**Estimating angler effort and catch with creel survey data in a   
Bayesian state-space framework**

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**1. Background**

Creel surveys can be used to achieve many different objectives but often their primary purpose is to estimate recreational fishing effort and catch rates that can subsequently be used to estimate catch. Therefore, the goal of a creel survey is to collect data that characterizes the true fluctuations in angler effort and catch rates over a given period of time, which are being influenced by a suite of underlying processes (e.g., abundance of fish, water temperature, turbidity, day of year, time of day, etc.). However, the true fluctuations in effort and catch rates can be obscured by variation in the data that is strictly due to the sampling process. This uncertainty in temporal measurements, or rather “inaccuracy” in observations, is referred to as observation error (De Valpine 2003).

Observation error can come in many different forms but typically arises in creel survey data due to three main reasons. First, true fishing effort and catch rates are continuous underlying variables. However, it is impossible to count fractions of anglers and for anglers to catch fractions of fish. Therefore, creel survey data will contain sampling error due solely to the fact that our observations are a discrete realization of a continuous process. Second, creel survey data typically provide a snap-shot of fishing effort at various times of the day and a sample of catch rates from a subset of anglers. Thus, creel estimates will almost always contain sampling error because fishing effort typically varies throughout a given day and individual anglers will almost always have varying rates of success. Lastly, creel data can be collected imperfectly whereby anglers can be miscounted and anglers can misreport their catch and time spent fishing. Ultimately, the influence of each one of these three sources of error has on the estimates will depend on the study design, characteristics of the fishery, and staff training. Nonetheless, if left unaccounted for, observation error can lead to biased estimates. Fortunately, analytical techniques have been developed which attempt to separate observation error and real “biological” signal and one such approach is referred to as state-space modeling.

State-space models offer a robust and flexible framework for characterizing the dynamics of a system that is subject to observation error (De Valpine 2002). Specifically, a state-space model works by partitioning a time series dataset into two parts: the process model and the observation model. First, the process model provides a mathematical description of the factors that influence the true unobserved (i.e., latent) “states” (e.g., daily catch rates), how the states are linked in time, and a way to account for fluctuations in the data that cannot be ascribed to measured covariates (i.e., process error). Second, the observation model specifies the relationships between the observed data and the unobserved states and aims to account for the error associated with the observations. State-spaces models can be fit using various methods, however, Bayesian methodologies have become a popular choice due to their ability to characterize complex nonlinear models and their clear depiction of parameter uncertainty (De Valpine 2003; Clark and Bjørnstad 2004; Patterson et al. 2008).

Inherently, creel survey data provide a time series of fishing effort and catch rates that will likely contain both process and observation error. Thus, a state-space model provides an ideal framework to analyze creel survey data but, to our knowledge, no one has used this approach. Therefore, we constructed a Bayesian state-space (BSS) model to analyze creel survey data with the ultimate goal of providing unbiased estimates of recreational catch that accurately depicts uncertainty. Our BSS model explicitly allows for serial auto-correlation in fishing effort and catch rates among days and covariance in fishing effort and catch rates among angler types (e.g., bank, boat) and sections of a river. The current version of the model is designed to analyze creel survey data that was collected using a roving creel study design (Pollock et al. 1994). However, our BSS model could be reparametrized to accommodate other creel study designs (e.g., access survey). For illustration, we applied our BSS model to one season of creel survey data that were collected from a fishery in the Skagit River watershed located in northern Washington that is primarily focused on catch-and-release of wild winter steelhead. This fishery is of great public interest as it not only provides one of the few recreational fisheries for wild winter steelhead in the Puget Sound region but is also part of a larger population that has been listed as Threatened under the federal Endangered Species Act (ESA) since 2007.

