instantaneous observations of fishing effort, as would often occur in a stratified random sampling strategy for estimating fishing effort. Patterns of daily fishing

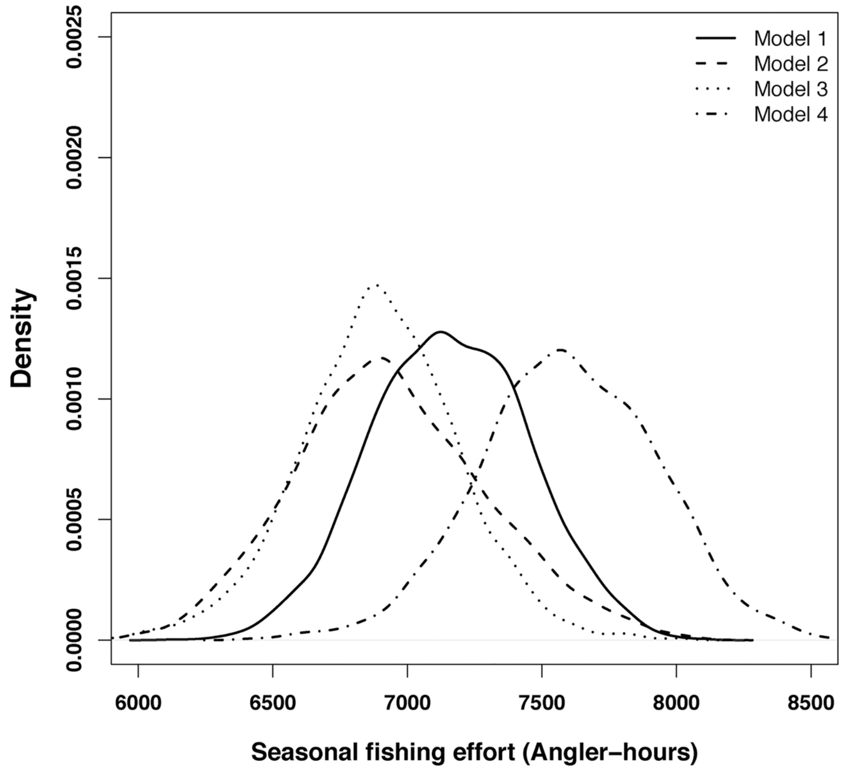

Fig. 1. Posterior predictive estimates of seasonal fishing effort on Kawkawa Lake in 2016, as estimated by Models 1–4.

Table 2
Structure of the four models evaluated along with descriptive statistics used to determine the most appropriate model to describe the data. Each model is reported with the effective number of parameters (p_D), deviance information criterion (DIC) and the relative difference between model DIC, the minimum DIC among models (DDIC) and the median and 95% credible intervals of mean squared error based on k-fold cross validation. Effective number of parameters (p_D) is defined as the difference between the mean of posterior deviance and deviance when means of each estimated parameter is used (). The model with the lowest DIC and median posterior error is bolded; all subsequent analyses are based on this model.

Model		p_D	DIC	DDIC	Median MSE	95% Credible intervals
1	$p_{f,t} \sim B(\mu_f \tau_f, \tau_f(1-\mu_f))$ $p_{b,t} \sim B(\mu_b \tau_b, \tau_b(1-\mu_b))$	6,859.8	55,023	599	28.0	19.9, 40.8
2	$p_{f,t} = f(D_t, T_t, P_t,)$ $p_{b,t} \sim B(\mu_b \tau_b, \tau_b(1-\mu_b))$	6,731.3	54,662	238	39.9	26.1, 60.0
3	$\boldsymbol{p_{f,t} \sim B(\mu_f \tau_f, \tau_f(1-\mu_f))}$ $\boldsymbol{p_{b,t} = f(D_t, T_t, P_t,)}$	**6,408.5**	**54,424**	**0**	**27.9**	**19.4, 40.7**
4	$p_{f,t} = f(D_t, T_t, P_t,)$ $p_{b,t} = f(D_t, T_t, P_t,)$	6,545.7	54,502	77	50.1	31.6, 82.3

effort in May through August were driven by nearly daily counts of anglers on the lake (Fig. 4). There were few angler counts after August and predicted angler counts were based almost entirely on hyperparameters with weekends experiencing higher predicted fishing effort than weekdays. Daily pattern based on creel data alone was much different than from the traffic counters, with much less seasonal variation than estimated with traffic counters. Seasonal fishing effort was predicted to be 8818 angler hours when only stratified angler counts were used to estimate effort. The 95% quantiles of posterior estimates of fishing effort from the creel survey and the traffic counters did not overlap, with creel estimates being significantly higher. As the number of angler counts declined, precision quickly declined, thought median seasonal fishing effort was relatively consistent (Fig. 4).

