CHINA CREEK WATER QUALITY

A Comparison Before and After Timber Harvest and Independent Power Project Construction

by

CATHERINE T. E. BUSCHHAUS

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Abstract

Stream water quality is of significance not only to human resource-users and stake-holders, but also to the resident species in the stream and riparian ecosystems. Many of the chemical, biological, and physical attributes that define water quality are inter-related; however, a thorough understanding of the complexity of these processes is important for watershed management. The China Creek watershed on Vancouver Island was disturbed in the mid-2000s by both timber harvest and construction of a power project weir intake. Modelled relationships between key physical variables collected at the Port Alberni water intake weir, including daily maximum stream temperature (ºC), daily maximum air temperature (ºC), and daily average specific conductance (µS/cm) showed a statistically significant difference before and after disturbance. During low flows, as indicated by high specific conductance, stream temperatures increased approximately 1ºC following disturbance. While discrete water sample measurements of chemical and biological parameters were available, the data were insufficient to determine whether concentrations changed with disturbance. Quantifying water-quality variables and their relationships to one another could be important in monitoring the recovery of processes, such as thermal regime, following disturbance in China Creek.

(KEY TERMS: China Creek; British Columbia; water quality; stream temperature; timber harvest; disturbance).

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Acknowledgements

One of my fondest memories from this project is an animated discussion between my two supervisors, Drs. R. Dan Moore and Valerie LeMay, about R programming quirks. I was fairly warned of these before embarking on my own adventure to learn R, but I could sympathize as I listened to their conversation seven months later. I am indebted to them for their mentorship, without which I could not have conquered R. I am also grateful for their enthusiasm which inspired my enjoyment of statistics and their encouragement that kept my expectations realistic. Rosie Barlak, from the Ministry of Environment in Nanaimo, BC, provided the bulk of the data for this study and graciously answered my many questions about China Creek. Ruth-Ann Devos, also from the Ministry of Environment in Nanaimo, BC, provided technical information on the China Creek data set. The City of Port Alberni also provided water flow data. These acknowledgements would not be complete without recognizing my support of faith, family and friends which spurred me on with encouragement, prayers, hand-written notes and home-cooked meals. Thank you for the joy you brought to this adventure.

To everyone in my community

who has helped this sapling grow,

with all my thanks.

Introduction

Complex interactions between biological, chemical, and physical parameters impact the water quality of small streams in the Pacific Northwest (PNW) of the US and Canada. Water quality is important in maintaining healthy species populations in streams and their surrounding watershed and for maintaining human water uses such as drinking water and recreation. The British Columbia (BC) government has published ambient water quality guidelines specific to the water use being considered. The guidelines are intended for assessment of water quality and protection of specific water uses, while water quality objectives are created for site-specific protection (BC Ministry of Environment 2010). The biological parameters of water quality include aquatic and terrestrial species complexes. The chemical parameters include concentrations of nutrients, dissolved carbon, hydrogen ions (pH), heavy metals, and other pollutants. The physical parameters include measurements of temperature, flow, turbidity, and specific conductance.

The chemistry of streams is influenced by multiple physical and biological factors. Geological weathering of soils and parent material leads to increased water concentrations of K^+, Mg^{2+}, Ca^{2+}, and Si and is augmented by increased precipitation and temperature (Feller 2005). While precipitation is considered a smaller factor than weathering in the PNW, it is the main source of Cl^- and SO_4^{2-} because the bedrock concentrations of these tend to be low (Feller 2005).

Hydrology also impacts the stream chemistry. As contact time of water with soil increases so does uptake of elements such as K, N, and P, thus decreasing their concentration in the water reaching the stream. The relationship between concentrations and stream flow depends on the identity of the element, with those affected by precipitation (Cl^- and SO_4^{2-}) increasing with discharge, and those more strongly impacted by weathering (K^+, Mg^{2+}, Ca^{2+}, and Si) diluting with discharge.

Water chemistry is also influenced by biological factors such as the watershed vegetation type. If there are red alder trees (*Alnus rubra*) surrounding the stream, their associated nitrogen-fixing activity leads to increases in NO_3^- levels in the stream (Feller 2005). Within the stream, the activity of primary producers, such as microalgae, influence the concentrations of biologically active compounds such as K^+, NH_4^+, NO_3^-, and PO_4^{3-} (Feller 2005). How concentrations of these compounds change with discharge depends on biological demand and the amount accumulated prior to the increased discharge (Feller 2005).

Forest harvest activities impact stream solution chemistry. Following clear cut logging, decreases in pH have been observed, likely caused by increases in nitric acid from the nitrification process (Feller 2005). There is also a release of organic acids from decomposing logging slash (Feller 2005). The H^+ ions displace positive cations (Feller 2005) and promote release of Fe^{2+} (Tremblay *et al*. 2009). This leads to a general increase in inorganic ions in solution following harvest, and hence an increase in specific conductance (Tremblay *et al*. 2009).

Nitrogen and phosphorous are considered key nutrients. Generally, streams through forests in the PNW have lower nutrient loads than streams through other land uses. However, one study showed that in the five years following forest harvest, monthly averages of NO_3^- and NO_2^- increased 0.29 mg L^{-1}(Gravelle *et al*. 2009). This increase is due to decreased uptake by plants, release of compounds stored by mycorrhizae, as well as changes in the balance of nitrification and denitrification (Feller 2005). The nitrogen export in a system is predicted best when both vegetation and soil types are considered (Zhu and Mazumder 2008). The inorganic nitrogen increase eventually declines with time following harvest or with increased distance downstream from the harvest site (Tremblay *et al*. 2009; Gravelle *et al*. 2009). In a watershed on Vancouver Island, BC, nitrogen transport levels differed with the age of the forests (Zhu and Mazumder

2008). In regeneration, young, mature and old growth forests, the nitrogen transport levels were 4, 0.75, 1.28, and 1.74 kg ha^{-1} $year^{-1}$ respectively (Zhu and Mazumder 2008). The effects of harvest on any particular stream will be unique based on the extent of harvest, proximity to the stream, watershed vegetation, and physical characteristics of the stream (Gravelle *et al*. 2009). Harvest activities do not seem to significantly impact PO_4^{3-} concentrations (Tremblay *et al*. 2009).

The amount of organic matter in a stream system also impacts water quality. In the PNW, organic inputs from coniferous trees do not vary seasonally, unlike inputs from deciduous trees in other regions (Richardson *et al.* 2005). The coniferous trees inputs also have slower rates of decomposition because of the thick, waxy epidermis (Richardson *et al.* 2005). Timber harvest can change organic matter dynamics in streams by increasing or decreasing the supply of organic matter and by changing decomposition rates and storage through influencing channel morphology and temperature (Richardson *et al.* 2005).

Physical parameters of streams, such as sedimentation, flow, and temperature, are also influenced by forest harvest. Sedimentation is augmented when either the supply of sediment to the system is increased through road construction or mass soil movements, or when the mobilization of sediments already in the stream increases with higher discharge (Gomi *et al.* 2005). The increase in sedimentation from direct soil disturbance is seen immediately following harvest; however, indirect effects continue for 3-15 years as windthrow of trees in the riparian buffer strips occurs and fine roots decompose further destabilizing soil (Gomi *et al.* 2005). The impact of sedimentation depends on harvest treatments, with little effect observed with partial cutting (Karwan *et al.* 2007), and on the proximity to the stream, with little effect observed when near-stream soils are not disturbed (Gomi *et al.* 2005).

Flow pathways and annual runoff are typically increased with timber harvest in rain-dominated watersheds of the PNW (Moore and Wondzell 2005). In a study at Carnation Creek on Vancouver Island, BC, water yield increased 9-16% for the year following clear cut harvest (Hartman *et al.* 1996). One factor influencing the increased water availability is the decrease in evapotranspiration with partial and clear cutting (Hubbart *et al*. 2007). For small streams, the magnitude of high flows and low flows are generally higher (Moore and Wondzell 2005). In addition to water flow from land to stream changing, these challenges may also be affected by sedimentation restricting hyporeic exchange (Moore and Wondzell 2005). For coastal streams, hydrological recovery after logging is estimated to require 10-20 years (Moore and Wondzell 2005).

Stream temperature is driven by a complex array of factors (Moore *et al.* 2005a; Gravelle and Link 2007). The temperature response post-harvest is similarly complex, primarily being driven by insolation changes, but also changes in hydrology and channel morphology, wind speed, and air advected from clear cuts (Moore *et al.* 2005a). Typically, temperatures of smaller headwater streams vary less than larger streams (Moore *et al.* 2005b). Riparian vegetation and buffers have been shown to have a large impact on limiting stream temperature change (Gravelle and Link 2007; Gomi *et al.* 2006). In rain-dominated PNW watersheds, summer maximum stream temperatures increase up to 13°C following harvest (Moore *et al.* 2005a). Recovery time for thermal regimes of PNW streams post-harvest is estimated to take 5-10 years if not further disturbed by debris flow (Moore *et al.* 2005a). There is a negative correlation between stream size and both harvest-impact on temperature change and recovery rate (Quinn and Wright-Stow 2008). The impacts of harvest on winter temperatures are less studied but seem to be smaller (Hartman *et al.* 1996; Moore *et al*. 2005b; Holtby 1988). Dams can also influence stream temperature if the water being released from the reservoir is warmer or cooler respectively the stream water (Olden and Naiman 2010).

