A Generalized Additive Mixed Effects Modeling (GAMM) Approach to Short-term River Temperature Forecasting for the Fraser River, British Columbia: Model Evaluation and Implications for Salmon Fishery Management

by

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Bachelor of Arts, University of British Columbia, 2007

Project Submitted in Partial Fulfillment of the
Requirements for the Degree of
Master of Resource Management

in the
School of Resource and Environmental Management
Faculty of Environment
Report No. 635

SIMON FRASER UNIVERSITY

Spring 2016

Approval

Name:	**Lindsay Gardner**
Degree:	**Master of Resource Management**
Report No.	**635**
Title:	***A Generalized Additive Mixed Effects Modeling (GAMM) Approach to Short-term River Temperature Forecasting for the Fraser River, British Columbia: Model Evaluation and Implications for Salmon Fishery Management***
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Date Defended/Approved: January 7, 2016

Abstract

Climate change is increasing the frequency and intensity of extreme lethal and sub-lethal temperature events in Canada's salmon-producing rivers. As a result, some salmon populations are increasingly vulnerable to in-river mortality during spawning migrations, making escapement and harvest objectives difficult to achieve. Harvest adjustments associated with river temperature forecasting are currently made on a limited basis to address temperature-related en route mortality of sockeye salmon in the Lower Fraser River in British Columbia; however, these forecast models are complex, data intensive, location specific, and costly to develop and operate. Here, I develop a Generalized Additive Mixed Modelling (GAMM) approach to provide broader spatial coverage, more flexible, and cost effective implementation of river temperature forecasting for use in in-season harvest management.

Keywords: Salmon; river temperature; climate change; river temperature forecasting; statistical model, salmon harvest adjustment.

Acknowledgements

I would like to thank David Patterson and Sean Cox for their supervisory support in this project, Michelle Jones and Eduardo Martins for their technical and coding support, and Lisa Thompson, Marla Maxwell, Chuck Parken, Richard Bailey, and Bronwyn Macdonald for providing data crucial to this study.

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1. Introduction

Water temperature plays a dominant role in the health, survival, and migration success of salmonids (Fry 1971). Elevated river temperatures (Isaak et al. 2012) and higher frequencies of weather extremes associated with climate change (Easterling et al. 2000) are adversely affecting some salmon populations as they migrate upriver (Cooke et al. 2004; Hinch et al. 2012). In British Columbia's Fraser River, mean annual temperature has increased by approximately 2°C over the past 50 years (Patterson et al. 2007b), making the number of days exceeding critical temperature thresholds for salmonids more frequent (Hague et al. 2011). Expected temperature increases of 2 - 4°C over the next several decades (Morrison et al. 2002; Ferrari et al. 2007) will likely have further negative effects on the survival of Fraser River salmon populations (Hague et al. 2011).

Some Pacific salmon populations migrate up river during the hottest weeks of the year, exposing them to more frequent occurrences of lethal or sub-lethal water temperatures (Martins et al. 2012). Exposure to high temperatures can raise mortality rates through a number of mechanisms, including increased susceptibility to parasites and disease (Crossin et al. 2008; St-Hilaire et al. 2002; Wagner et al. 2005), cardiac limitations due to oxidative stress (Steinhausen et al. 2008), reduced swimming ability (Lee et al. 2003), depletion of energy reserves (Rand and Hinch 1998), delayed migration (Hyatt et al. 2003), and reduced spawning activity (Hodgson and Quinn 2002). Higher natural mortality rates will lead to a reduced ability to meet spawning escapement and harvest objectives. In response to high temperatures, fishery managers can be proactive and adjust allowable harvest to facilitate higher escapement, thus incorporating elevated mortality into salmon management plans (e.g. Macdonald et al. 2010).

In-season harvest adjustments are made to some migrating populations based on continually updated estimates of run size and timing; however, these adjustments rarely incorporate river temperature, despite evidence that rising water temperatures are having a negative impact on in-river survival (Pelletier et al. 2007). For example, only 17% of North American fisheries agencies incorporated extreme temperatures into catch-and-release guidelines as of 2007 (Pelletier et al. 2007). Two examples exist in Canada where extreme temperatures influence salmon fishery management. Recreational fisheries in

Atlantic Canada close when minimum daily water temperatures reach 20°C, and do not reopen until temperatures remain below this threshold for a minimum of 2 consecutive days (Dempson et al. 2001; Breau and Caissie 2013). A limitation of this approach is that it provides no lead-time or notice to fishermen of impending closures. In a second example, total allowable catch (TAC) of Fraser River sockeye salmon is adjusted during the fishing season to compensate for potentially higher en route mortality during warmer periods (Patterson and Hague 2007). These in-season adjustments are based on 10-day temperature and flow forecasts from complex, location-specific models (Hague and Patterson 2014). Expanding on these efforts to incorporate environmental variables such as river temperature into in-season fishery management beyond these specific examples could prove valuable as rising temperatures increasingly threaten migrating salmon populations.

Several obstacles currently limit using water temperature and other environmental variables for in-season salmon management. First, estimates of en route loss (i.e. the number of salmon that will not successfully complete the spawning migration) caused by high temperature are highly uncertain (Patterson et al 2007a), so temperature-related fishery interventions are difficult to justify. Although en route loss is estimated for some sockeye salmon populations in the Fraser River, data on a population-level scale is not currently available for most other salmon populations or species. Second, environment-based fishing restrictions may be too disruptive to First Nations, recreational, and commercial fisheries that depend on the resource. For example, managers typically adjust harvest pre-season based on available knowledge about abundance, migration timing, and water temperature (e.g. Dempson et al. 2001; Boyd et al. 2010; Breau 2013). Reacting too often, or too suddenly, to changing environmental conditions within the season could make the fishery too unpredictable. Third, while river temperature forecasting models can help reduce uncertainty about fishery closures noted above – by allowing managers to make harvest adjustments based on environmental variables in-season – most river temperature forecasting models are complex, expensive to develop and maintain, and require large amounts of in-season data that may not be available in a timely manner. Finally, uncertainty in forecasting model inputs and outputs (Caissie et al. 2007; Hague and Patterson 2014) could cause stakeholders to mistrust the models and resulting decisions.

Despite these obstacles, two approaches - hydrologic models and statistical models - have been used to generate short-range water temperature forecasts for in-season harvest adjustments. Hydrologic, or physical models, represent complex heat transfer processes based on physical inputs such as dew point, solar radiation, wind speed, air temperature, and hydrology (Foreman et al. 2001; Benyahya et al. 2007). The technical complexity, extensive data requirements, and cost of development and operation limit their broad applicability to in-season management (Benyahya et al. 2007). By contrast, statistical models require less physical input data and typically use readily available measurements of air temperature, river flow, and water temperature along with historical seasonal trends to generate short-term river temperature forecasts. Although simple statistical models may have fewer parameters, they can still be robust for forecasting short-term river temperatures (Benyahya et al. 2007), while requiring less specialized knowledge to operate compared to more complex hydrologic models. Statistical models have been developed for fisheries management and used to forecast river temperature in the Fraser River, BC (e.g. Hague and Patterson 2014), the Miramichi River, NB (Caissie et al. 2001) and Klamath River, USA (Huang et al. 2011), but these are location-specific, and not readily portable to other rivers both within and across watersheds. Therefore, I sought alternative statistical methods that may be more flexible to generate short-term temperature forecasts in a wider range of rivers, where high temperature events may threaten migrating fish populations.

In this paper, I evaluate a generalized additive mixed effects model (GAMM) for short-term forecasting of river temperatures in the Fraser River watershed. A GAMM approach models in-season temperatures by combining a linear regression model for daily water temperature with a sinusoidal smoothing spline of seasonal trends. A GAMM provides a flexible method for fitting non-linear covariate effects via the smoother (Hastie and Tibshirani 1995), rather than fitting a time-series or seasonal harmonic model (e.g. Kothandaraman 1971; Caissie et al. 2001). This approach can allow lead-time to reduce fishing pressure during extreme temperatures that would otherwise exacerbate thermal stress and related en route mortality. In evaluating the GAMM method of river temperature forecasting, I use 6-20 years of water temperature data in nine river locations throughout the Fraser River watershed (Figure 1). Model performance is based on forecast accuracy compared to observed mean daily temperatures, and the frequency of errors that occur when predicting specific temperature thresholds related to thermal tolerance limits of salmon populations. I compare forecasting performance of the GAMM to the short-term forecasting models that are operational for the Fraser River (at Hope).

I constructed a GAMM to forecast water temperature using 3 steps: 1) selecting the best model from relevant input variables and random effect structures; 2) model verification – testing model performance based on simulated (known) water temperature data; and 3) prediction – forecasting water temperature and comparing results with existing models using actual predicted weather and observational data. I constructed a simulator to verify the model forecasts (5-day predictions), and compared simulated results to historical observed data (Figure 2). I selected a 5-day forecast window to provide sufficient accuracy in forecast results, while also supplying lead-time for potential harvest adjustments. Because in-river fisheries can be concurrent with high river temperatures, advanced warning of these events can allow for adequate preparation. A 5-day window allows advance notice for fishing guides and independent anglers in the event that harvest restrictions are implemented. All steps were conducted using R version 3.1.2 (R Core Team 2014).

2. Methods

2.1. Data Sources

I obtained historical daily river temperatures in the Fraser River watershed from Fisheries and Oceans Canada's (DFO) Environmental Watch Program (Thompson et al. 2010). River temperature data from 1995-2014 were examined for nine rivers varying in size and climate (DFO): the Fraser River at Shelley, Quesnel, Horsefly, Chilcotin, Thompson, South Thompson, Coldwater, Fraser at Hope and Chilliwack (Figure 1, Table 1). These rivers had multiple years of discharge and water temperature data, as well as air temperature records nearby, with which to test model accuracy. Data sources for discharge and air temperature included Water Survey of Canada (www.wateroffice.ec.gc.ca) and the Meteorological Service of Canada (www.climate.weatheroffice.gc.ca). Data were subset to seasonal timeframes between June 15 and September 21 to encompass the warmest period of water temperatures.