**2. Methods**

**2.1. Data analysis – Bayesian state-space (BSS) model**

*2.1.1. Process model*

Total catch *C* on a given day *d* for a particular gear type *g* and river section *s* was modeled with Poisson error as a function of two independent and unobserved state variables and an offset:

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| --- | --- | --- |
|  |  | (1) |

where *λC* was the mean daily catch rate (i.e., CPUE; fish per angler-hour), *λE* was the mean daily effort (i.e., instantaneous number of anglers), and *L* was the total amount of available fishing hours per day (e.g., sunrise to sunset).

The first unobserved state, mean daily catch rate *λC*, was modeled as a log-linear function of the season-long catch rate intercept plus a residual accounting for day-to-day deviations from

the seasonal intercept:

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| --- | --- | --- |
|  |  | (2) |

where the catch rate residual was assumed to be serially auto-correlated and thus modeled as a function of the residual in the previous day multiplied by an auto-regressive (AR), mean-reverting lag-1 coefficient *φC* plus a process error term :

|  |  |  |
| --- | --- | --- |
|  |  | (3) |

where the CPUE process errors were multivariate normally distributed, with mean zero and covariance matrix :

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| --- | --- | --- |
|  |  | (4) |

where was the product of a constant process error variance and an correlation matrix :

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| --- | --- | --- |
|  |  | (5) |

where was specified one of two ways. One specification of was an identity matrix, which modeled CPUE process errors for each pairwise gear and section combination as being uncorrelated. An alternative specification of modeled CPUE process errors as being equal to the correlation between a particular gear and section combination (denoted *i*) and any other gear and section combination (denoted *j*).

The second unobserved state, mean daily effort *λE*, was modeled as a log-linear function of the season-long effort intercept plus a residual accounting for day-to-day deviations from the seasonal intercept plus a fixed effect accounting for the effect of day type on effort, where is an indicator variable denoting whether an individual day was either a weekday or weekend/holiday:

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|  |  | (6) |

A weekend effect was included to account for the possibility of angler effort being higher on weekends and holidays relative to weekdays. The effort residual was assumed to be serially auto-correlated and thus modeled as a function of the residual in the previous day multiplied by an auto-regressive (AR), mean-reverting lag-1 coefficient () plus a process error term :

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| --- | --- | --- |
|  |  | (7) |

where the effort process errors were multivariate normally distributed, with mean zero and covariance matrix :

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| --- | --- | --- |
|  |  | (8) |

and was the product of a constant process error variance and an correlation matrix :

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| --- | --- | --- |
|  |  | (9) |

where was modeled the same as ; either as an identity matrix or with effort process errors being equal to the correlation between a particular gear and section combination (denoted *i*) and any other gear and section combination (denoted *j*).

*2.1.2. Data and observation model*

There are many different types of creel survey sampling designs (see Pollock et al. 1994). However, regardless of the specific study design, there are generally two main components of the creel data collection process. The first component of the creel data collection process consists of angler interviews whereby individual anglers or groups are asked a pre-defined list of questions. The list of questions asked during an interview can vary based on the goals of a specific creel survey but at minimum anglers are asked how many fish have been caught (i.e., brought to “hand”) and over what duration so that their catch rate can be calculated.

Catch rate data are intended to characterize the number of fish that are captured (i.e., caught) by anglers for a given amount of angling effort. This is referred to as catch per unit effort (CPUE) and typically calculated as catch per hour. We modeled the catch *C* of individual anglers or groups *a* for a given day *d*, gear type *g* and river section *s* with Negative Binomial error:

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| --- | --- | --- |
|  |  | (10) |

where is the latent (i.e., unobserved) mean hourly catch rate, is an offset for the number of hours an individual angler or group fished, and is the over-dispersion parameter accounting for among angler (group) variability in CPUE.