Temperature is a critically important water quality parameter because of its impact on biochemical and biological processes such as growth rate, distribution of and interactions between organisms (Moore et al. 2005b). A comprehensive understanding of stream temperature and the influence of harvest activity is important because of the impact of temperature on resident species (Gravelle and Link 2007). For example, in Carnation Creak on Vancouver Island, BC, warmer stream temperatures caused by logging activity and warmer weather led to salmon (*Oncorhynchus*) fry developing faster and emerging six weeks earlier (Scrivener and Andersen 1984). This early emergence was associated with a decrease in survival from fry to smolts (Holtby *et al.* 1989). However, temperature was not the only factor that changed with logging and impacted fry survival; For example, gravel bed characteristics also changed (Hartman *et al.* 1996). Temperature change was the primary cause of changes in the timing of smolt migration from the stream to the ocean (Holtby *et al.* 1989). While the effects of temperature increase are often sub-lethal, their cumulative impacts could lead to species composition shift (Holtby 1988). It is important to note that impacts on temperature in Carnation Creek, BC were not observed until 12% of the watershed had been logged (Scrivener and Andersen 1984), and the months that temperature change impacted salmon survival were restricted to late winter and early spring (Holtby 1988).

Hartman categorized the impacts of timber harvest on streams into three categories: short-term impacts (0 to 3-20 years) from the removal of vegetation, mid-term impacts (manifesting at 5-10 years) from large floods and root decomposition, and long-term impacts (manifesting at 10-20 years) from loss of large wood and habitats (Hartman *et al.* 1996).

This study focuses on the short-term impacts of watershed disturbance on water quality in China Creek, Vancouver Island, BC. Watershed disturbance in the mid-2000s included concurrent timber harvest and power plant weir intake construction. The objective was to examine changes in physical, chemical and biological water-quality variables before and after disturbance. How these water quality variables relate to one another may further indicate changes in stream processes before and after disturbance.

It is hypothesized, based on trends observed in literature (Feller 2005; Moore 2005), that pH will decrease in the short term, while organic nitrogen content and stream discharge will increase. Short-term sediment loads are expected to increase based on published results (Gomi *et al.* 2005). The magnitudes of these responses are uncertain as they depend on the extent of harvest and buffer strips (Feller 2005), neither of which is quantified well enough for China Creek to compare to past studies.

Summer stream temperatures are hypothesized to increase, as observed in previous studies (Moore *et al.* 2005a). How the winter stream temperatures will change is uncertain because it is relatively less studied and seems to depend on treatment type (Moore *et al.* 2005a). In the Carnation Creek, BC study, winter post-harvest stream temperatures increased (Scrivener and Andersen 1984). However, in the University of British Columbia (UBC) Malcolm Knapp Research Forest near Maple Ridge, BC, the winter stream temperatures decreased following logging and slashburning (Feller 1981).

Methods

Study Area

China Creek drains into the Port Alberni Inlet, on the west coast of Vancouver Island, BC (Figure 1). China Creek is a fourth order stream approximately 21 km long, draining from an elevation of 1575 metres. The lower reaches are located in the Coastal Western Hemlock (mm2 subzone) biogeoclimatic zone, while the upper reaches extend into the Mountain Hemlock (mm1 subzone) biogeoclimatic zone (Epps *et al.* 2010). The watershed receives an estimated annual precipitation of 2450 mm. Of this, six and 81% occurs as snow in the lower and upper reaches respectively (Epps *et al.* 2010), giving the watershed a hybrid, or rain and snow dominated, hydrological regime. While the average monthly air temperatures have not been recorded in the upper reaches, in the lower reaches these vary between 2.1-17.9°C (Epps *et al.* 2010). The surrounding soil is mainly glacial till, volcanic rock, and limestone, with the latter contributing to the neutral to basic water pH due to calcium inputs (Carmanah Research Ltd. 1997).

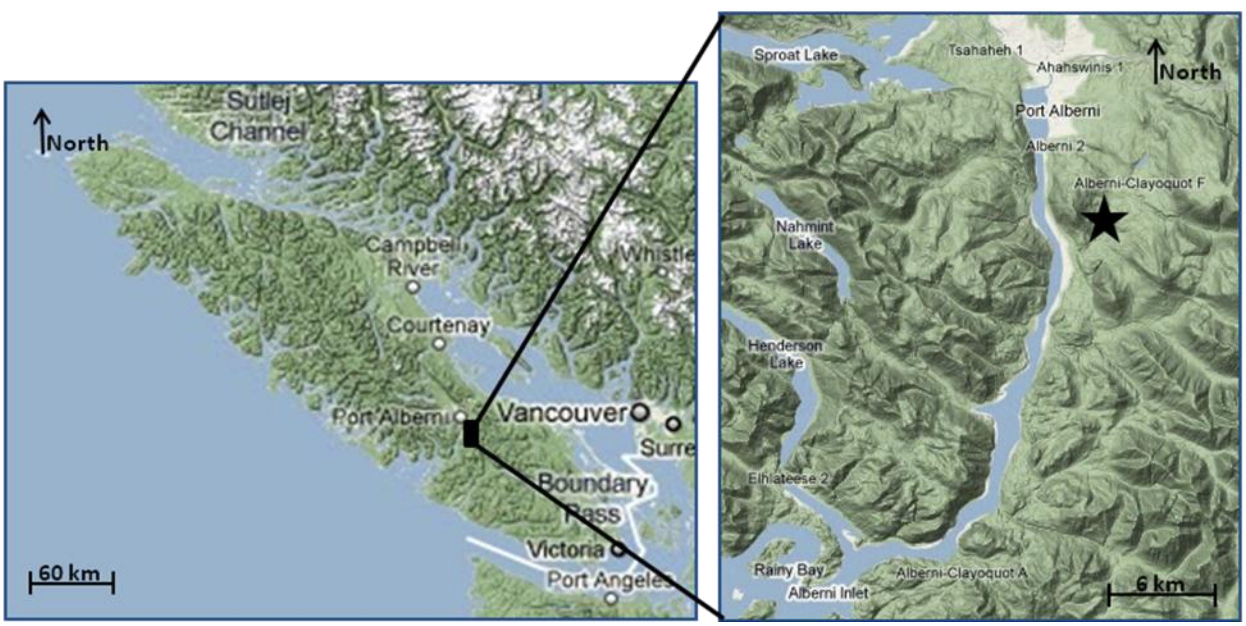

Figure 1: China Creek drains into the Port Alberni Inlet which cuts deeply into the west coast of Vancouver Island, BC. (Source: maps.google.ca).

There are two lakes within the watershed, some of which have species of cutthroat (*Oncorhynchus clarkii*) and rainbow trout (*O. mykiss*) (Epps *et al.* 2010). China Creek itself has five species of Pacific salmon (chinook (*O. tshawytscha*), pink (*O. gorbuscha*), coho (*O. kisutch*) and chum (*O. keta*)), and well as Dolly Varden char (*Salvelinus malma*), and steelhead (*O. mykiss*) (BC Ministry of Environment 2008). In addition, the presence of two endangered species, the Vancouver Island water shrew (*Sorex palustris brooksi*) and the red-legged frog (*Rana aurora*), has been noted (Trudy Chatwin, pers. comm., 2005 in Epps *et al.* 2010).

In the 1930s and 1940s, approximately 70% of the watershed was logged (Epps *et al.* 2010), much of it to the streambank, making the majority of the current forest 60-70 years old. The watershed was partially logged again in the mid-2000s leaving an effective clear cut area of 7% at the end of 2004 (Streamline Environmental Consulting Ltd. and Ostapowich Engineering Services Ltd. 2005). Some of this recent harvesting occurred upstream from the MOE water quality monitoring site used in this study and the intake for City of Port Alberni water (Rosie Barlak, pers. comm., 21 December 2009). From December 2004 to November 2005, the Upnit Power Corporation constructed an Independent Power Project (IPP) on China Creek (BC Hydro 2009). The weir intake is 2 km upstream of the MOE monitoring site used in this study, and the water is returned to the stream 2.6 km downstream of the monitoring site (Figure 2) (Rosie Barlak, pers. comm., 29 March 2010). Other anthropogenic disturbances throughout the watershed include sedimentation from logging roads, and disturbance from ATV use, hunting, and hiking in the area (Epps *et al.* 2010). Natural disturbance by landslides has also occurred (Epps *et al.* 2010).