4. Discussion

There are a variety of methods for monitoring fishing effort, including on-site surveys (creel surveys; McCormick and Meyer, 2017; Soupir et al., 2006), off-site surveys (phone, mail or internet questionnaires; Barrett et al., 2017) or remote monitoring (e.g. aerial counts and cameras; Parkinson et al., 1988; van Poorten et al., 2015). Each is appropriate for a variety of situations and resulting estimates will have different precision. We suggest traffic counters as an additional tool for fishing effort estimation, which can be used in remote or high-traffic areas. Our analysis overcomes most issues with using traffic counters to monitor fishing effort, namely separating fishing from non-fishing traffic and estimating total fishing time. Moreover, uncertainty in fishing time and the seasonal pattern in traffic patterns for anglers and non-anglers are appropriately accounted for. Our proposed method produces relatively precise estimates of fishing effort and can be used in situations where fishing effort is related to traffic approaching one or more lake access points and where some independent observations of fishing versus non-fishing traffic can be obtained.

Although we have demonstrated our method on a relatively mixed-

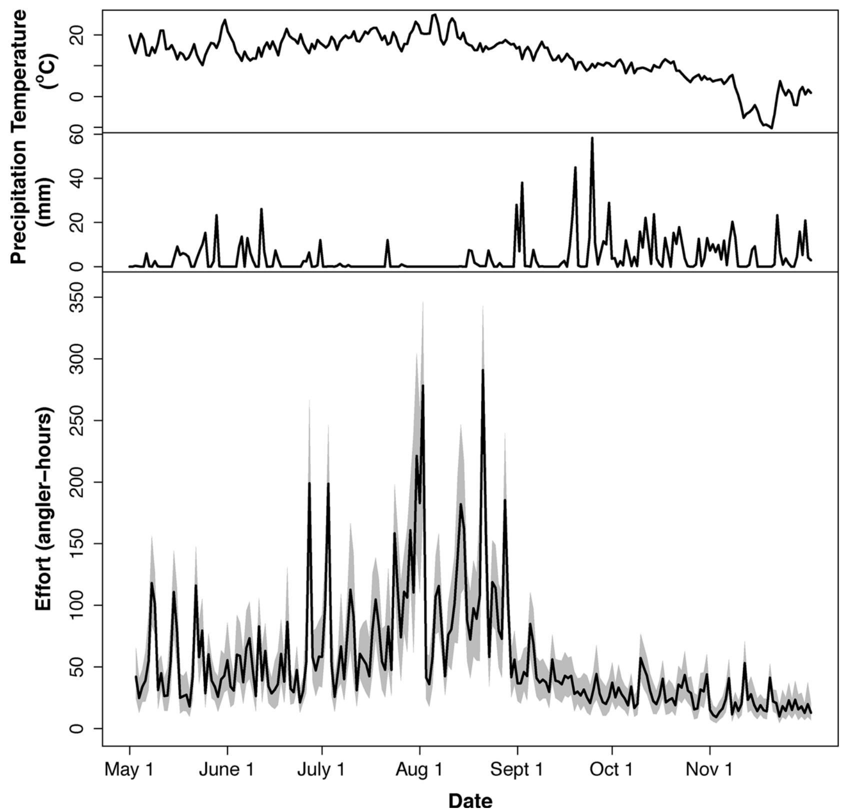

Fig. 2. Mean daily temperature (top), precipitation (middle) and estimated fishing effort (bottom) on Kawkawa Lake from May 1 to December 1, 2016 using Model 3. Dark line in bottom panel indicates median daily estimate, shaded area is 80% credible intervals.

use lake, the number of independent counts of anglers needed for reliable fishing estimates was quite high. However, estimates of seasonal fishing effort were significantly lower than when using only creel data. Although we have no true estimate of fishing effort, this does point to a potential error in creel estimates of effort, which assume relatively uniform fishing effort through the day absent any known daily