2.2. Step 1: Model Selection

The following variables were used as fixed effects in a mixed-effects model: discharge, air temperature, water temperature, and location. Discharge (Q, m^3/s) was chosen as a predictor variable to account for the inverse relationship between discharge and river temperature (Webb et al. 2003). Air temperature (A, °C) was included due to the high correlation between air and water temperature (Kothandaraman 1972), (Stefan and Preud'homme 1993) from heat exchange processes (Mohseni and Stefan 1999). Current water temperature (T, °C) is a predictor of water temperature in the near future (Caissie et al. 1998). Finally, location (L) was included as a fixed effect due to the differences in mean temperature at each location, as well as the location-specific effects of air and discharge on river temperature. Air temperature, river temperature and discharge are collected in a variety of locations on a relatively consistent basis throughout the year, and consequently, they can be used to predict short-term river temperature (5 days). Using a model with all fixed effects, I selected a random effect structure (using restricted maximum likelihood, REML) from combinations in which the model intercept varies by year, and the discharge and air temperature effects vary by location, with and without an intercept. Once a random effect structure was selected, model selection was applied to determine the best approximating fixed effects structure using Akaike's Information Criterion, adjusted for small sample size (AIC_c) (Table 2). The selected model (lowest AIC_c value, Regional GAM Model, "RGM") was refitted using REML, and included 1-day lagged water temperature, air temperature and discharge terms, as well as interaction terms for discharge-location and air temperature-location:

$$T_{i,j} = (\alpha + \mu_j) + \beta_1 A_{i-1,j} + \beta_2 Q_{i-1,j} + \beta_3 T_{i-1,j} + \beta_4 A_{i-1,j} * L + \beta_5 Q_{i-1,j} * L + f(day_i) + \varepsilon_{i,j} \quad (1)$$

$$\varepsilon_{i,j} \sim N(0, \sigma_e^2),\ \mu_j \sim N(0, \sigma_\mu^2)$$

where $T_{i,j}$ = predicted river temperature on day *i* in year *j*, α = intercept, $A_{i-1,j}$ = 1-day lagged air temperature, $Q_{i-1,j}$ = 1-day lagged discharge, $T_{i-1,j}$ = 1-day lagged water temperature, $A_{i-1,j}*L$ = interaction of air and location, $Q_{i-1,j}*L$ = interaction of discharge and location, and *f* represents a cubic regression spline smoothing function of Julian day, which allows the model to fit the seasonal trend. Interaction terms were included to account for the location-specific effects of air and discharge on river temperature. The residual error (ε), and year-specific variation of intercept (μ_j) are normally distributed with a mean of zero. I fit this model to all air temperature, water temperature and discharge data across all locations, excluding the final three years in each location for model verification. Standard diagnostics (QQ plot, residual plot, auto-correlation plots) confirmed the model met homoscedasticity, normality and independence of residuals assumptions (Appendix A).

2.3. Step 2: Model Verification

I evaluated model performance by predicting water temperature at 5-day intervals for each day throughout a 95-day season, from June 15 - September 21 of the final three years available in each location (Figure 2). To forecast 5 days ahead, the RGM forecasts river temperature for the following day, and uses this forecasted temperature to predict the next daily temperature until day 5 is reached. Because forecasted inputs for A and Q are not available for all locations, I used historical observed inputs for all forecasts. I conducted 1000 simulations of each 5-day forecast, storing the mean and standard deviation of the forecasts for each day (Figure 2).

I compared temperature forecasts to historical observed data and calculated summary statistics using mean raw error (MRE), root mean square error (RMSE) and mean absolute error (MAE):

(2) $$MRE = \frac{1}{n}\sum_{1}^{n}\left(\hat{T}_w - T_w\right)$$

(3) $$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(\hat{T}_w - T_w\right)^2}$$

(4) $$MAE = |MRE|$$

where n = total number of forecasts (95), $\hat{T}_w$ is the predicted daily water temperature and T_w is the observed daily water temperature. MRE is used as a measure of forecast bias, while RMSE and MAE measure forecast accuracy and precision, in the former by weighting larger errors more heavily than MAE, and in the latter by calculating the average absolute error (Cummings et al. 2011).

I also evaluated the forecast model by examining the probability of exceeding critical temperature thresholds that may be used to prompt management intervention where necessary. These thresholds were determined by adding the location-specific mean temperature with 1, 1.5 and 2x the standard deviation to respective summer mean temperatures. These values approximate upper thermal tolerance limits for some salmon populations migrating through the warmest locations. For example, the high temperature limit in the Fraser River at Hope is 21°C, which represents a lethal or sub-lethal temperature for certain sockeye populations exposed for several days (Eliason et al. 2011). I used forecast and observed day-5 temperatures to compute the probability of the following events:

a –The forecasted and observed temperature were both above the threshold value – “true positive”;

b – The forecasted temperature was below the threshold, but the observed temperature was above the threshold – false negative or “missed event”;

c – The forecasted temperature was above the threshold, but the observed temperature was below the threshold – false positive or “false alarm”; and

d – The forecasted and observed temperature were both below the threshold value – “true negative”.

Type I (false positive) error rates are defined by:

(5) $$T1 = \frac{c}{a+c}$$

Type II (false negative) error rates are defined by:

(6) $$T2 = \frac{b}{a+b}$$

For a false positive error, harvest restrictions may unnecessarily limit fishing opportunity because river temperature was predicted to be warmer than the critical threshold (T_{crit}), but observed temperatures were below the threshold. Conversely, failure to predict a high temperature event, a false negative error, may both fail to compensate for additional natural mortality as well as expose migrating fish to the compounded strain of thermal distress and interactions with fishing gear.

2.4. Step 3: Model Prediction

I ran 5-day forecasts using the RGM on the same dates as currently used in-season temperature forecast models in the Fraser River at Hope to test prediction accuracy against current in-season models: the Institute of Oceanographic Sciences River Temperature Model (IOSRTM), and the Hope Statistical Model (HSM). The IOSRTM is a deterministic hydrologic model based on physical processes such as heat transfer and hydrology, as well as meteorological inputs (solar radiation, cloud cover, dew point, air temperature, wind speed) to predict river temperature at a specific site downstream (Foreman et al. 1997). HSM is a stochastic model that combines seasonal (harmonic) and non-seasonal components (A, Q and T) as inputs (Hague and Patterson 2014). All three models used predicted air temperature and discharge to forecast water temperature. Air temperature and discharge forecasts were retrieved from Environment Canada and the IOSRTM, respectively.

The IOSRTM and HSM models were included in post-season analyses conducted for 2013-2015, and run twice weekly from late June – early September. This study compares all results at 5 forecast days for consistency, although the IOSRTM and HSM were originally developed to be optimized to 10 days.

3. Results

Model Selection

I compared models with all possible combinations of fixed and random effects to determine the relative support for each model using AIC_c. The final model (i.e. lowest AIC_c value, Equation 1) includes *Location* as an interaction term with both air temperature and discharge (Table 2), acknowledging the varying effect that these variables have on water temperature at different location. Parameter estimates in the final model are listed in Table 3; estimates are in reference to Chilliwack mean river temperature as the model intercept.

Model Verification

Across locations, river temperature forecasts from the RGM showed mean raw error (MRE) values ranging from 0 – 0.8°C; root mean square error (RMSE) values of 0.29 – 1.38°C; and mean absolute error (MAE) values of 0.23 – 1.09°C (Figure 3). The Coldwater River had the largest variability in water temperature among the rivers examined (SD = 4.64°C; Table 1), and produced the largest errors (MRE 0.90°C, RMSE 1.38°C, MAE 1.09°C), whereas the Fraser River at Hope produced the smallest errors (MRE -0.006°C, RMSE 0.28°C, MAE 0.23°C; Figure 3). River temperature forecast errors averaged across locations showed a MRE of 0.32°C, RMSE of 0.75°C and MAE of 0.54°C (n=6,951). These errors indicate that the RGM has relatively low bias overall, with an average of 0.54°C difference between observed and predicted river temperatures.

Average false positive and false negative error rates vary by location and threshold, but are larger at low versus high thresholds on average (i.e. 1 SD from the mean, versus 2 SD; Table 4). Because high threshold temperatures are less frequent, errors in predicting these temperatures are also less common. The frequencies of false negative and false positive errors are comparable, representing an equal trade-off between the two errors. Consistent with MRE results, these false positive and false negative errors indicate that the model tends neither to over- nor under-predict overall.

Model Prediction: Performance Evaluation

For the years I evaluated, the RGM produced lower MRE, RMSE and MAE values (Figure 5), indicating higher precision and accuracy compared to current models (n=51). Uncertainty associated with predictor variables can be a significant source of uncertainty in water temperature forecasts. However, although the MAE of air temperature forecasts was between 0.88°C and 2.22°C (days 1-4), air temperature had a similar effect on water temperature forecasts, whether observed or predicted. RGM false positive errors represented a lower proportion of total forecasts over the threshold (0.04, SD 0.05) in comparison to those from IOSRTM (0.21, SD 0.14) and HSM (0.23, SD 0.24). RGM false negative errors are higher than false positives in proportion to total forecasts over each threshold (0.23, SD 0.23), but are lower than the IOSRTM (0.32, SD 0.11), and the HSM (0.50, SD 0.27). Threshold error rates can vary between years. For example, the IOSRTM model missed 15 events across all three thresholds in 2013 (out of 48 forecasts), compared to only one missed event in 2014. This variability generates uncertainty as to how well each model will predict in coming years. The RGM, by contrast, shows more consistency across years, most notably at lower thresholds, producing two missed events in 2013, and three in 2014.

4. Discussion

Migrating salmon populations face compounding effects of thermal stress (Hinch et al. 2012; Cooke et al. 2004) and fishing pressure (e.g. Boyd et al. 2010) as river temperatures increase due to climate change (Easterling et al. 2000; Isaak et al. 2012). In-season harvest adjustments, assisted by short-term temperature forecasting (Caissie et al. 1998; Benyahya et al. 2007), represent one approach to mitigating these stresses. While different approaches have been taken to develop accurate short-term temperature forecasts (e.g. Foreman et al. 1997; Benyahya et al. 2007; Hague and Patterson 2014), most have been limited by data availability, complexity, technical difficulty, and cost. The Regional GAM Model (RGM) is an alternative statistical approach that can provide cost effective and widespread river temperature predictions with low data requirements. Whereas current in-season models have involved extensive parameterization to the Fraser River at Hope, and, in the case of IOSRTM, require considerable technical expertise to operate, the RGM provides a relatively simple platform to fit new locations.

RGM 5-day forecasted temperatures, predicted using historical observed inputs, were within 1°C of observed temperatures in the majority of rivers I examined, showing low positive bias overall (MRE 0.32°C). This finding is noteworthy, especially in rivers such as the South Thompson River and the Fraser at Hope, where temperatures in some predicted years were well above normal (e.g. 2013 & 2014). In these instances, negative MRE values would be expected, since the model was fit to many years, very few of which exhibited such high temperatures. The GAMM approach is not constrained by a harmonic to fit seasonal river temperature fluctuations, possibly making it better equipped to forecast extreme temperatures more accurately than other statistical methods that rely on seasonal harmonics (e.g. HSM). High river temperature and discharge variability may contribute to the larger errors in model predictions, as is demonstrated by the greater errors for Coldwater River forecasts. This result is consistent with Moore et al. (2014), who show higher temperature and flow variability in smaller catchment sizes. Because the Coldwater River has a mean (summer) discharge of only 5 m^3/s (CV 1.8), there may be other variables, such as groundwater influxes or rainfall, exerting stronger influence on river temperature than model inputs at this location.

Uncertain predictor variables are one of the primary sources of uncertainty in statistical water temperature forecasts (Breau and Caissie 2013; Hague and Patterson 2014). However, using forecasted air temperature and discharge had relatively little effect on temperature prediction accuracy for the Fraser River at Hope, probably because discharge projections are largely dependent on conditions and data from up-river. Accurate discharge forecasts are not as readily available for other locations, and as a result, in-season forecasts with predicted input variables may be less accurate in other parts of the region. Although air temperature forecasts (as opposed to actual values) have been found to decrease river temperature accuracy (Hague and Patterson 2014), air temperature forecast errors had minimal effect on water temperature forecasts for the Fraser River at Hope for the RGM.