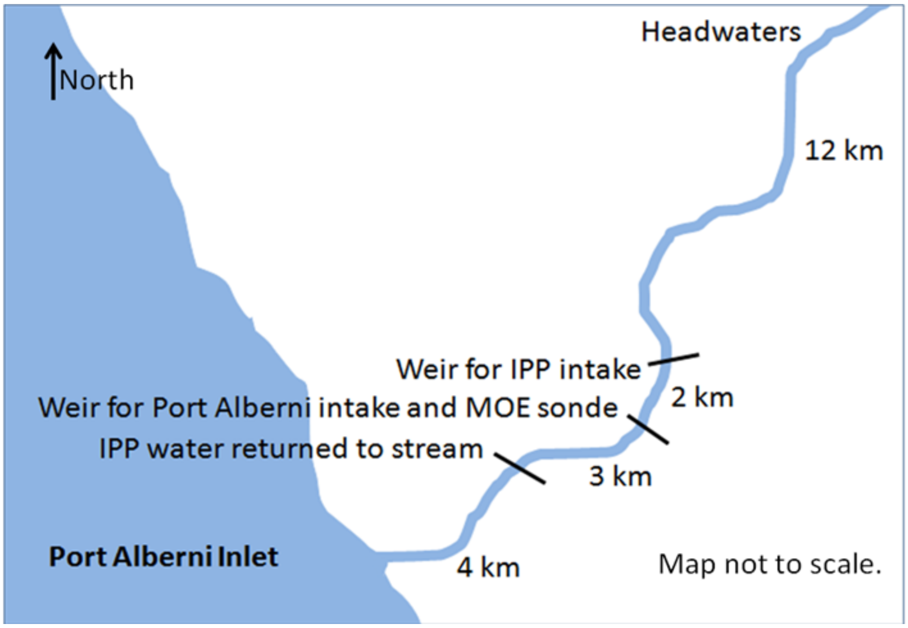

Figure 2: Schematic drawing of water intakes, returns, and sonde locations on China Creek, near Port Alberni, BC.

Field Measurements

The MOE maintained a water quality monitoring sonde approximately halfway between the headwaters and mouth of China Creek (124° 45.702' W, 49° 10.686' N) (Figure 2) to obtain data for use in the development of water quality objectives and subsequent objective attainment monitoring. Continuous water monitoring data, collected every 15 minutes, with a few exceptions, were collected with a Geoscientific probe between 2003-2005 and with a YSI probe between 2008-2009. For turbidity, the probes had a zero and negative baseline respectively, leading to negative nephelometric turbidity units (NTU) records in the 2008-2009 data (Rosie Barlak, pers. comm., 27 January 2010). Common to all years were measurements of temperature (°C), specific conductance (µS/cm), and mean turbidity (NTU). Discrete water samples were collected at the same location from 1-16 times a year in 1998, 2001-2005, and 2009. These measures included dissolved and total concentrations of various metals (mg/L), hardness (mg/L), UV absorption (AU/cm), fecal coliform and *Escherichia coli* counts (CFU/100mL), and pH. In addition, turbidity and conductivity were measured to validate the continuous water monitoring probe readings. Observed values less than the minimum detectable limit were recorded as such, and the value of the limit noted.

At this same site on China Creek, the City of Port Alberni has a weir for water intake and recorded water levels each non-statutory weekday. These water level data were recorded in terms of the height of water in metres flowing over the weir. Environment Canada operates two climate stations in the region. The site nearest China Creek (Cox Lake climate station, 49° 12.000' N, 124° 45.000' W, 163 m elevation), however, had an incomplete data set for the years MOE had been measuring water quality. The next closest climate station at the Port Alberni airport (Port Alberni (Aut) 49° 19.200' N, 124° 55.800' W, 76.2 m) had more consistent data.

Data Processing

The continuous water monitoring data required cleaning prior to analysis to correct for gaps in data and obvious outliers caused by equipment failure, water freezing around the probe, or the probe being exposed. Gaps of less than three hours were filled by linear interpolation. The continuous water monitoring data were also corrected for calibration drift using Aquarius before release by the MOE (Ruth-Ann Devos, pers. comm., 26 January 2010). Calibration drift occurs naturally as the probe is fouled with sediment over time. Stream temperatures greater than 30°C, and specific conductance recorded as 0 or 1 µS/cm were manually removed because these values are not realistically expected in PNW coastal streams (Dan Moore, pers. comm., 10 February 2010). The expert recommendation for correcting the incongruity between turbidity baselines in the two data sets was a constant offset to a zero baseline for the 2008-2009 values (Dan Moore, pers. comm., 29 January 2010). There was confidence in this correction for comparing to BC

Water Quality Guidelines (BC Ministry of Environment 2010), but not for detecting patterns of change. Therefore, these measurements were not corrected and were omitted from analyses.

The discrete water sample measures included many values less than the minimum detectable limit. Following standard practice, these values were assumed to be half of the detectable limit (Gravelle *et al.* 2009). With improvement in equipment accuracy over the decade, the minimum limits decreased. The 1998 values were omitted as they had a substantially higher limit. For the 2001-2009 measurements, the values below detection were considered to be half the value of the largest minimum detection limit.

Data Analyses

The discrete water sample measures from 2001 to 2009 of *E. coli*, fecal coliform, dissolved nitrate, dissolved phosphate, orthophosphate, dissolved organic carbon, pH, hardness, total calcium, total copper, and total magnesium were graphed to examine noteworthy trends through time. These particular variables were selected from those measured by the MOE because of a published link with forest practices or water use, and because they are representative of the variables with the most measurements. The data from the discrete water samples were compared to BC Water Quality Guidelines, where sampling frequency allowed (BC Ministry of Environment 2010).

Analysis of the continuous water monitoring data collected every 15 minutes in 2003-2005 and 2008-2009 focused on stream temperature because of its ecological significance and status as "master variable" (Moore *et al.* 2005a). This China Creek study examined the relationship between daily maximum stream temperatures (Tw_{max}) and two variables, daily mean specific conductance (SC_{mean}) and daily maximum air temperature (Ta_{max}). The latter variable was measured at the Port Alberni climate station. Models for predicted Tw_{max} values were built using measured Tw_{max} values with either Ta_{max} alone or Ta_{max} and SC_{mean} as predictor variables. A dummy variable was added to designate pre- and post-disturbance periods. Partial F-tests were run to determine significant differences between models with and without the dummy variables, and thus if there were significant differences in stream temperature before and after disturbance. If possible, how the relationship between stream temperature and the predictor variables changed was examined using model equations or graphs. Models and statistical tests were done with R version 2.10.0 for Windows, using a significance level (α) of 0.05.

The pre-disturbance period dates are May 2003-May 2004, with the latter being an estimate of when logging may have begun. The post-disturbance dates are May 2004-August 2005 and April 2008-December 2009. Models were compared and a best fit model chosen for each of the following data sets: full, low flow (SC_{mean} > 75 µS/cm), summer (June-August), and winter (October-March).

Since weather conditions control daily changes in surface energy input, air temperature has been used to account for solar radiation (Gomi *et al.* 2006). Despite the complexity of factors influencing stream temperature, past studies have used air temperature alone as a predictor variable (Stefan and Preudhomme 1993). Water levels, a covariate for discharge, were measured differently before and after harvest activities, making them unsuitable for comparison. Instead, specific conductance was used as an indicator of flow levels. The median SC_{mean} value was chosen as a correlate for lower flows because ion concentrations, and hence SC_{mean}, increase when discharge decreases (Moore *et al.* 2005). Summer months cannot simply be used to represent low flow months because there is artificial control of water levels in China Creek (Epps *et al.* 2010).

Autocorrelation, or dependence of measurements on previous measurements, is a concern with any continuous water monitoring data because it violates an assumption necessary for reliable statistical tests using standard methods. Some previous studies using continuous water monitoring data for stream parameters have avoided this dilemma by using data from only one time of year; however, this is not an option when multiple years of data are not available (Gomi *et al.* 2006). Gomi *et al.* used generalized least squares regression to deal with auto-correlated residuals (2005) for stream temperature measurements. A similar treatment was not possible in this study because of the gaps in the data. Auto- and cross-correlation were examined using SAS version 9.2 for Windows.

Results

Discrete Water Samples

The graphs of the discrete water sample measures (*E. coli*, fecal coliform, dissolved nitrate, dissolved phosphate, orthophosphate, dissolved organic carbon, pH, hardness, total calcium, total copper, and total magnesium), did not reveal any detectable trends either before or after the period of disturbance (Appendix A). There were insufficient data to compare the pre- and post-disturbance periods using statistical tests. This lack of data was seen particularly in the post-disturbance period, such as in the dissolved nitrate measures (Figure 3).