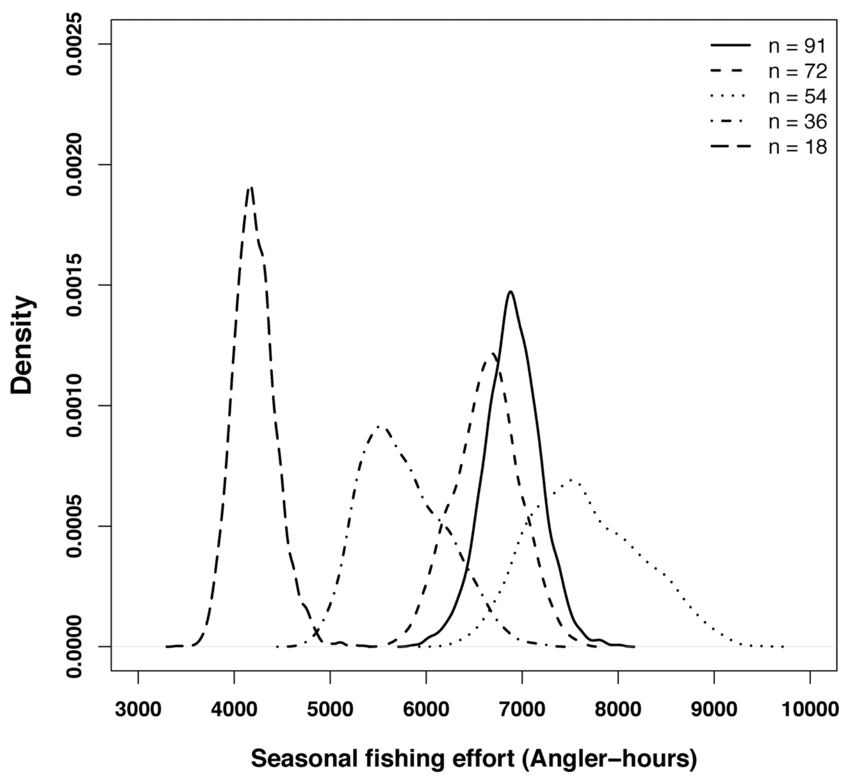

Fig. 3. Posterior predictive estimates of seasonal fishing effort on Kawkawa Lake using Model 3 with varying amounts of supplemental data. Sample size (*n*) is defined as the number of days with supplemental data.