Compared to other models used for in-season harvest adjustment, the RGM demonstrates lower false positive and false negative error rates, and less variability in their frequency, which reduces uncertainty in model forecasts. Because RGM error rates are more balanced between false positive and false negative errors, management trade-offs could be more equally offset using this model (Table 6). By contrast, the HSM and IOSRTM are more prone to false negative errors; in other words, actual temperatures exceed thresholds more often when they were predicted to fall below them, which could lead to potentially higher stress-induced mortality. False positive and false negative errors bear opposing consequences on a fishery; false positive errors may unnecessarily limit fishing opportunity, whereas false negative errors may cause higher mortality due to unforeseen high water temperatures. Forecasting performance for management planning depends on the target species' biological thermal limit(s), management priorities (conservation and/or maximizing fishing opportunity), forecast uncertainty, and the coincidence of run timing and extreme river temperatures. For example, choosing a low temperature threshold in the South Thompson River could ensure a conservative approach to managing en route mortality risk by lowering the potential for false negative errors. The trade-off, however, is that fishing opportunity may be dramatically reduced due to temperatures exceeding this threshold for the entire salmon migration through this region. Ultimately, managers must identify their objectives such that the threshold adopted and harvest control measures employed will successfully meet these goals (Cummings et al. 2011; Thornes and Stephenson 2001).

Recreational fishing management is a sector where in-season temperature forecasting may be particularly useful for mitigating the impact of extreme temperatures on salmon. Recreational salmon angling occurs primarily in rivers during adult migration, and a common method of restricting angling impacts is limiting a fishery to catch-and-release (Lucy and Studholme 2002; Cooke and Suski 2005). In general, catch-and-release improves the overall sustainability of recreational fishing (Policansky 2002); indeed, since 1984, stock declines in Atlantic Canada have prompted mandatory release for conservation purposes (O'Connell et al. 1992). However, the implicit assumption of catch-and-release – that fish will survive post-release (Wydoski 1977) – is improbable during high temperature events (Boyd et al. 2011; Gale et al. 2011). During these increasingly frequent occurrences, release mortality rises as temperature-related sub-lethal effects are exacerbated by factors such as hooking injury, air exposure, and handling time (Wilkie et al. 1996; Gale et al. 2013). In-season river temperature forecasts can assist management in areas where salmon migrations coincide with high temperatures, by providing notice of upcoming temperature increases, and notifying the fishing community of more restrictive limits to fishing.

Elevated salmon mortality due to rising river temperatures can be ameliorated by improving river temperature forecasting ability and robustness for in-season harvest adjustment. Indeed, expanding the ability to make harvest adjustments to fisheries especially affected by high temperatures may help to mitigate en route loss among different species. In this study, I found that the RGM produces short-term forecasts of similar accuracy to current approaches, and can be flexible to various river types and environments. Compared to current in-season prediction models, the RGM has similar error rates (observed versus predicted). But by contrast, the RGM produces lower false negative errors, and is more cost effective due to minimal data requirements and technical simplicity. The ability to forecast river temperatures with a level of uncertainty that is acceptable to managers will likely become a useful tool for salmon conservation efforts in the future.

5. Tables

Table 1: Summary statistics for nine river locations throughout the Fraser River watershed for June 15-September 21 of years available at each location. Discharge variation is calculated using coefficient of variation (CV) due to the large range in scales.

Location	Daily water temperature				Daily discharge				Average day of maximum temperature	Elevation	Geographic coordinates	Lake-headed	Air temperature	Years of data available
	Max	Min	Mean	Std Dev	Max	Min	Mean	CV						
Fraser at Shelley	19.0	7.9	13.3	2.2	4260	378	1302	0.50	04-Aug	575m	N 54° 00' W 122° 62'	N	Prince George	1995-2009
Quesnel	20.6	7.8	14.7	2.5	594	66	239	0.50	10-Aug	474m	N 52° 58' W 122° 29'	Y	Quesnel	1995-1996, 1998-2012
Horsefly	21.9	7.7	14.6	2.7	180	3	30	0.90	05-Aug	750m	N 52° 19' W 121° 24'	N	Williams Lake	1995-2012
Chilcotin	17.9	7.9	13.4	1.7	621	30	225	0.32	10-Aug	586m	N 51° 51' W 123° 02'	N	Williams Lake	1996-2011
Thompson	21.3	10.3	16.3	2.2	3740	332	1317	0.56	13-Aug	195m	N 50° 43' W 121° 16'	Y	Kamloops	1995-2008
South Thompson	22.8	9.7	17.2	2.6	1410	127	521	0.59	15-Aug	347m	N 50° 49' W 119° 41'	Y	Kamloops	1995-1998, 2000-2014
Coldwater	23.8	3.5	14.0	4.1	63	0	5	1.80	09-Aug	605m	N 50° 06' W 120° 47	N	Kamloops	2006-2012
Fraser at Hope	21.6	11.3	16.4	2.08	12,900	1390	4610	0.45	11-Aug	41m	N 49° 23' W 121° 26'	N	Kamloops	1995-2014
Chilliwack	17.2	7.9	12.3	1.8	154	7	46	0.72	18-Aug	10m	N 49° 09' W 121° 57'	Y	Chilliwack	1999-2000, 2006-2007, 2009, 2011

Table 2: Strength of evidence for alternative candidate models examining fixed effects of current and lagged air temperature (A), water temperature (T), discharge (Q) and location (L) on short-range water temperature predictions. Models were compared using small-sample bias-corrected Akaike's Information Criterion (AICc), differences in AICc (∆AICc) and normalized Akaike weights (AICcWt) representing the strength of evidence for each model. K represents the number of parameters in each model. The highest ranked model ($T_i \sim A_{(i-1)} + Q_{(i-1)} + T_{(i-1)} + L$) has a ∆AICc of 0.

Model	Description	K	AICc	ΔAICc	AICcWt	Cum.Wt
$T_i \sim A_{(i-1)}*L + Q_{(i-1)}*L + T_{(i-1)}$	A*L, Q*L, & T	32	15813	0	1	1
$T_i \sim A_{(i-1)} + Q_{(i-1)}*L + T_{(i-1)}$	Lagged A & T, forecasted Q and location	24	16050	237.29	0	1
$T_i \sim A_{(i-1)}*L + Q_{(i-1)} + T_{(i-1)}$	Lagged Q & T, forecasted A, & location	24	16146	333.81	0	1
$T_i \sim A_{(i-1)} + Q_{(i-1)} + T_{(i-1)}$	Lagged T, forecasted A & Q, & location	16	16335	522.42	0	1

Table 3: Coefficients of final model. The intercept of the model represents Chilliwack mean river temperature; all other locations vary by adding individual location coefficients to this value.

Parameter	Estimate	Std.	Error	t	value
Intercept	2.278	0.238	9.571	<	2.00E-16
Flow, 1-day lag	-0.005	0.001	-5.005	0.000	***
Air, 1-day lag	0.017	0.013	1.331	0.183	
Temperature, 1-day lag	0.817	0.005	153.791	<	2.00E-16
Location effects					
Coldwater	-0.097	0.276	-0.351	0.725	
Chilcotin	-0.280	0.241	-1.161	0.246	
Fraser at Shelley	-0.932	0.246	-3.787	0.000	***
Horsefly	-0.890	0.238	-3.740	0.000	***
Fraser at Hope	-0.300	0.243	-1.238	0.216	
Quesnel	-0.175	0.244	-0.719	0.472	
South Thompson	0.515	0.245	2.104	0.035	*
Thompson River	0.874	0.251	3.484	0.000	***
Interaction effects: Flow, 1-day lag					
Flow *Coldwater	-0.001	0.003	-0.233	0.816	
Flow*Chilcotin	0.004	0.001	4.004	0.000	***
Flow*Fraser at Shelley	0.005	0.001	4.864	0.000	***
Flow*Horsefly	0.001	0.001	1.082	0.279	
Flow*Fraser at Hope	0.005	0.001	4.972	0.000	***
Flow*Quesnel	0.003	0.001	2.945	0.003	**
Flow*SouthThompson	0.004	0.001	4.157	0.000	***
Flow*Thompson	0.005	0.001	4.697	0.000	***
Interaction effects: Air, 1-day lag					
Air*Coldwater	0.021	0.015	1.428	0.153	
Air*Chilcotin	0.031	0.014	2.274	0.023	*
Air*Fraser at Shelley	0.074	0.014	5.287	0.000	***
Air*Horsefly	0.080	0.013	5.931	0.000	***
Air*Fraser at Hope	0.044	0.013	3.287	0.001	**
Air*Quesnel	0.058	0.014	4.242	0.000	***
Air*South Thompson	0.026	0.013	1.965	0.049	*
Air*Thompson	0.000	0.014	0.004	0.996	

Table 4: **False positive and false negative errors as proportions of total forecasts over each threshold across all locations, as well as frequency of correct and incorrect predictions. Thresholds for each location represent 1, 1.5 and 2x the mean summer temperature for available years in each location.**

Location	Threshold	Proportion false pos	Proportion false neg	Correct above	False negative	False positive	Correct below
Fraser at Shelley	16	0.17	0.09	20	2	4	236
	17	0.23	0.23	10	3	3	246
	18	0.33	0.33	2	1	1	258
Quesnel	17	0.32	0.11	40	5	19	205
	18	0.43	0.16	16	3	12	238
	20	0	0	0	0	0	269
Horsefly	17	0.18	0.15	68	12	15	182
	19	0.22	0.28	18	7	5	247
	20	0.10	0.18	9	2	1	265
Chilcotin	15	0.28	0.12	52	7	20	206
	16	0.82	0.89	2	16	9	258
	17	1.00	1.00	0	1	1	283
Thompson	19	0.54	0.45	12	10	14	246
	20	0	0	0	0	0	282
	21	0	0	0	0	0	282
South Thompson	20	0.10	0.07	70	5	8	202
	21	0.13	0.16	27	5	4	249
	22	0.50	0.50	1	1	1	282
Coldwater	18	1.00	1.00	0	1	1	197
	20	0	0	0	0	0	199
	22	0	0	0	0	0	199
Fraser at Hope	18	0.03	0.03	160	5	5	115
	20	0.13	0.21	27	7	4	247
	21	0.33	0.00	6	0	3	276
Chilliwack	14	0.20	0.17	20	4	5	144
	15	0.09	0.17	10	2	1	160
	16	0.00	0.43	4	3	0	166

Table 5: **Comparison of mean raw error (MRE), root mean square error (RMSE) and mean absolute error (MAE) values from IOSRTM, HSM and RGM 5-day forecasts in the Fraser River at Hope, for years 2013 (n=18), 2014 (n=16), 2015 (n=17), using forecasted input variables. Error rates from the RGM are lower than those of the IOSRTM and HSM overall.**

	IOSRTM			HSM			RGM		
	MRE	RMSE	MAE	MRE	RMSE	MAE	MRE	RMSE	MAE
2013	-1.02	4.09	1.08	-0.72	2.89	0.72	-0.22	0.36	0.30
2014	0.27	1.03	0.47	-0.40	1.51	0.69	-0.14	0.33	0.28
2015	0.08	0.34	0.50	-0.43	1.86	0.93	-0.18	0.30	0.24
Average	-0.22	1.71	0.69	-0.50	2.09	0.78	-0.18	0.33	0.27

Table 6: **Frequency of correct predictions above each threshold (18°C, 19°C and 20°C), and frequency (and proportion) of false positive and negative errors in the Fraser at Hope. 5-day forecasts are for years 2013 (n=18), 2014 (n=16), and 2015 (n=17); total forecasts = 51.**

		IOSRTM			HSM			RGM		
	Threshold	Correct above	False positive	False negative	Correct above	False positive	False negative	Correct above	False positive	False negative
2013	18	7	0	6	11	0	1	12	0	1
	19	2	0	7	3	0	5	6	1	0
	20	2	0	2	1	0	3	3	0	1
2014	18	10	3	1	7	1	3	11	0	1
	19	6	2	0	3	1	2	6	1	0
	20	2	1	0	0	0	2	0	0	2
2015	18	14	0	1	10	0	4	13	1	1
	19	9	2	1	5	1	5	9	0	3
	20	1	2	2	1	2	2	1	0	1
Average	18	10.3	1.0	2.7	9.3	0.3	2.7	12.0	0.3	1.0
	19	5.7	1.3	2.7	3.7	0.7	4.0	7.0	0.7	1.0
	20	1.7	1.0	1.3	0.7	0.7	2.3	1.3	0.0	1.3

6. Figures

Figure 1: Map of the Fraser River watershed, showing real-time and historic data collection sites included in this study.