The second component of the creel data collection process consists of angler counts. Angler counts are intended to characterize fishing pressure by providing a snap-shot of angler effort on a given day and time. When an effort count encompass the entire spatial area of a fishery and anglers are perfectly detected, this survey is referred to as census count, or rather tie-in effort count. The number of anglers observed during a census count of effort at given time *i* within a day *d* for a particular gear type *g* and river section *s* was modeled with Negative Binomial error, parameterized as a Gamma-Poisson mixture:

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| --- | --- | --- |
|  |  | (11) |

where was the latent mean hourly effort and *εE* was the Gamma random variate accounting for overdispersion in the census effort counts due to within-day variability in angler pressure. Effort counts were modeled as a Gamma-Poisson mixture to enable explicitly modeling the effort deviation from the daily mean at the time *i* of a particular census count for use in additional likelihoods. Specifically, these additional likelihoods come in the form of “index” effort counts.

As the name implies, index effort counts are designed to characterize angling pressure at a subset of locations within the boundaries of the total fishing area. Index effort counts are often employed because it is typically impractical to census fishing effort during each angler count. Therefore, index effort counts are usually conducted multiple times per day on each survey day while census counts are conducted once per day on a subset of survey days. On the subset of survey days when census counts are conducted, the census count is paired with one of the index counts so that they occur at the same time. In order to model the relationship between the census effort count and the index effort count on day *d* at time *i*, the same residual from the daily mean effortmust be applied to both the index and census effort counts.

Index effort counts can be conducted in many different ways. Anglers can be directly enumerated in the subset of index sites and/or indirectly enumerated via counts of their vehicles and/or boat trailers. It may be advantageous to enumerate anglers indirectly if vehicles and boat trailers are more visible and located at a smaller number of possible locations, which would result in a higher proportion of the total angling effort being enumerated. However, if vehicles and boat trailers are enumerated, these indirect counts need to be converted to an estimate of anglers in order to be paired with the catch rate data. Regardless of whether anglers are directly and/or indirectly enumerate, the relationship between angler effort that occurs in the standardized index reaches relative to angler effort throughout the entire river needs to be quantified. Therefore, index counts of anglers *I*, vehicles *V*, and boat trailers *T* at given time *i* within a day *d* for a particular gear type *g* and river section *s* were modeled with Poisson error:

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| --- | --- | --- |
|  |  | (12) |
|  |  | (13) |
|  |  | (14) |

where is the fixed proportion of angler effort observed in an index area, which are assumed to be a subset of the total. For vehicle and trailer count likelihoods, and are the proportions of vehicles and trailers per angler, respectively. The proportion of anglers with trailers and vehicles were assumed to be less than one per angler and consequently and were estimated using a binomial distribution:

|  |  |  |
| --- | --- | --- |
|  |  | (15) |
|  |  | (16) |

where *V* and *T* are the number of vehicles and trailers that individual angler groups *a* brought to the river, respectively, and *A* is the number of anglers that are part of that particular group. The bias terms and can be thought of as expansion factors describing how many more or less vehicles and trailers were counted relative to how many anglers were present and the number of trailers and vehicles expected based on the proportions of anglers bringing trailers and vehicles to the river. The bias term can be less than, equal to, or greater than one depending on what proportion of the total number of vehicles and trailers are counted (i.e., observer efficiency) and what proportion of vehicles and trailers belong to anglers versus non-anglers. For example, if 100% of vehicles can be enumerated but angler and non-angler vehicles cannot be differentiated and 30% of the vehicles belong to non-anglers, then the estimated bias term will be less than one. For direct counts of anglers can be thought of as the observer efficiency (i.e., the average proportion of anglers that were observed fishing in the index areas relative to the entire river section) and will be between 0 and 1.

*2.1.3. Prior distributions and MCMC simulations*

Bayesian analyses of state-space models require that prior probability distributions be specified for all parent and global variables (e.g., initial states, variances, fixed effects). In general, most prior distributions were designed to be vague (see Table 1), thereby allowing the likelihoods to dominate in determining the posterior. We tested the sensitivity of priors by simulating datasets and evaluating the results for bias. It is worth noting that the choice of certain priors will vary based on the specific attributes of a particular fishery (e.g., mean daily effort and mean daily catch rate).