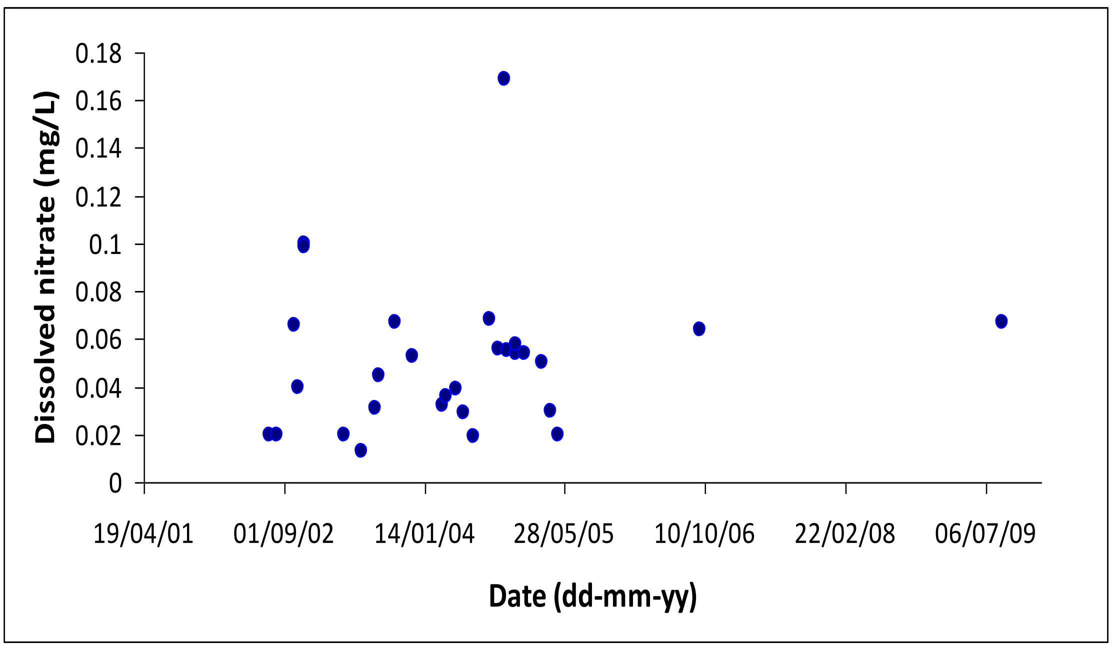

Figure 3: Dissolved nitrate concentrations in China Creek between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

There was substantial variation within each variable, but the majority were below the BC Water Quality Guidelines for drinking water both before and after disturbance (Appendix A).

Continuous Water Monitoring Data

Full Data Set

The continuous water monitoring data measures of Tw_{max} and SC_{mean}, along with the Ta_{max}, were auto-correlated through time. This was observed in their pattern of variation through time (Figure 4). Each observation was dependent on neighbouring observations.

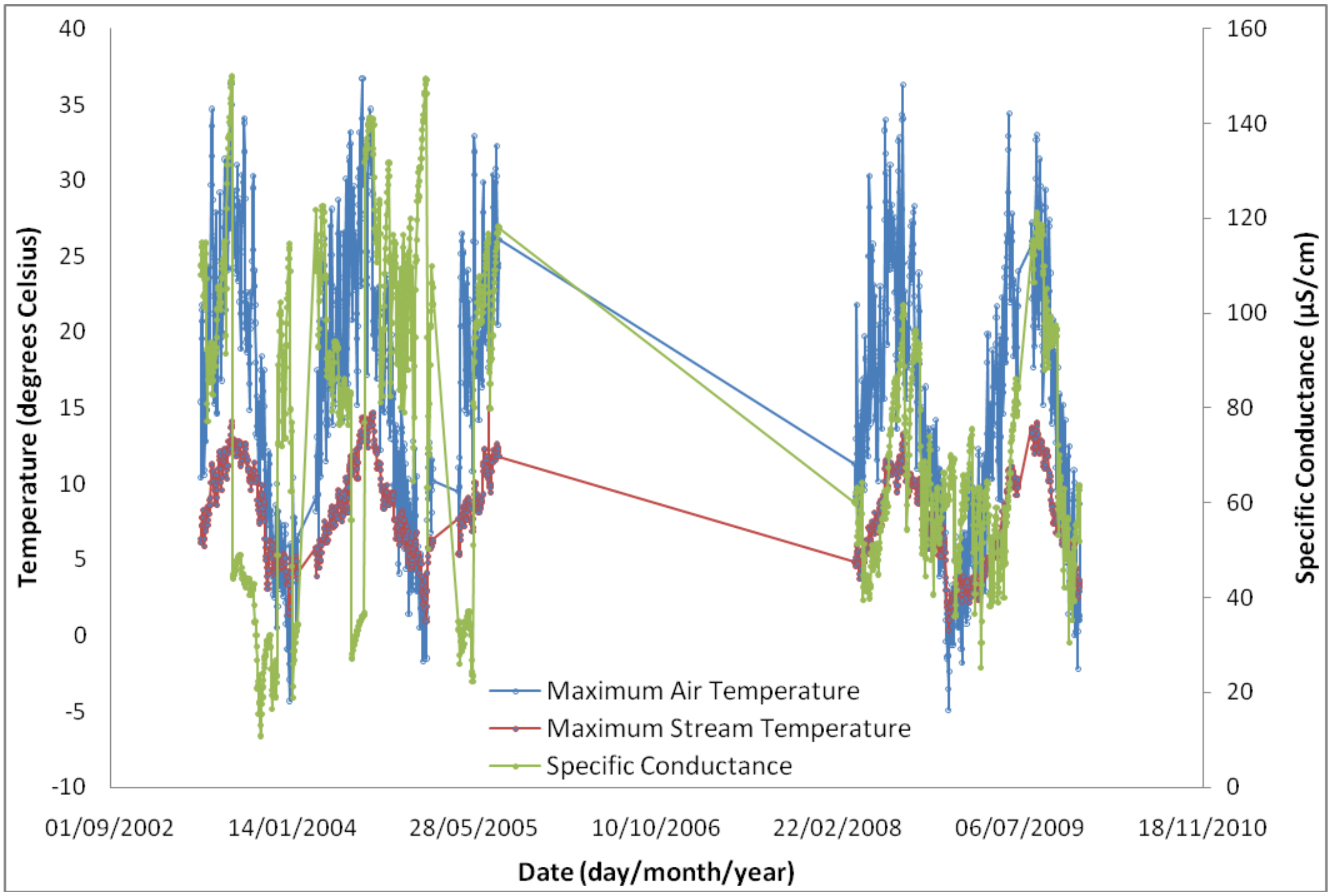

Figure 4: Maximum daily water temperatures (Tw_{max}), maximum daily air temperatures (Ta_{max}), and daily mean specific conductance (SC_{mean}) for the full continuous water monitoring data set from China Creek, Vancouver Island.

Tw_{max} measurements were strongly related to each other (Figure 5), as indicated by the large auto-correlation factor (ACF). The Tw_{max} observations remained strongly related at 20 observations removed.

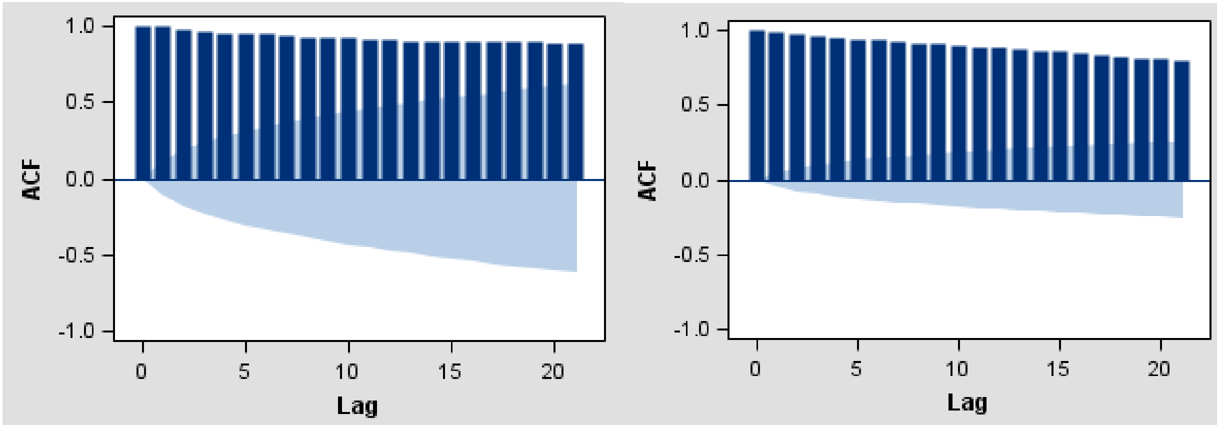

Figure 5: Auto-correlation between Tw_{max} values pre-disturbance (left) and post-disturbance (right) for the full China Creek continuous water monitoring data set, where ACF is the auto-correlation factor.