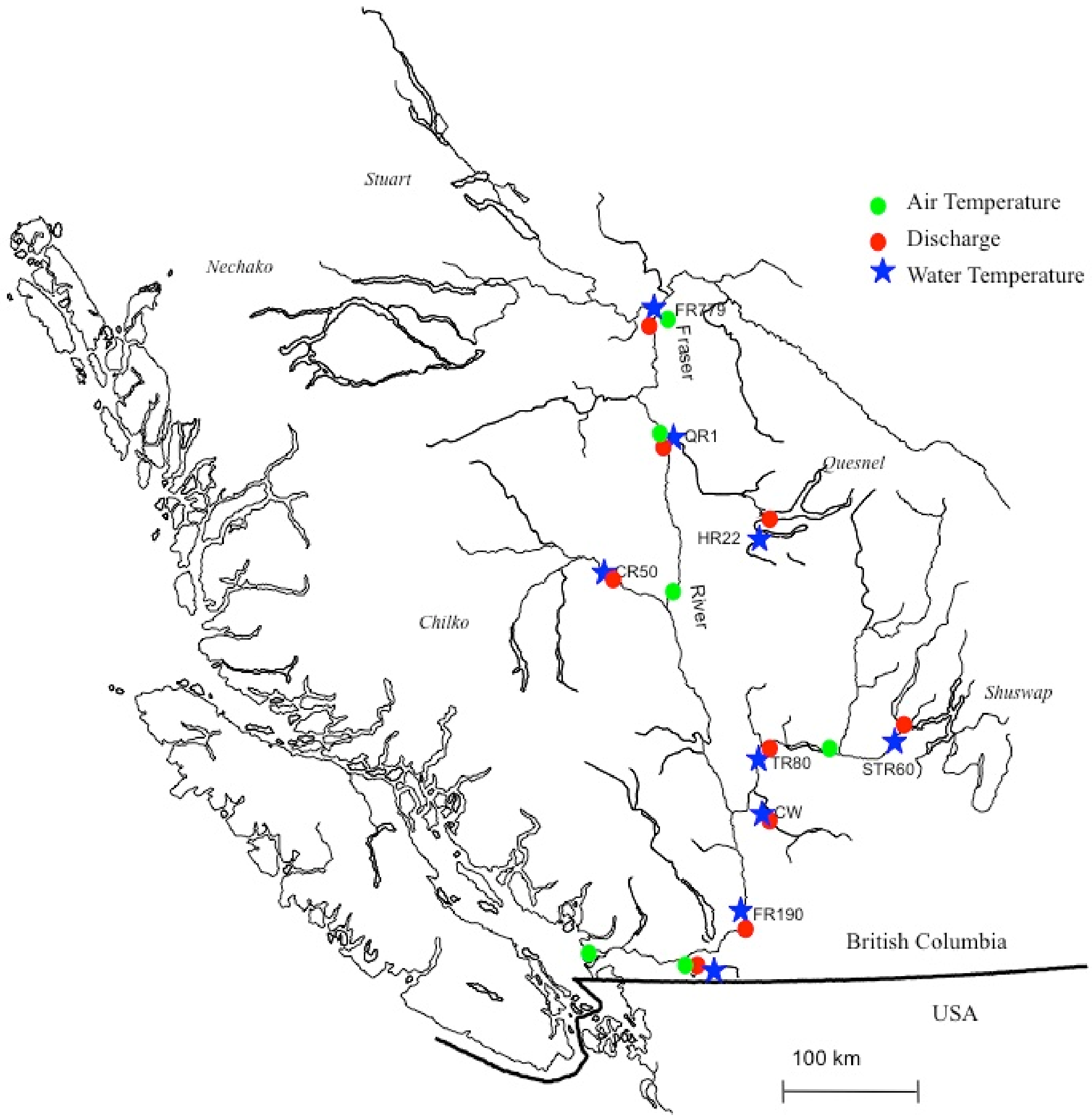


Figure 2: **Simulation model flow diagram outlines the key steps in the simulation model, which predicts 5 days in advance, one day at a time, for each of nine locations in the Fraser River watershed. The forecast window encompasses 95 days throughout each year and location, from June 15 – September 21; 1000 simulations were conducted for each day within this time period. Prediction averages and standard deviations were stored.**

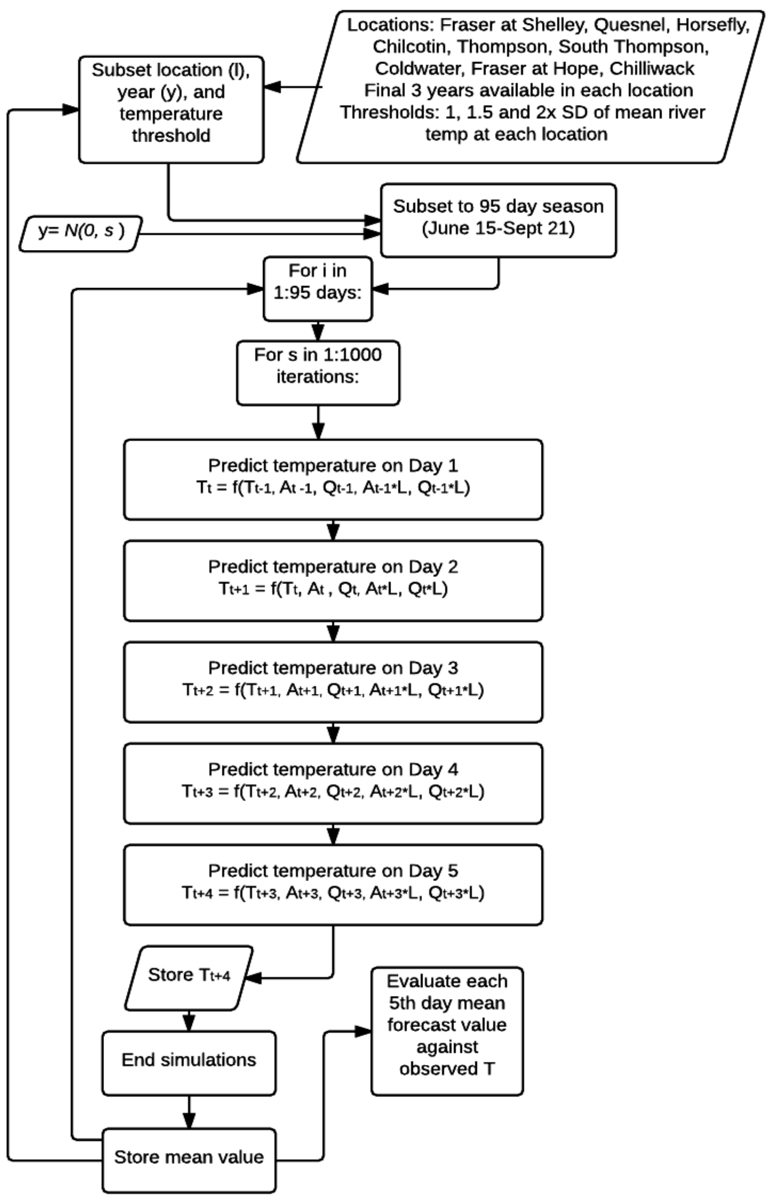


Figure 3: **Comparison of average forecasting performance among locations with observed air temperature and discharge during the forecast period. Figure shows average 5-day forecast bias measured by mean raw error (MRE), root mean square error (RMSE) and mean absolute error (MAE) of the Regional GAM Model (RGM) by location, in degrees (°C).**

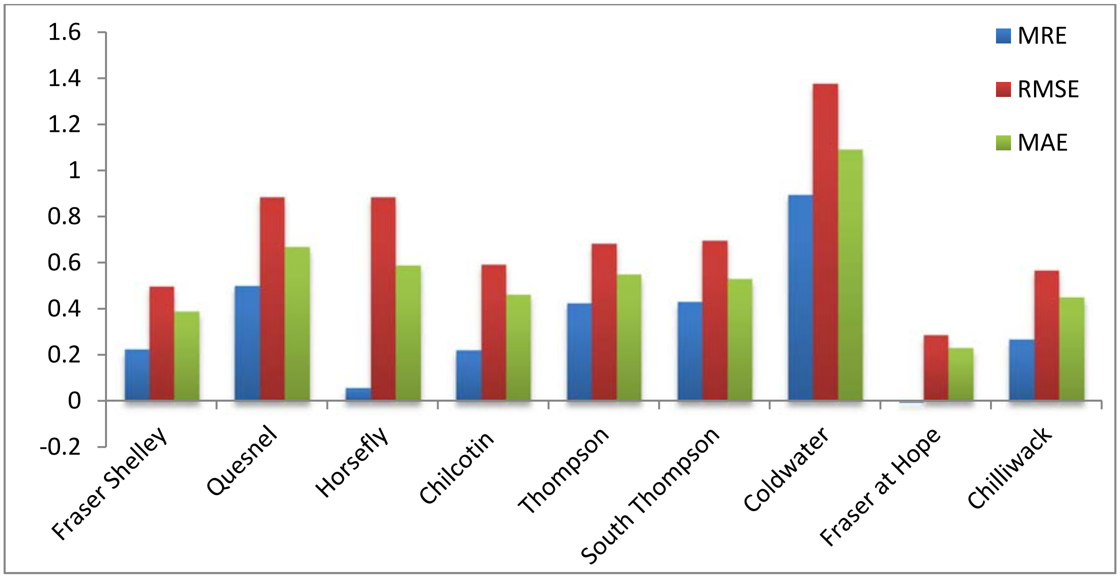


Figure 4: **False positive (Type I) and false negative (Type II) error rates (%) of 5-day forecasts at low, medium and high thresholds for all locations. High, medium and low thresholds are set at each location based on the standard deviation of the mean summer temperature. Thresholds were set at 1, 1.5 and 2x the standard deviation of the mean.**