The creel state-space models were analyzed using the software program Stan (Carpenter et al. 2017) to generate posterior probabilities of all unknown parameters in the model. Stan implements gradient-based MCMC methods termed “Hamiltonian Monte-Carlo” via the “No-U-Turn” sampler and often provides improved sampling efficiency that leads to faster inference when compared to other MCMC software implementations (Ames and Au 2018). We interfaced with Stan using Program R (R Development Core Team 2019) and the *rstan* package (Stan Development Team 2018a). We ran four Markov chains with a burn-in period that was greater than or equal to 50% of the total number of iterations. The total number of iterations that were specified per chain was dependent on model convergence. Models were accessed for convergence using a range of diagnostic tools offered in the *ShinyStan* package (Stan Development Team 2018b) including, visual examination of posterior distributions and trace plots, calculation of effective sample sizes (ESS) and , and checking for divergent transitions (Stan Development Team 2018c). Based on these steps, we assume that our reported posterior distributions are accurate and represent the underlying stationary distributions of the estimated parameters.

**2.2. Data collection – 2019 Skagit River fishery**

Creel surveys on the Skagit River were initiated on February 1st, 2019, which marked the opening day of the river, and will continue through the end of the season that ends on April 30th, 2019. The fishery was open on parts of the mainstem Skagit River (from the Dalles Bridge in the town of Concrete up to the Cascade River Road Bridge in Marblemount) and its main tributary, the Sauk River (from the mouth of the Sauk up to the Darrington Bridge). Fishing regulations mandated: Selective Gear Rules, Night Closure, and catch and release only for all game fish, except up to two hatchery steelhead may be retained (see WDFW Emergency Fishing Regulations).

A stratified random survey design was used to conduct roving-roving creel surveys following the methods outlined in Malvestuto et al. (1978), Pollock et al. (1994) and Hahn et al. (2000). First, the survey was stratified by day-type (weekday or weekend) and four to five sample days were randomly selected consisting of two to three weekdays and both weekend days per week. Second, the survey was stratified within each sample date by shift (AM or PM). The second temporal stratification is typically used to allocate sampling effort to either an AM or PM time frame. However, both “shifts” were sampled on each survey date and the stratification was mainly used for scheduling staff. Specifically, AM shifts began approximately at sunrise and continued for the next six to eight hours on the river while PM shifts began six to eight hours before sunset and lasted until sunset. On each survey date, two technicians were assigned to each shift, where generally one technicians would survey the mainstem Skagit River and would survey the Sauk River.

During each sample day, technicians conducted both index effort counts and angler interviews. Generally, three index effort counts were conducted per day and the start times were randomly selected. Effort counts were designed to be “instantaneous” in that all index sections of a particular river was surveyed in approximately one hour or less. During each effort count, the technician would survey the predefined set of index locations and enumerate the number of parked vehicles and boat trailers. In between effort counts, anglers were opportunistically interviewed. When a group of anglers were fishing together, the data for the group was collected as a single interview. During an interview, the angler (group) was asked a predefined list of questions that included: angler type (boat, shore), gear usage (fly, gear), number of anglers in the group, number of vehicles and boat trailers brought to the river, when fishing started and ended, trip status (incomplete, complete), fishing location (Skagit, Sauk), and number of fish caught. If any fish were caught, additional information was collected for each individual fish, including: species, origin (hatchery, wild), and fate (harvested, released). On a subset of sample days, census effort count (i.e., ‘tie-in’ surveys) were conducted by helicopter. Anglers were directly enumerated and classified as either a boat or shore angler. Tie-in surveys occurred on one to two sample days per week concurrent with the midday index effort count.

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| **Table 1.** Prior distributions for model parameters | | |
| Parameter | Default Prior | |
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| V |  |
| T |  |
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