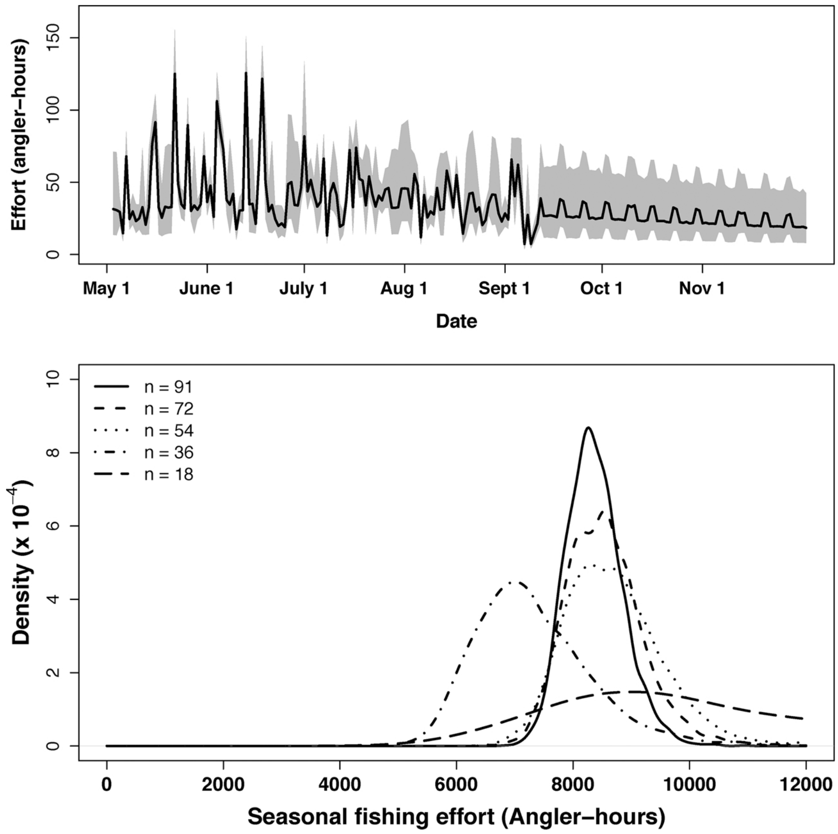

Fig. 4. Daily estimated fishing effort (top) with mean (dark line) and 80% credible intervals (shaded area). Bottom panel shows how seasonal fishing effort estimate changes as fewer data points are used to fit to the model.

distribution of fishing effort. In this sense, traffic counters with supplemental data provide a potential improvement in accuracy of fishing effort estimates. Overall, we suggest that traffic counters may be more appropriate on remote lakes where a high proportion of boating traffic is devoted to fishing, thereby resulting in more precise estimates of p_f and p_b. The result is fewer independent counts of traffic or anglers on the lake required to provide sufficiently accurate estimates of seasonal fishing effort. We cannot be prescriptive on the number of independent counts needed for any particular situation; appropriate sample size planning (Barrett et al., 2017) will be required to determine appropriate sampling frequency.

Traffic counters are not appropriate for monitoring fishing effort in all situations and it is important to understand their limitations. Fishing effort can originate from launched boats, privately docked boats, and boats arriving from other water bodies. Shore-based anglers can also be a significant portion of anglers at a water body, unlike the situation at our study site. If most anglers do not come from launched boats, or if the relative proportion derived from each method systematically varies throughout the year, traffic counters may not be appropriate or the analysis of these data will require a more complex estimation of p_f and p_b. However, this is not to say our analysis underestimates fishing effort if effort originates from sources other than a boat launch. Since traffic counters are only used as an index of fishing effort, our analysis may be accurate as long as fishing effort from all sources is correlated in timing. An additional requirement of traffic counters is the provision of independent information on relative proportion of fishing and non-fishing traffic to the launch and actively fishing per hour. We have shown that effort estimates may be sensitive to sample size of observations of fishing effort and traffic. In most situations where so many independent counts were deemed necessary, it may be that traffic counters are not necessary and sufficient accuracy can be gained just from creel surveys. The decision on how many independent data observations will depend on the dynamics of the fishing location (i.e. require some sample size planning; Barrett et al., 2017).

Although there are benefits to using traffic counters concurrent with a creel survey (Steffe et al., 2008), it is not necessary. The benefit of combining the two survey methods is the ability to estimate total catch and harvest available through the creel survey (Steffe et al., 2008). However, if fishing effort is the sole information needed, it may be logistically advantageous to install a traffic counter concurrently with a motion-detecting camera, which photographs vehicles arriving and departing from the lake. Photos from the camera could be sub-sampled by a set number of days, which would provide trip times (if individual vehicles could be identified upon arrival and departure) and the relative proportion of fishing boats, non-fishing boats and vehicles with no boat. This method entirely removes the need for on-site counts of anglers and traffic, thereby making traffic counters well-suited for remote locations.

Like all technology, traffic counters may be prone to failure. van Poorten et al. (2015) treated camera data as a covariate of fishing effort, so that camera failure resulted in a need for imputation to ‘fill in’ missing observations using data from adjacent monitored fisheries. Likewise, Hartill et al. (2016) used Generalized Linear Models to predict trailer boats based on similar data at adjacent sites, due to their high temporal correlation; Lancaster et al. (2017) used a Generalized Linear Mixed Model to fill in compliance data using environmental and geographic data. The choice of which method to use for imputation will influence overall estimates, as each imputation method has its own assumptions (Garcia-Laencina et al., 2010). Our method for estimating fishing effort from traffic counters treats observations as data to fit, so missing data do not need to be imputed. The state-space model simply estimates trips based on hyper-parameters assuming all estimated parameters are exchangeable. Doing so allows information to be drawn from the entire data series to inform estimates of effort. Moreover, traffic counters can be used in isolation, rather than requiring similar lakes to be concurrently monitored. In this way, traffic counters are a novel effort monitoring tool and may be useful in situations where other methods were previously impractical.

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