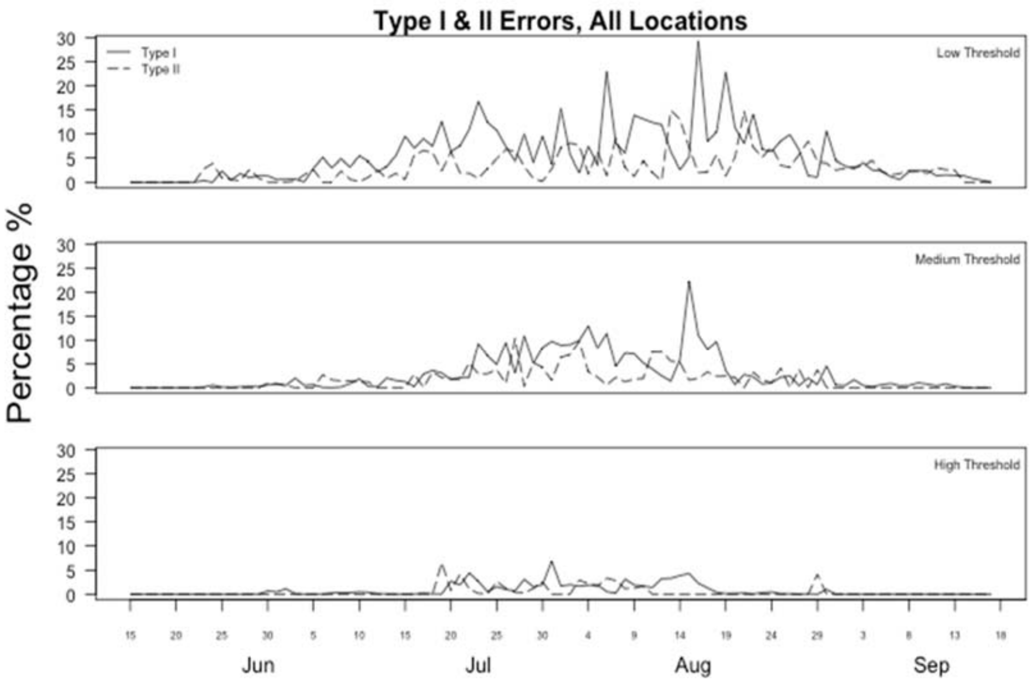


Figure 5: **Mean raw error (MRE), root mean square error (RMSE) and mean absolute error (MAE) in degrees (°C), comparing current in-season models (IOSRTM and HSM) with the RGM in the Fraser River at Hope. All models use forecasted predictor variables (A & Q), and are compared in years 2013-2015.**

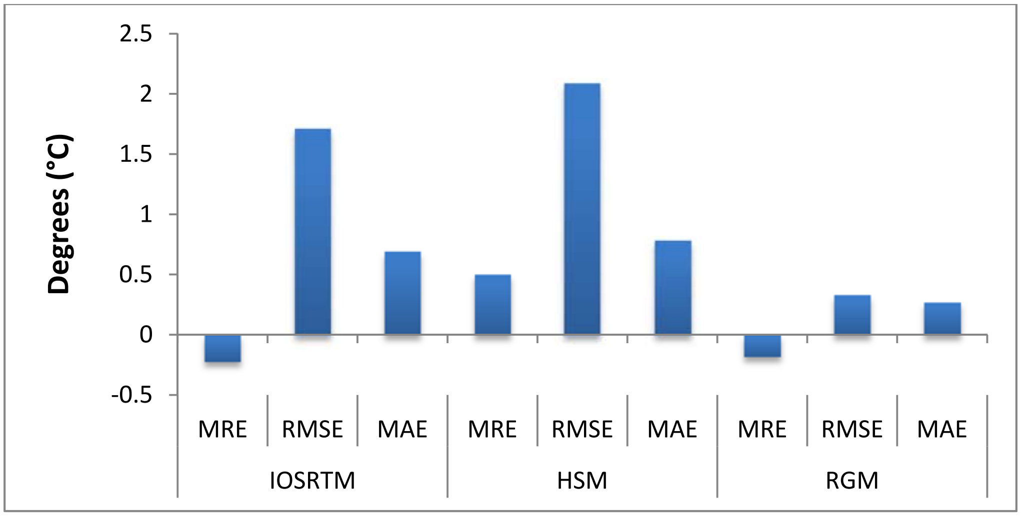
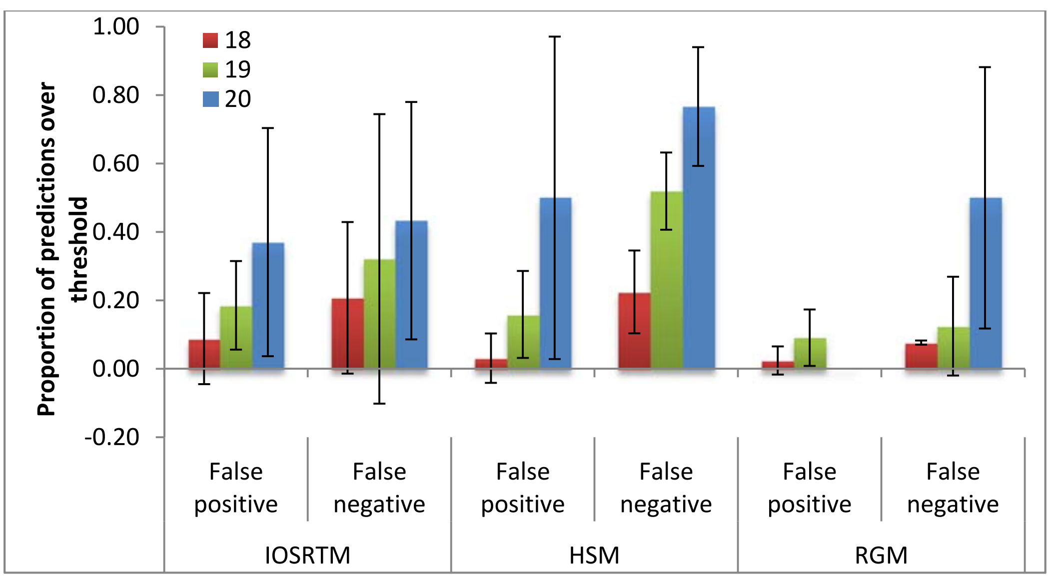


Figure 6: **False positive and false negative errors as proportions of total forecasts above each threshold, in years 2013-2015. The RGM demonstrates lower errors of both types at low thresholds, but false negative errors are comparable to current models at a 20°C threshold.**



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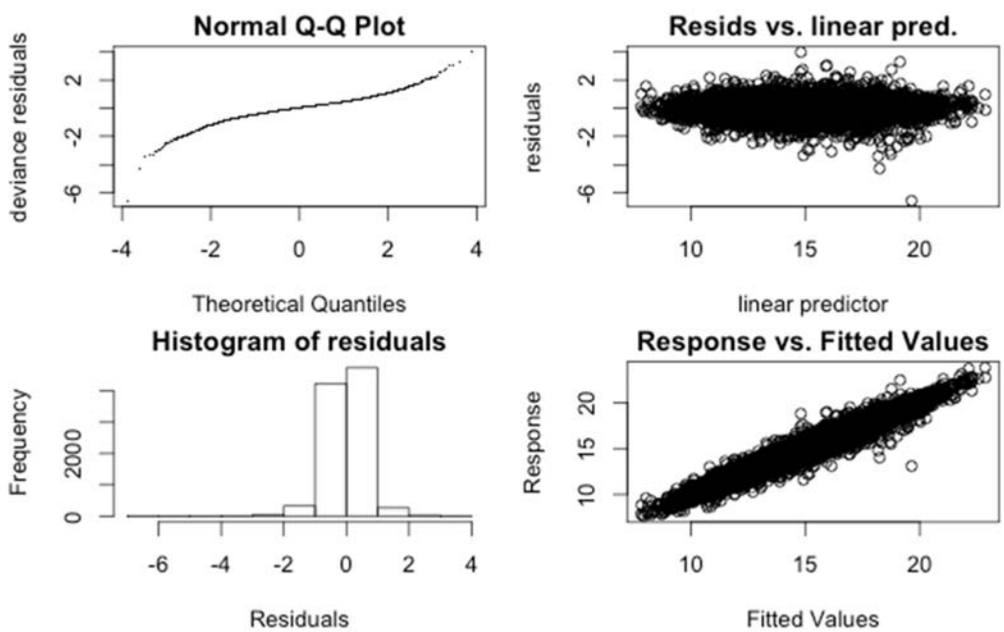
Appendix A.

Model Diagnostics

Table A1: **Diagnostic plots of the GAMM, fit to nine river locations, (n=9,624). Plots show that the GAMM approach meets homoscedasticity, normality and independence of residuals assumptions.**



Appendix B.

Adapting in-season recreational salmon fishery management to changing climate conditions

Fisheries managers have the dual mandate of maximizing fishing opportunity while conserving healthy fish populations (la Mare 1998); both of these objectives are further complicated by changing environmental conditions. Recreational fisheries are gaining popularity worldwide, consequently causing a growing recognition of their potential impact on total exploitation, estimated to be approximately 12% of total global fisheries (Cooke and Cowx 2004). A large portion of global recreational fisheries are catch and release (C&R) (Cooke and Cowx 2004), which normally assumes negligible effects to fish populations. This assumption may be incorrect because there still may be unaccounted for consequences such as temperature-related C&R mortality (Gale et al. 2013). Integrating river temperature into in-season management may provide a potential to adapt recreational fishery management to changing climate conditions via reduced temperature related mortality. More accurate predictions of spawning escapement can help to ensure the fulfillment of the conservation/fishing-opportunity dual mandate. Recreational fishery dynamics often involve a complex set of factors and motivations beyond catch alone (i.e. relaxation, pride, etc.), which complicate fishery management decisions, and result in unintended outcomes. Considering water temperature during in-season decision-making could lead to unforeseen consequences, such as foregone catch, missed fishing opportunity, or unintended increases in mortality. In this section, I explore some considerations associated with integrating river temperature into in-season decision-making, and illustrate some potential effects through real and simulated case studies.

Recreational fisheries are normally open access, making it challenging to manage total harvest and total mortality. A variety of harvest control measures are used across North America in an attempt to limit effort and/or harvest including: catch and release restrictions, bag limits, slot limits (i.e. size), seasonal openings and closures, and limited entry fisheries. Some restrictions, such as limited entry fisheries, cannot be altered in-season, whereas others, such as closures and changes to bag limits, may be adjusted as environmental conditions change. Daily bag limits (DBLs) are a common tactic for limiting effort (Cox et al. 2002). Although several studies have found that bag limits are ineffective at limiting effort, since daily catch is most often below catch limits (Radomski et al 2001; Cox et al. 2002), changing angler dynamics could create a situation where more restrictive bag limits could successfully limit harvest in freshwater salmon fisheries.

Catch-and-release angling is also a common way to restrict harvest. For example the 1984 salmon management plan in Atlantic Canada (O'Connell et al 1992), in which large Atlantic salmon (≥63cm) were legislated to be released. Finally, fishery closures are currently used in Canada to limit harvest of threatened populations under high temperatures (DFO; Breau and Caissie 2013). Although other methods exist to limit harvest, such as size limits, data limitations narrowed the focus of this study to bag limit reductions, mandatory release and fishery closures.