SC_{mean} was also auto-correlated, though not as strongly as Tw_{max} (data not shown). In addition to being auto-correlated, the continuous water monitoring data measures were also cross-correlated (Figure 6). There was a lack of independence between the Tw_{max} and Ta_{max} measures (Figure 6) and the Tw_{max} and SC_{mean} measures (data not shown).

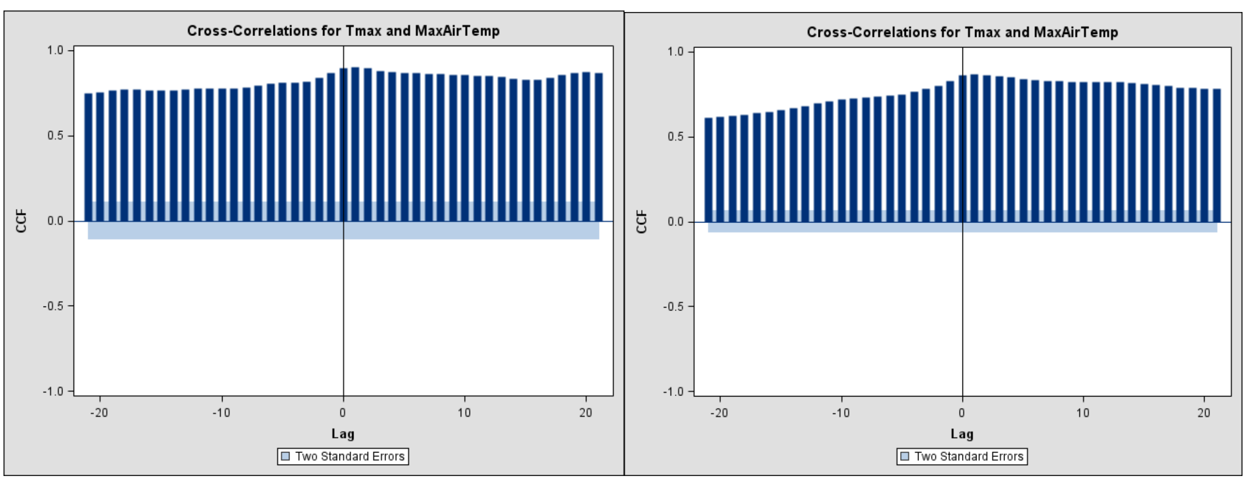

Figure 6: Cross-correlation between Tw_{max} and Ta_{max} values pre-disturbance (left) and post-disturbance (right) for the full China Creek continuous water monitoring data set, where CCF is the cross-correlation factor.

Because of the auto- and cross-correlation in the data, the assumption of independence of observations was not met. This led to biased estimates of standard error in statistical tests, and thus the F- and partial F-tests in the results may not be reliable. However, the estimates of the real coefficients and the goodness of fit measures remained unbiased.

For the continuous water monitoring data, Ta_{max} had a positive relationship with Tw_{max} (Figure 7), while SC_{mean} did not display a clear relationship with Tw_{max} (Figure 8).

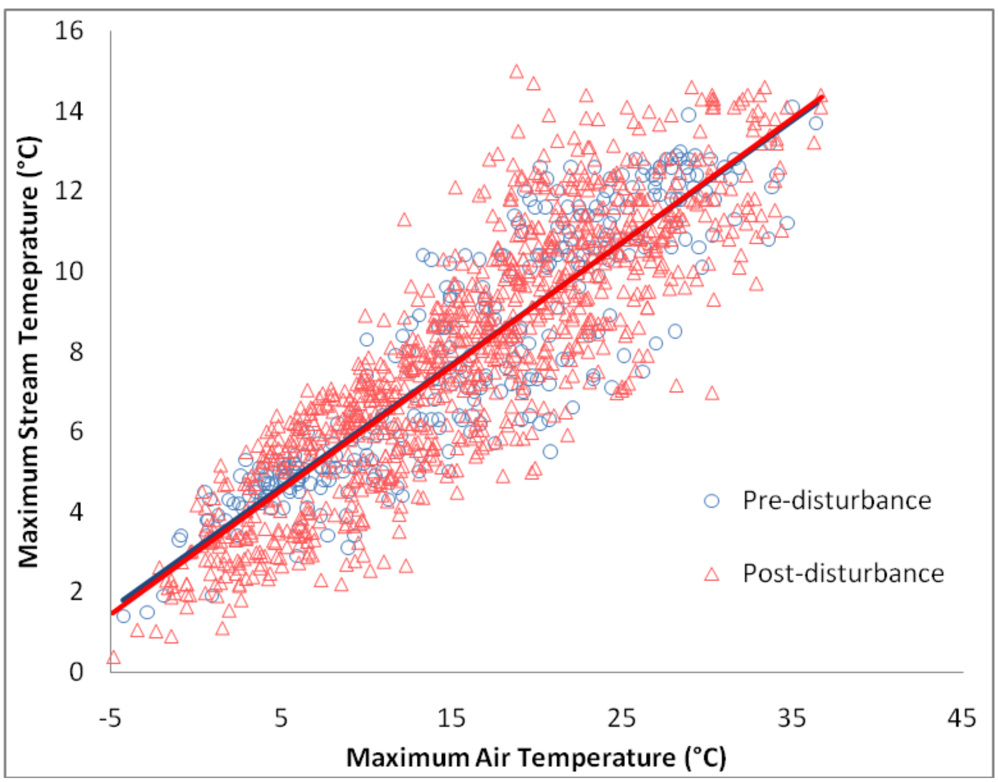

Figure 7: Relationship between daily maximum water temperatures (°C) from China Creek and daily maximum air temperatures (°C) from Port Alberni climate station from May 2003-August 2005 and April 2008-December 2009 ($R^2 = 0.76$, $p < 2.2 \times 10^{-16}$).

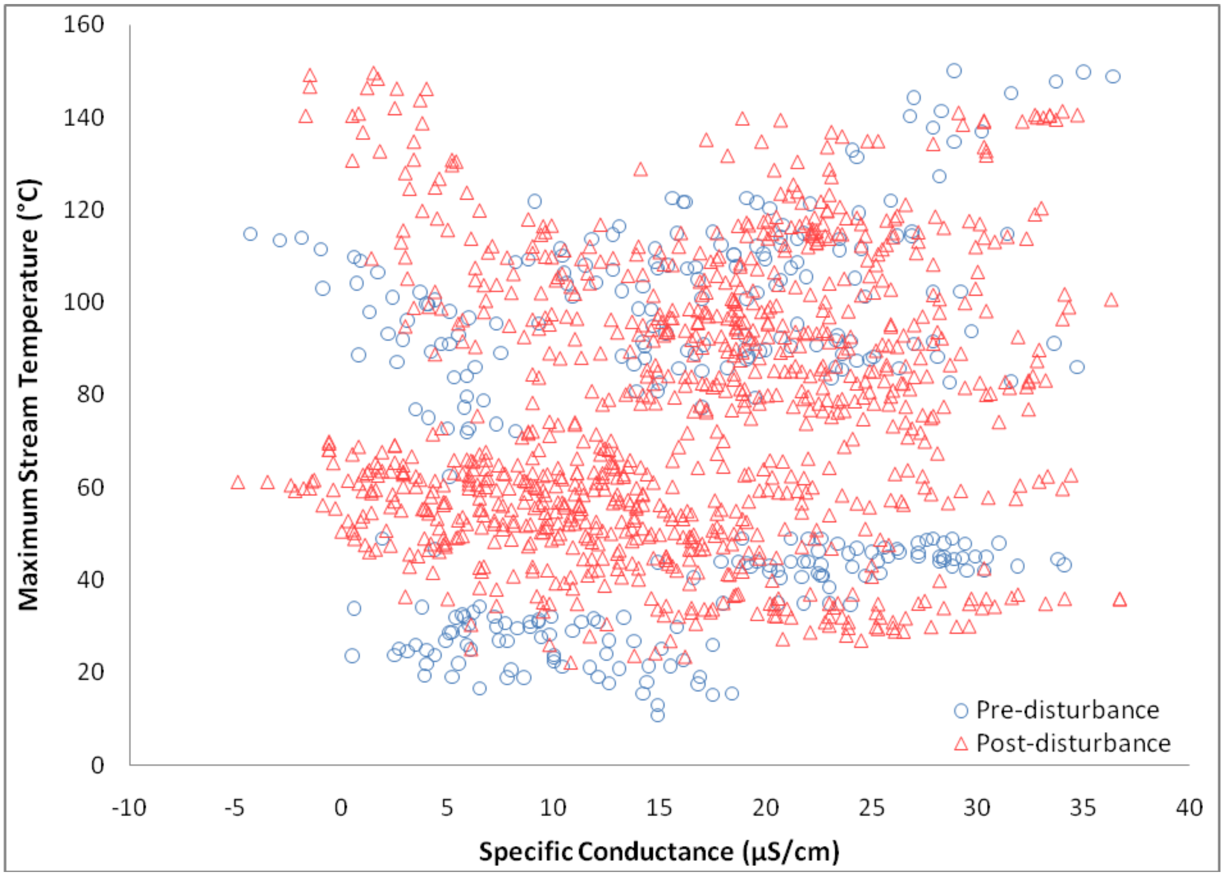

Figure 8: Relationship between daily maximum water temperatures (°C) and average daily specific conductance (µS/cm) for China Creek data from May 2003-August 2005 and April 2008-December 2009 (R^2 = 0.06, p *< 2.2x10^{-16}).*