This paper explores the potential impacts of incorporating water temperature information in conjunction with different harvest regulations into in-season management. Managing for temperature effects on migrating salmon could include some consideration for the temperature threshold at which additional mortality (i.e. from fishing) is no longer acceptable, in order for escapement targets to be met. Temperature related mortality rates vary between species (Coutant 1977), and populations (Eliason et al. 2011). In addition, a range of factors affect mortality of fish in warm water, including the number of consecutive hot days, the number of degree days (cumulative temperature experienced by adult salmon during freshwater) (Hinch et al. 2012) and the amount of thermal refugia present in the river (Torgernsen et al. 1999). A range of studies have investigated en route mortality due to thermal stress (e.g. Rand et al. 2006, Keefer et al. 2008; Martins et al. 2012, Beer and Anderson 2013), and catch and release mortality in high temperatures (Wilkie et al. 1996; Boyd et al. 2010, Gale et al. 2011). However, specific mortality rates and critical thresholds remain undefined for most populations of Pacific salmon (Keefer et al. 2015). Consequently, determining a specific threshold above which all salmon are susceptible to mortality is not realistic. Of the studies conducted to date, including some studies for Chinook salmon (*Oncorhynchus tshawytscha*), temperature related en route mortality ranges from 0-90% in temperatures ranging from 18-25°C (Wilkie et al. 1996; Wilkie et al. 1997; Anderson et al. 1998; Dempson et al. 2002; Boyd et al. 2010; Keefer et al. 2010; Gale et al. 2011). In the absence of concrete thresholds, managers must accept this level of uncertainty, and possibly use local information on natural mortality rates, as well as data presented in the literature to identify an appropriate threshold for management decisions.

Migrating salmon often face river temperatures exceeding 21°C in the South Thompson River (DFO), a tributary to the Thompson River and Fraser River in British Columbia. Summer Chinook migration occurs during the warmest weeks of summer, making this population an ideal case study for integrating temperature thresholds into in-season management. Recreational fishing represents roughly 30% of total harvest of South Thompson Chinook (DFO), and although this population is not currently facing stock declines, the South Thompson region could be one of the first areas to exceed thermal tolerance limits during Chinook migration. Therefore, considering temperature effects early may be a pre-emptive way to prepare management for impending temperature-related threats, and may become necessary for sustainable fisheries strategies in the future.

This study uses South Thompson Chinook salmon as a case study to assess abundance, catch and fishing opportunity when incorporating river temperature into in-season management during up-river migration. In addition, I assess the considerations and consequences associated with in-season management responses to extreme temperatures.

Methods

This section aims to quantify the effects of temperature threshold-triggered harvest restrictions on recreational fishing mortality, catch and fishing opportunity in the South Thompson River. To address this question, I used a retrospective analysis to determine the effects of various management responses on historical temperature and fishery data. I then simulated possible future conditions to test the effects of these management responses under more extreme circumstances.

Data Sources

Fishery data were obtained from DFO fisheries management (pers. comm. Marla Maxwell and Bronwyn MacDonald, DFO), including Chinook spawning escapement, run timing, run size in the South Thompson River via annual run reconstruction data[1]. Recreational weekly catch data were obtained from DFO stock assessment creel surveys. Creel surveys consist of interviews with recreational fishers to determine total catch and effort. Surveys were conducted at 3 access points in the South Thompson representing most fishing locations (based on the presence of boat launches). Interviews were conducted in 8-hour shifts, either morning or afternoon-evening, 5 days-per-week including weekends; catch-per-unit effort (CPUE) was assessed by helicopter fly-overs throughout the fishery opening.

Temperature Thresholds

In this study, a 20°C (mean daily temperature) threshold was selected as a trigger for potential management interventions. At 20°C, I applied en route mortality rates which were approximated based on similar Chinook and other salmonid research in which monitoring time allowed at least 3 days of monitoring post-angling (to incorporate delayed mortality), or where temperatures resembled those found in the South Thompson River. Specifically, I applied a 20% mortality rate to all fish experiencing temperatures over this threshold (Dempson et al. 2001; Boyd et al. 2010), and mortality rate of 40% for captured-and-released fish in temperatures exceeding this threshold (Wilkie et al. 1996; Tufts et al. 2000; Anderson et al. 1998; Keefer et al. 2010; Gale et al. 2011). These data are also reflected in anecdotal information from the South Thompson River (pers. comm. Richard Bailey), where lower Chinook mortality rates have been recorded, but where estimates could be inaccurate due to coarse run size estimates and river turbidity. Thus, in the absence of more specific mortality estimates, conservative (i.e. high) mortality rates were chosen for this study.

[1] Run timing data from the run reconstruction was an average across a number of unspecified years. Catch in the South Thompson River is not proportionate to run timing in this river, and appears to be negatively associated. This may be due to a recent run timing shift that has not been incorporated into the calculation.

Harvest Restrictions

Harvest restrictions evaluated in this analysis include daily bag limit (DBL) reductions, mandatory release, and fishery closures. I assessed the effects of these harvest restrictions on catch, effort and total mortality when temperatures exceeded 20°C on any day in a given week. For a decreased DBL, catch was reduced from 4 to 1 per angler in weeks affected by high temperatures and remaining catch was added to temperature-related mortality in-river. Effort was reduced according to Smith (1999), who found a 26% reduction in boat trips in Barkley Sound as a result of a modified DBL from 5 to 1. I assessed the effects of mandatory release during hot periods by setting catch to zero during these periods. Because a switch to mandatory release may reduce the number of anglers, effort was reduced by 20%. Mortality was calculated by adding a catch and release mortality rate to the T_{crit} mortality rate, applying it to those fish hooked and released (total catch during the week), then adding it to the mortality of fish in the river. To test the effects of a fishery closure, catch and effort were set equal to 0 in all weeks where temperatures exceeded the threshold, and a T_{crit} mortality rate was applied to the fish in the South Thompson River during that week.

In order to simulate for possible future conditions, and river systems with varied run sizes and fishery dynamics, I analyzed 5 additional scenarios under warm weather conditions (Table B1). To understand the effect of a bag limit reduction (in the event that bag limits were effective at limiting harvest originally), I assumed that in all scenarios, a higher proportion of anglers reach their daily bag limits. As such, average catch per angler-day was set to 3, making the overall effect of this reduction 66%. The first scenario involved a smaller run size (2013 run size reduced by 50%); the second scenario saw higher catch rates (3x 2013 weekly sport catch); the third is a combination of these. Because the South Thompson River data presents unusual trends in terms of catch and run timing[2], the final two scenarios represented alternative situations that provide an indication of management trade-offs where effort and catch track weekly abundance more closely. The fourth scenario treats catch as a constant proportion (15%) of weekly

[2] Run timing is an average across several (undetermined) years, whereas catch data is recorded annually. Catch and catch per unit effort increase in the South Thompson River as run size declines in all years examined; this may not reflect fishery dynamics in other regions, and may incorrectly summarize the fishery dynamics in the South Thompson.

abundance, which is set at 2013 levels, and the bag limit reduction reduces catch by 66%. The fifth scenario assumes effort is a constant proportion of weekly abundance, with 1/3 of 2013 South Thompson run size, and catch per unit effort equal to 0.25 fish/hour across all weeks. This final scenario represents conditions where CPUE is relatively high, and run size is low.

Results

Harvest Restrictions

Mortality

Using 2013 fishery data, total mortality (fishing mortality plus temperature-related mortality, M) was virtually unaffected by a DBL redution and mandatory release, and a closure reduced total mortality by 386 fish. In all simulated scenarios in which catch was high (scenarios 1, 3, 4 and 5), bag limit reductions reduced mortality by a larger margin than mandatory release (Table B3). This reflects the assumption that if catch is relatively high, a larger proportion of anglers are catching a higher proportion of the daily bag limit on average, prior to any restriction. With elevated catch at 2013 abundance in the South Thompson River (Scenario 1), DBL reductions and mandatory release reduced M by 4% and 3% respectively, whereas a closure reduced M by 6%. Scenario 2 (run size = 0.5*2013 levels), bag limit reductions had no effect on M; mandatory release limited M by 2%; a closure reduced M by 4%. Scenarios 3-5, in which abundance was low, or proportional to weekly catch rates, showed similar results. DBL reductions reduced M by 7-8%, mandatory release by 5-6%, and closures by 10-12% (Table B3, Figure B1).

Catch

Effects of harvest restrictions on catch in 2013 show that bag limit reductions have almost no effect on catch, whereas a full closure and mandatory release result in zero catch in weeks affected by high temperatures (Figure B2). In all simulated scenarios, full closures and mandatory release, again, result in zero catch; however, a DBL reduction resulted in 1/3 of original catch.

Effort

Under the assumption that a reduced DBL or mandatory release would decrease the attractiveness of fishing by some (unknown) margin, these restrictions result in a 26% and 20% reduction in effort respectively in all scenarios whereas a closure resulted in zero effort (Figure B3). With a reduced DBL, effort could remain high, but was dependent on whether anglers continue to fish after reaching their 1-fish bag limit (resulting in higher catch and release mortality), or stop fishing altogether (resulting in reduced effort).

Discussion

Managers are often faced with competing objectives, which are complicated by changing environmental conditions. Managing in-season affords more control over a fishery in changing conditions, and in some instances, can assist in reaching harvest and escapement goals more predictably (Carney and Adkison 2014). This study aimed at analyzing the effects of adapting in-season salmon fishery management to increasing water temperatures, by allowing river temperature thresholds to trigger recreational fishing restrictions in weekly time steps. In addition, this study assessed some of the considerations necessary for the inclusion of temperature in fishery management decision-making. The results presented here suggest that when catch represents a large proportion of total run size (Scenarios 1, 3 and 4, Figure B1), fishery closures and reduced bag limits may have nearly the same effect on mortality. The choice of management intervention during extreme temperature events therefore depends not only on temperature and abundance, but fishery dynamics, and “how …and why people fish” (Radomski et al. 2001).

All harvest restrictions had a low relative effect on mortality in the South Thompson River under current conditions (Figure B1) of high abundance and low catch. Temperature-related M was defined as an instantaneous fixed proportion of weekly abundance. Consequently, variations in harvest restrictions had a small relative effect on mortality, catch and effort. However, this was not the case for simulated conditions that might reflect the future in a warming climate, and under different fishery dynamics. In high-temperature rivers with high catch and low abundance, warm seasonal temperatures could signal additional fishery restrictions to ensure escapement targets are met. In a scenario where fishery dynamics track abundance (either catch or effort), results are similar, in that bag limit reductions have a minimal relative effect on mortality but allow fishing opportunity to continue. However, this assumes adherence to reduced bag limits, which may be difficult to enforce. Another key assumption made by this study (for simplicity, and due to weekly catch data) is that when temperature hits a critical threshold, temperature-related mortality is instantaneous. In reality, mortality rates likely increase at unknown rates according to factors such as the rate of temperature increase, the number of degree-days experienced by fish, and available thermal refugia. In addition, management decisions are made on a weekly basis in this study due, again, to the weekly time-scale of the data. In real conditions, more severe restrictions such as closures may not cause such dramatic limitations to fishing.