Four models for predicted Tw_{max} were created using the full data set (Table 1). A partial F-test revealed no significant difference between the models using Ta_{max} without (Model 1a) or with (Model 1b) the inclusion of a dummy variable for pre- and post-disturbance (p = 0.84, Table 1). However, a partial F-test of the models with Ta_{max} and SC_{mean} showed a significant difference between the one without (Model 2c) and the one with (Model 2d) the inclusion of a dummy variable ($p < 2.2\text{x}10^{-16}$, Table 1). Thus, maximum stream temperature changed from before to after disturbance in China Creek.

Table 1: Comparison of statistics for models predicting daily maximum stream temperature for China Creek on Vancouver Island, BC. Pre-disturbance dates are May 2003-May 2004 and May 2004-August 20005, and post-disturbance dates are April 2008-December 2009.

Model	**y = maximum daily stream temperature** **x = maximum daily air temperature**		**y = maximum daily stream temperature** **x_1 = maximum daily air temperature** **x_2 = average daily specific conductance**	
Dummy variable	No dummy variable	Dummy variable for pre- and post-disturbance	No dummy variable	Dummy variable for pre- and post-disturbance
Full data	Model 1a p-value < 2.2×10^{-16} $R^2 = 0.76$ RSE = 1.53	Model 1b p-value < 2.2×10^{-16} $R^2 = 0.76$ RSE = 1.59	Model 1c p-value < 2.2×10^{-16} $R^2 = 0.77$ RSE = 1.49	Model 1d p-value < 2.2×10^{-16} $R^2 = 0.80$ RSE = 1.40
Partial F-test	p value = 0.84		p value < 2.2×10^{-16}	
Low flow data	Model 2a p-value < 2.2×10^{-16} $R^2 = 0.74$ RSE = 1.49	Model 2b p-value < 2.2×10^{-16} $R^2 = 0.77$ RSE =1.40	Model 2c p-value < 2.2×10^{-16} $R^2 = 0.75$ RSE = 1.46	Model 2d p-value < 2.2×10^{-16} $R^2 = 0.78$ RSE = 1.36
Partial F-test	p value < 2.2×10^{-16}		p value < 2.2×10^{-16}	
Summer data	Model 3a p-value <2.2×10^{-16} $R^2 = 0.43$ RSE = 1.29	Model 3b p-value <2.2×10^{-16} $R^2 = 0.43$ RSE = 1.29	Model 3c p-value <2.2×10^{-16} $R^2 = 0.49$ RSE = 1.23	Model 3d p-value <2.2×10^{-16} $R^2 = 0.55$ RSE = 1.18
Partial F-test	p value = 0.38		p value <5.72×10^{-7}	
Winter data	Model 4a p-value < 2.2×10^{-16} $R^2 = 0.67$ RSE= 1.21	Model 4b p-value < 2.2×10^{-16} $R^2 = 0.67$ RSE= 1.21	Model 4c p-value < 2.2×10^{-16} $R^2 = 0.67$ RSE= 1.21	Model 4d p-value < 2.2×10^{-16} $R^2 = 0.68$ RSE= 1.19
Partial F-test	p-value = 0.34		p-value = <5.25×10^{-5}	

The best fit model (Model 1d) for the full data set was:

$$\text{Predicted } Tw_{max} = 3.852611 + 0.313910 * Ta_{max} - 0.012558 * SC_{mean} - 2.410538 * x_{3i}$$

$$- 0.016512 * Ta_{max} * x_{3i} + 0.035382 * SC_{mean} * x_{3i},$$

where x_{3i} is the dummy variable and equals 0 for pre- and 1 for post-disturbance data. This model best met assumptions of a linear relationship between x and y variables, equal variance of errors and normal distribution of y values for each x value. The model explained 80% of the variance. Because this model had multiple variables, it was difficult to determine the way stream temperatures changed following harvest. However, comparison of 3D graphs of pre- (Figure 9) and post-disturbance (Figure 10) relationships may reveal changes for specific Ta_{max} and SC_{mean} ranges.

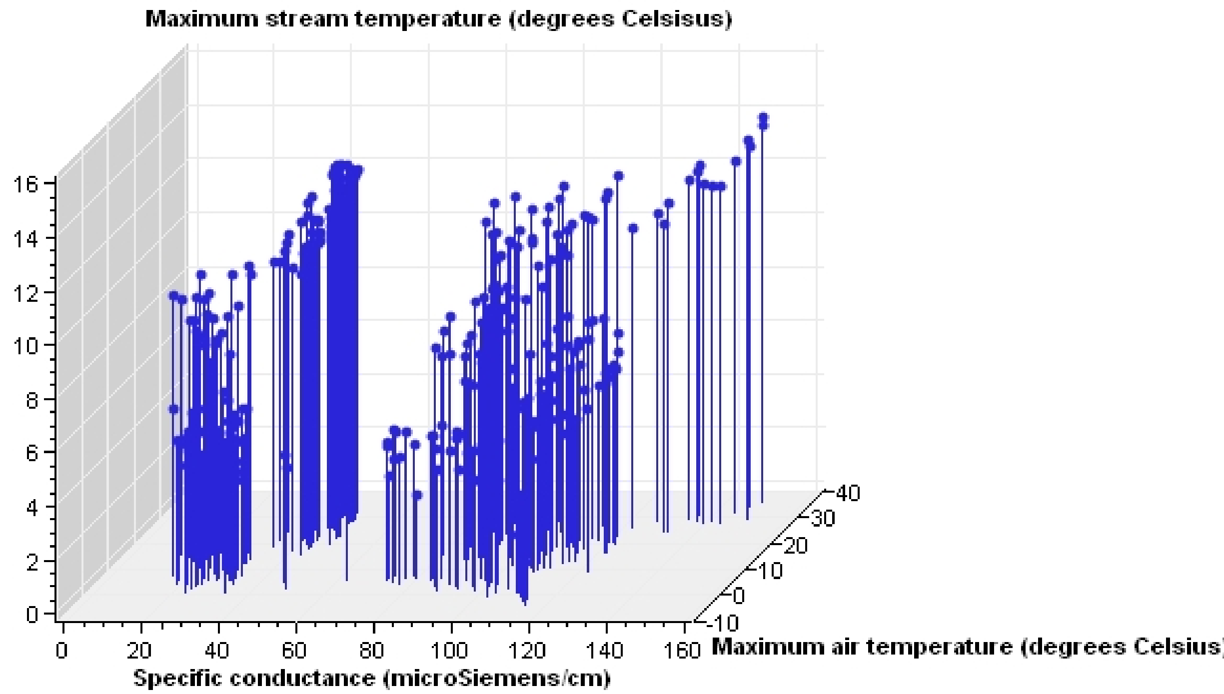

Figure 9: Relationship between daily maximum water temperatures (°C), daily maximum air temperature (°C), and average daily specific conductance (µS/cm) for China Creek post-disturbance from May 2003-August 2005.

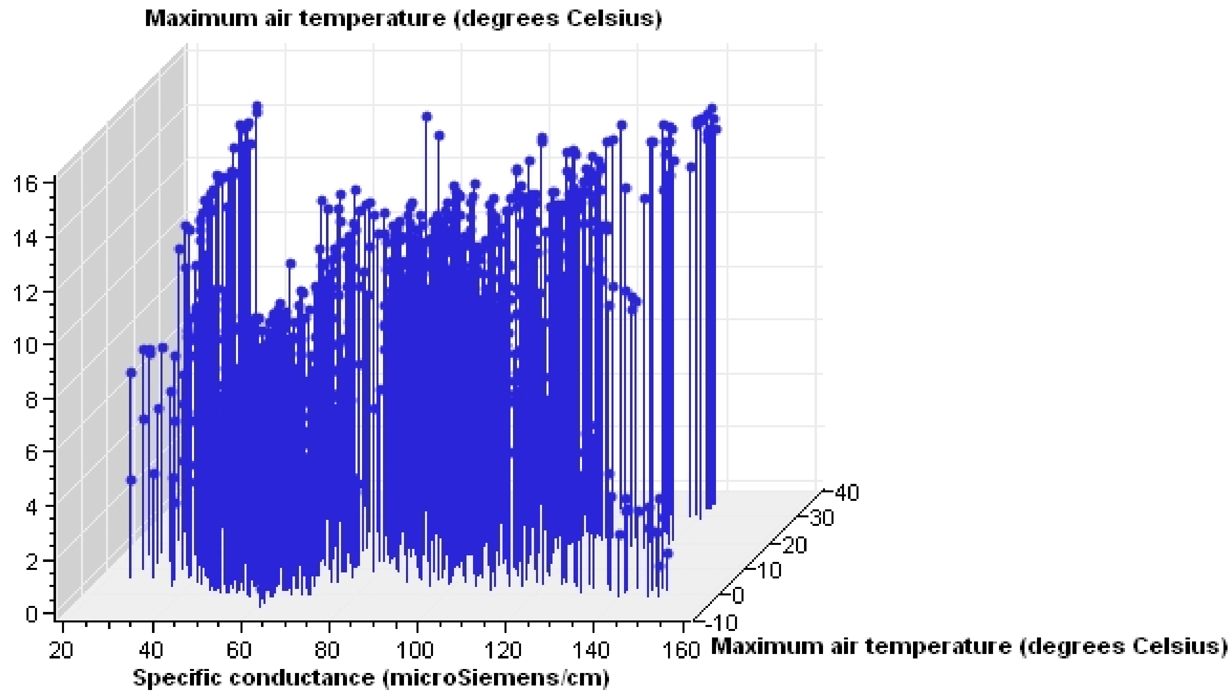

Figure 10: Relationship between daily maximum water temperatures (°C), daily maximum air temperature (°C), and average daily specific conductance (µS/cm) for China Creek post-disturbance from April 2008-December 2009.

Low Flow Data

The subset with SC_{mean} > 75 µS/cm was considered representative of low flow periods. The limit 75 µS/cm was chosen as it is the approximate median of all SC_{mean} values. The upper quartile 100 µS/cm was tested to compare sensitivity. The upper quartile data produced a stronger relationship between Ta_{max} and Ta_{max} (R^2 = 0.80) compared to using the median (R^2 = 0.74). However, using the upper quartile did not change the significance of F-tests, so the median was preferred.

As with the full data set, there was a positive relationship between Tw_{max} and Ta_{max} during low flows (Figure 11). For the post-disturbance measures, there was some lack of fit at low Ta_{max} values (Figure 11); however there were also fewer data points at these lower temperatures.

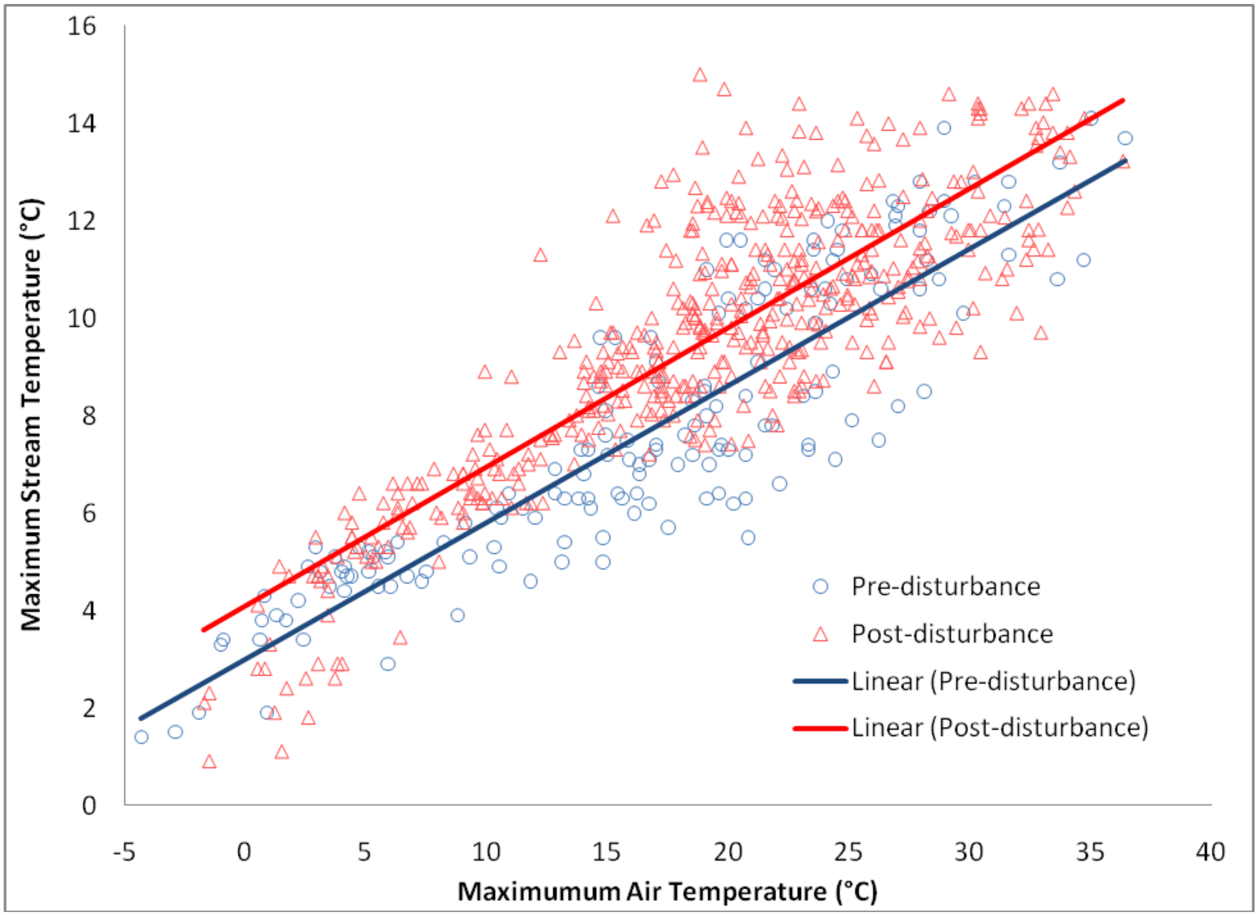

Figure 11: Relationship between daily maximum water temperatures (°C) from China Creek and daily maximum air temperatures (°C) from Port Alberni climate station data during low flows. Pre-disturbance dates are May 2003-May 2004 and May 2004-August 20005, and post-disturbance dates are April 2008-December 2009. (R^2= 0.78, p = *< 2.2x10^{-16}).*

As with the full data set, four models were created for the low flow data. The partial F-test showed a significant difference between the models using Ta_{max} without (Model 2a) or with (Model 2b) the inclusion of a dummy variable for pre- and post-disturbance ($p < 2.2x10^{-16}$, Table 1). There was also a significant difference between the models using Ta_{max} and SC_{mean} without (Model 2c) or with (Model 2d) the inclusion of a dummy variable for pre- and post-disturbance ($p < 2.2x10^{-16}$, Table 1).

For the two low flow models with dummy variables, Models 2b and 2c, there was little difference in the strength of relationship (R^2_{adj} = 0.77 and 0.78 respectively, Figure 1). Model 2b met the assumptions of linearity and normality better than Model 2c, while both have a small lack of equal variance. Therefore, the simplest best fit model (Model 2b) for low flow data was:

$$\text{Predicted } Tw_{max} = 2.98591 + 0.28173*Ta_{max} + 1.08834*x_{2i}$$

where x_{2i} is the dummy variable and equals 0 for pre- and 1 for post-disturbance data. The interaction between Ta_{max} and period was not significant (p = 0.73), and therefore was dropped from the model. Model 2b showed there was a significant difference in stream water temperatures for low flow data before and after disturbance, with an increase of approximately 1°C following disturbance.

Summer Data

The summer data included the months of June-August. As with the full data set, the partial F-test showed no significant difference between the models using Ta_{max} without (Model 3a) or with (Model 3b) the inclusion of a dummy variable for pre- and post-disturbance (p = 0.38, Table 1). However, there was a significant difference between the models using Ta_{max} and SC_{mean} without (Model 3c) or with (Model 3d) the inclusion of a dummy variable for pre- and post-disturbance ($p < 5.72x10^{-7}$, Table 1). The models with Ta_{max} and SC_{mean} (Models 3c and 3d) met the assumptions of linearity and normality better than the models with $Ta_{max,}$ (Models 3a and b). All four models had a small lack of equal variance. There was a notable increase in the goodness of fit for the Ta_{max} and SC_{mean} models as well. For example, for Model 3d the R^2_{adj} was 0.52, while the R^2_{adj} for Model 3b was 0.44.