DBL reductions result in only slightly reduced mortality compared to no intervention, permitting virtually the same level of fishing effort. However, whether this type of restriction would be effective depends on the dynamics of the fishery. The South Thompson River experiences significant harvest inequality (DFO, unpublished data), where most anglers catch few fish (Cook et al. 2001). A reduced bag limit would have almost no effect on recreational fishing mortality in this situation, because most anglers catch 0-1 fish per trip, and catch per unit effort (CPUE) is low (based on DFO creel data from 2002, 2008 and 2013). Indeed, bag limits have been found to affect only a minority of anglers because most in-river sport catch falls below daily bag limits (McPhee et al. 2002; Radomski 2003), and reduced bag limits fail to limit the number of anglers entering the fishery (Cox et al. 2002). Bag limit reductions can be advantageous in situations where catch is both proportional to abundance, and where a substantial proportion of anglers catch more fish per trip. If both of these conditions are not met, DBL reductions will have little effect on effort, catch or mortality. Should a bag limit reduction be effective, however, it may lead to higher capture-and-release fishing, a practice that leads to higher mortality in extreme warm temperatures. Overall, the effectiveness of a DBL restriction could be muted since there is currently no limit to the number of anglers that can enter the fishery; the effects of the reduced DBL could be offset by a greater number of anglers.

Capture-and-release has historically been used as a way to reduce fishing mortality from angling in response to low abundance, while still maintaining an active sport fishery (Arlinghaus et al. 2007), since a released fish is generally expected to survive (Wydoski 1977). However, during extreme temperatures, thermally stressed salmon are far less able to recover from these encounters, causing higher-than-normal mortality (Dempson et al. 2002; Gingerich et al. 2007; Boyd et al. 2010). Indeed, water temperature has been cited as the most important factor influencing salmon mortality, post-release (ICES 2009). While switching to a catch-and-release fishery during hot weather may spare some fish from certain mortality (catch), mortality rates are likely to remain high due to handling time, stress, air exposure, and injury, all of which are exacerbated by high temperatures (Gale et al. 2013). Additionally, un-landed fish are vulnerable to interactions with fishing gear, which can also have lethal effects (Cooke & Suski 2005). A catch-and-release fishery in hot weather will be ineffective at reducing total mortality by a significant margin, and is unlikely to be an effective way of mitigating this additional pressure on migrating populations.

Fishery closures in response to high temperatures show the most promise in terms of conservation, limiting fishing entirely during days and/or weeks that the fishery is closed. Closures can also be flexible in the severity with which they are implemented. For example, fishing may be closed in weekly time-steps, or only on days observed or predicted to be above a specified threshold. Alternatively, closures could target specific portions of the run size to ensure escapement targets are met. Breau and Caissie (2013) identify the need for decision-makers to find the appropriate balance between frequent, potentially short interventions, longer but less frequent interventions, or no intervention at all. If forecasts were to occur on a daily basis, fluctuating temperatures around an adopted threshold could trigger a considerable amount of interference in the fishery. Fishery closures due to extreme environmental conditions have been implemented in Atlantic Canada, where a temperature threshold set at 20°C (daily minimum) has triggered recreational salmon fishery closures, reducing fishing days by 35-65% in some years (Dempson et al. 2001). Temperatures must be below this threshold for 2 consecutive days before fishing restrictions are lifted. While longer closures would reduce fishing opportunity further, they may result in higher predictability and stability of the fishery.

Closures could be unpopular among the angling community, but there may be a growing recognition among anglers that fishing in hot weather causes undue mortality, and is therefore unwise. Nguyen et al (2013) found that fishermen were more likely to forego fishing opportunities in hot weather, recognizing that high temperatures cause increased mortality among migrating fish. This study also found that a large proportion of anglers support voluntary education, suggesting that there is a willingness to understand and mitigate potential threats, in the interest of preserving the sport. An intermediate measure to address the additive effects of temperature and fishing may therefore involve educating anglers pre-season on the effects of fishing in hot weather, and assessing whether a greater awareness has any measureable effect on in-river mortality.

Selecting temperature thresholds may also determine how restrictions impact a fishery. For example, a low threshold relative to average peak temperatures will most often result in long, infrequent interventions whereas a higher threshold that is near peak temperatures will likely result in frequent interventions throughout the fishing season, especially if temperatures hover near peak temperatures. Critical temperature thresholds for salmonids vary considerably between (Coutant 1977), and within species (Hilborn et al. 2002; Crozier et al. 2007; Eliason et al. 2011), yet for most populations, they remain undefined (Keefer et al. 2015). In the absence of a definitive critical threshold, a threshold must be selected from a range of temperatures that are biologically relevant to the species being managed, but also ensure that management objectives be met (Breau 2013).

Fishery dynamics

The South Thompson River presents an unusual case study, in that fishing effort increases dramatically as weekly abundance declines. Although this may be an artifact of how the annual run reconstruction data is averaged to obtain run timing, it could also be an anomaly in fishery dynamics. In either case, the results of this study, through the use of simulated scenarios, show that fishery dynamics determine the most effective management strategy. For example, as shown by current conditions in the South Thompson River, if anglers rarely catch more than one fish per trip, a reduced bag limit will have no effect, whereas a closure over a warm period of time has a higher likelihood of reducing mortality.

Recreational fisheries literature suggests that the numerical response of angler predation to fish abundance should be self-regulating: as fish abundance decreases, quality of fishing also declines, thus reducing the attractiveness of angling (Johnson & Carpenter 1994; Hansen et al. 2000). However, anglers are driven by motivations other than catch alone; some include relaxation, enjoying the outdoors, and pride (Holland & Ditton 1992). In addition, anglers respond to catching fish differently, whereby one angler may be satisfied with one fish and willing to go home, while another may be motivated to continue fishing after an initial success (Smith 1999). In the second scenario, if fish abundance declines, fishing effort may continue at high levels, even if only directed towards catch-and-release. This fishing pressure could exacerbate temperature related mortality occurring during hot periods, prompting the need for a precautionary approach beyond a catch-and-release fishery. Due to the complex set of angler motivations beyond catch alone, and due to the diffuseness of recreational fisheries, declines may not be apparent, or reflected by angler effort (Post et al. 2002). This complexity also highlights the degree to which manager assumptions and individual fishery dynamics affect the outcome of each harvest restriction.

Assumptions

Incorporating temperature into decision-making requires several assumptions regarding biological limits of fish, en route loss as a result of temperature, and fishery dynamics. Due to the lack of concrete scientific information, outcomes are dependent upon the critical threshold chosen by managers, and what assumptions are made regarding the mortality rate at that threshold. In the absence of scientific evidence, these mortality rates and thresholds may be adopted from best available literature, and from anecdotal information. Furthermore, any harvest restrictions implemented in order to mitigate temperature-related mortality must be based on a range of factors, including local fishery dynamics, the biological limits of the species, environmental conditions, and availability of thermal refugia. All such factors contain a high level of uncertainty that will need to be incorporated into management frameworks.

Conclusion

In areas where active fishing coincides with extreme river temperatures, optimal solutions may reside with decisions made pre-season, rather than in-season. For example, fisheries vulnerable to extreme temperatures could remain closed to sport fishing altogether, or kept closed by default, only opening if temperatures are below a threshold for a defined period of time, to manage angler expectations. Alternatively, managers could opt for a limited entry fishery in vulnerable areas, to be distributed by lottery to limit exploitation. The number of licenses available might consider a pre-season forecast (i.e. hotter than average, normal, etc.) and expected run size, and be further restricted by lower bag limits.

If in-season harvest restrictions were implemented in response to temperature forecasts, in-river salmon fisheries could experience losses in fishing opportunity as temperatures continue to increase. However, it could be integral to preserving some stocks that become increasingly vulnerable to extreme temperatures. While recreational catch is just a small portion of total escapement in the area of study, managers must also consider in-river loss due to temperatures across the entire migration. Integrating harvest control rules into in-season management based on forecasted temperatures could have mixed results, depending on the critical threshold adopted by managers, and river temperatures relative to that threshold. There is growing interest in incorporating stream temperatures into in-season management. Total allowable mortality rules will need to incorporate temperature-related mortality estimates in the future. In order to meet those objectives, fishery closures during hot periods will result in the lowest mortality (of the harvest restrictions explored). While mandatory release and reduced bag limits have advantages in some cases, neither reduces mortality by a margin that would justify interference.

Tables

Table B1: Equations to obtain total catch, mortality and effort under 3 types of harvest restrictions: a fishery closure, a reduced bag limit, and mandatory release. H = Hours, C = Catch, rC = Reduced catch to lower bag limit, M = Mortality, T_{crit} = critical threshold adopted, CR_M = Catch and release mortality rate, R = Proportion of run size by week (escapement + total recreational catch)

Harvest Restriction	Catch (C)	Mortality (M)	Effort (H)
No intervention	C	$M = (R - C) * T_{crit} + C$	H
Closure	C = 0 if above T_{crit}	$M = R * T_{crit}$	H = 0 if above T_{crit}
Bag limit reduced to 1	C reduced by any catch over 1	$M = (R – rC)* T_{crit} + rC$	H* 0.74
Mandatory Release	C reduced to 0 if above threshold	$M = (R* T_{crit}) + C * (CR\_M+ T_{crit})$	H= H*0.8

*Note: assumes commercial and FN catch are removed from the run at lower reaches.

Table B2: Effects of daily bag limit (DBL) reduction, mandatory release and fishery closure on total mortality of South Thompson Chinook, in absolute numbers.

Scenario	Description	Total run size	Total mortality (no intervention)	Mortality as % of run size (no intervention)	Total Mortality		
					Bag limit reduction	Mandatory release	Closure
2013 Data	2013 conditions	67,935	13,084	19%	13,075	12,891	12,698
Scenario 1	High catch, abundance = 2013	67,935	17,597	26%	14,790	15,592	13,587
Scenario 2	Catch = 2013, low abundance	33,698	8,130	24%	8,090	7,462	6,794
Scenario 3	High catch, low abundance	33,698	10,542	31%	7,997	8,799	6,794
Scenario 4	Catch proportional to weekly abundance	67,935	21,739	32%	16,277	17,663	13,587
Scenario 5	Effort proportional to weekly abundance, low abundance	20,381	6,114	30%	4,688	5,095	4,076

Table B3 Effects of daily bag limit (DBL) reduction, mandatory release and fishery closure on total mortality of South Thompson Chinook, by percentage change from total mortality with no intervention.

Scenario	Description	Total run size	Mortality as percentage of run size (no intervention)	Percentage Change		
				Bag limit reduction	Mandatory release	Closure
2013 Data	2013 conditions	67,935	19%	0%	0%	1%
Scenario 1	High catch, abundance = 2013	67,935	26%	4%	3%	6%
Scenario 2	Catch = 2013, low abundance	33,698	24%	0%	2%	4%
Scenario 3	High catch, low abundance	33,698	31%	8%	5%	11%
Scenario 4	Catch proportional to weekly abundance	67,935	32%	8%	6%	12%
Scenario 5	Effort proportional to weekly abundance, low abundance	20,381	30%	7%	5%	10%

Figures

Figure B1: Mortality under 4 harvest regimes, in weeks 1-7 of fishing season in 2013, and in Scenarios 1-5, representing variations in fishing dynamics (high/low abundance, high/low catch).

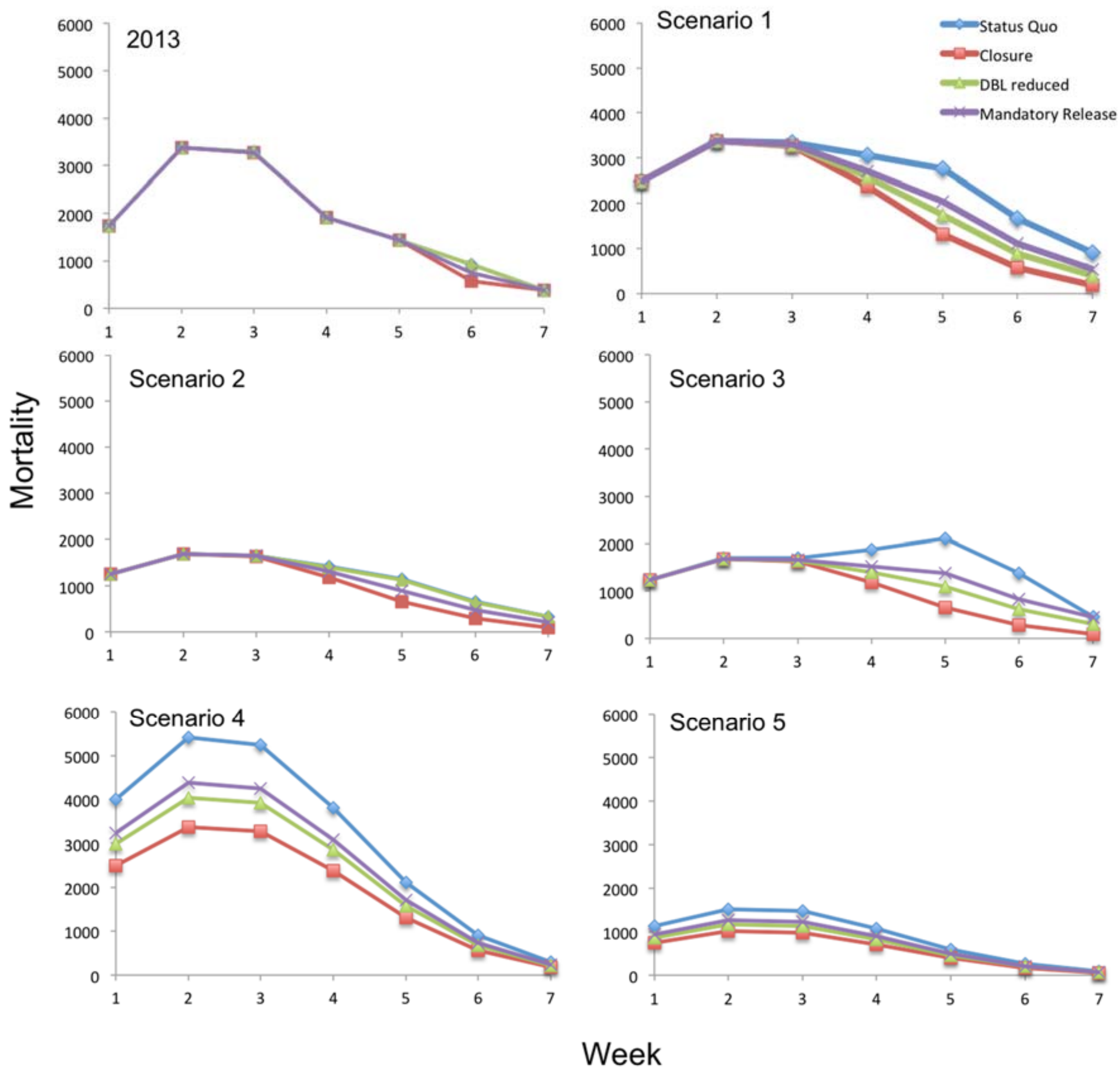


Figure B2: **Catch under 4 harvest regimes, in weeks 1-7 of fishing season in 2013, and in Scenarios 1-5, representing variations in fishing dynamics (high/low abundance, high/low catch).**

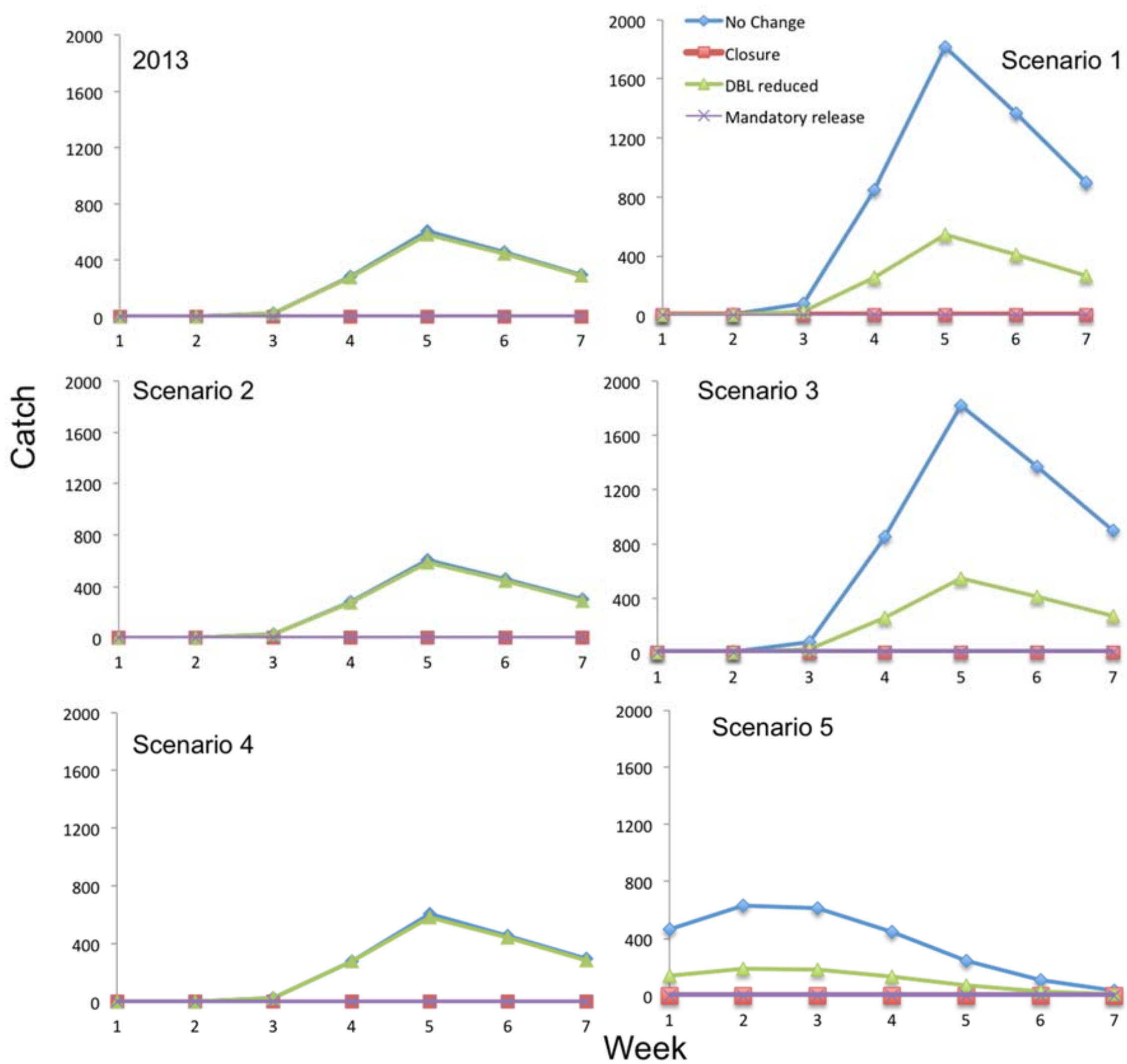
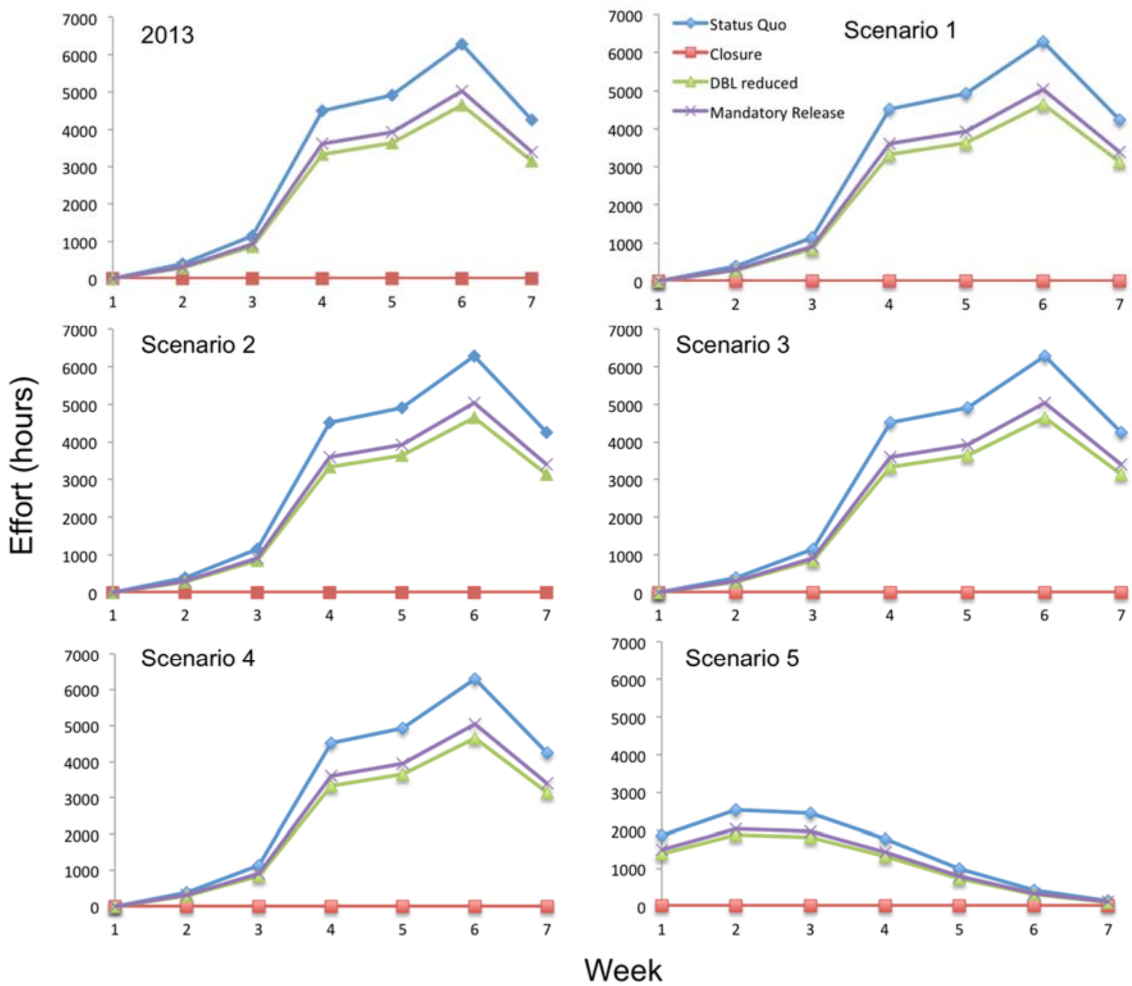


Figure B3: **Effort under 4 harvest regimes, in weeks 1-7 of fishing season in 2013, and in Scenarios 1-5, representing variations in fishing dynamics (high/low abundance, high/low catch).**



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