Model 3d was the best fit model for the summer data. The t-tests showed that interaction between Ta_{max} and dummy variable (p = 0.48) and the intercept adjustment by SC_{mean} (p = 0.21) did not contribute significantly to the model in the presence of the other variables. With these terms omitted from the model, the best fit model (Model 3d) was:

$$\text{Predicted } Tw_{max} = 7.333868 + 0.182247*Ta_{max} - 2.800900*x_{3i} + 0.024417*SC_{mean}*x_{3i}$$

where x_{3i} is the dummy variable and equals 0 for pre- and 1 for post-disturbance data.

While the summer data still did not meet the assumption of independence of observations, of all four data sets, auto-correlation of summer data was smallest. Auto-correlation was minimal by the time observations were 15 days apart for the pre- and post-disturbance periods (data not shown). Cross-correlation of Tw_{max} and Ta_{max} for summer month showed strong relationship for only four days in the pre-disturbance period, and for 15 days in the post-disturbance period (data not shown).

Winter Data

The winter data included the months of October-March. As with the full data set, the partial F-test showed no significant difference between the models using Ta_{max} without (Model 4a) or with (Model 4b) the inclusion of a dummy variable for pre- and post-disturbance ($p = 0.34$, Table 1). However, there was a significant difference between the models using Ta_{max} and SC_{mean} without (Model 4c) or with (Model 4d) the inclusion of a dummy variable for pre- and post-disturbance ($p < 5.23 \times 10^{-7}$, Table 1). All four models met the assumptions of linearity, though there was some departure from normality at low and high levels. All four models had a small lack of equal variance. Model 4d had a slightly better fit, and in the presence of the other variables, all the variables contributed significantly to the model (all *p*-values < 0.01).

The best fit model (Model 4d) for winter data was:

$$\text{Predicted } Tw_{max} = 3.938440 + 0.282040*Ta_{max} – 0.011536*SC_{mean} – 1.557739*x_{3i} + 0.056978*Ta_{max}*x_{3i} + 0.017177*SC_{mean}*x_{3i}$$

where x_{3i} is the dummy variable and equals 0 for pre- and 1 for post-disturbance data.

Therefore, for full, low flow, summer, and winter data sets there was significant difference in the stream temperature before and after disturbance. For the low flow data, air temperature contributed significantly to stream temperature. The post-disturbance stream temperatures increased approximately 1ºC for all ranges of air temperature. For the full, summer, and winter data sets, air temperature and specific conductance (an indicator of discharge) together contributed significantly to stream temperature. It was difficult to determine how stream temperatures changed following disturbance for the latter three data sets because of the multiple variables and interactions involved.

Discussion

Discrete Water Samples

The discrete water samples data in China Creek measure chemical and biological water quality parameters, and thus they are essential to a holistic understanding of how disturbance impacts this watershed. However, there were insufficient data to test the hypothesis that pH would decrease while sediment loads, and nitrogen content would increase. Even if it is difficult to deduce the factors impacting chemical trends (Feller 2005), it is important to monitor them consistently to have sufficient data to determine trends through time. For example, plant-nutrient availability variations between season and watershed can be assessed (Gravelle *et al.* 2009). With consistent collection, such data can also contribute to the general understanding of how nutrients respond to harvest over a range of watershed types (Gravelle *et al.* 2009).

Continuous Water Monitoring Data

Modelling the continuous water monitoring data did not support the hypothesis that maximum stream temperature would increase in summer months following harvest disturbance. However, in low flow periods there was an increase in maximum stream temperature after disturbance. This is not unusual because there is a faster temperature response where streams are shallower than in deeper reaches and pools (Moore *et al.* 2005). The MOE sonde is located in an artificially created pool on China Creek, so it may be that the volume of water buffers changes in temperature, and hence the impacts of forest harvest in increasing stream temperature are only observed during low flows.

The IPP weir and intake are upstream of the MOE water measurement and Port Alberni intake site, so changes in flow and water level do not simply reflect hydrological processes. The artificial controls of water flow in China Creek include withdrawals of water at the IPP weir and release of water from Lizard Lake by Port Alberni during summer low flows (Epps *et al.* 2010). The thermal regime in lakes is complex, and the temperature of the water being released into the stream depends on the degree of thermal stratification in the lake. The latter varies with season and time since the most recent windstorm. In addition to impacting thermal regime, the IPP may have impacted specific conductance. Ruth-Ann Devos notes some unusual data points that may have been a result of the upstream power plant flushing out their screens because both temperature and turbidity spiked simultaneously (pers. comm., 27 January 2010). Moore *et al.* (2008) noted that increased fine sediment can decrease specific conductance.

The overlapping disturbances make it complicated to determine whether changes are due to harvesting, IPP weir intake construction, or natural factors such as storm events. The analysis in this study is further limited by incomplete knowledge of when the disturbances occurred. For example, while the IPP weir intake construction dates are known to be December 2004 to November 2005 (Epps *et al.* 2010; BC Hydro 2009), it is unknown when the most recent harvest began and there is only a suggestion that it ended in late 2004 (Streamline Environmental Consulting Ltd. and Ostapowich Engineering Services Ltd. 2005). The lack of data collection between August 2005 and April 2008 may be a contributing factor. Since thermal recovery can occur within 5-10 years (Moore *et al.* 2005a), it is possible that by the time measurements were resumed the largest short-term treatment effects had passed.

There may be other non-anthropogenic factors impacting the results of this study. For example, the relative contribution of ground water inflow can influence stream temperature. If ground water inflow increases following forest harvest, it may dampen the temperature increase (Moore *et al.* 2005a). Secondly, many previous studies focus on rain-dominated watersheds (Moore *et al.* 2005a), while China Creek has a mixed hydrological regime. The added influence of snow within the watershed may alter the temperature changes observed with forest harvest. Thirdly, the results in this study may be influenced by larger climatic patterns. Kiffney *et al.* (2002) found that El Niño, La Niña, and Pacific Decadal Oscillation cycles all influenced stream and air temperatures in the Malcolm Knapp Research Forest, BC, especially when the cycles coincided with one another. In general, when precipitation and discharge were increased, air and stream temperatures decreased (Kiffney *et al.* 2002). As climate change scenarios are contemporary concerns, it is important to note that Mohseni and Stefan (1999) found stream-air temperature models unsuitable for predicting stream temperatures in different climate change scenarios. Finally, the use of SC_{mean} as a covariate with stream flow levels is problematic because in addition to discharge, specific conductance is also influenced by nitrification rates and pH which can change with forest harvest (Feller 2005).

Interpretation of the results of this study is limited because without more information about the extent of harvest and site preparations, it is difficult to compare to past studies. Yet, even if information was comprehensive, such comparisons would be limited by differences in watershed characteristics such as climate, vegetation type, and hydrological regime (Moore *et al.* 2005a). Also, these characteristics can produce compounding effects, such as vegetation type changing hydrology and increasing shading on the stream (Moore *et al.* 2005a). In Carnation Creek the physical conditions that changed with logging recovered at different rate (Hartman *et al.* 1996). This further complicates the difficulty in teasing apart different effects when comparing across watersheds.

It is important to note that even if the effects could be separated, this would not establish a cause and effect relationship. A simple before-after study, such as this study of China Creek, lacks statistical rigour. The most rigorous and effective study design is a before-after/control-impact (BACI) study, also known as a paired catchments study (Moore *et al.* 2005a). An effective future study of China Creek temperature regimes would be to pair it with another watershed on west coast Vancouver Island with data for the same water quality variables over the same time period. Future studies should correct the auto- and cross-correlation of measurements to meet the independence of observations assumption, and thus gain greater reliability of F- and partial F-tests. Continued and consistent monitoring of China Creek water quality would allow a future study to examine how variables continue to change in the long term (more than five years) following disturbance.

While the results suggest an increase in maximum stream temperature during low flows, it is uncertain whether the results hold downstream for two reasons. First, water flow regime will change yet again below the Port Alberni water intake and the MOE monitoring site used in this study, especially since the water intake is approximately double in the summer due to increase domestic water use (Epps *et al.* 2010). Second, it is uncertain how far downstream disturbance impacts can be observed (Feller 2005). Clear documentation of harvest locations in the China Creek watershed were not available for this study, so it is hard to predict whether effects will be ameliorated or intensified downstream. Moore *et al.* (2005a) draw attention to the role of buffers and fraction of total flow in determining downstream impacts of cumulative warming. It would therefore be useful to have more accurate measures of stream flow (instead of a covariate) and stream temperature for a range of reaches along China Creek. This information would be invaluable in determining whether temperature regime changes might have a negative impact on the aquatic life in China Creek, particularly the Pacific salmon species.

Stream-air temperature models have simplicity in a single, easily measured predictor variable. However, the strength of the model is greatest when a monthly instead of a daily temperature average is used (Stefan and Preudhomme 1993). This may be due to the lag time of water temperatures after air temperatures than would make daily predictions less accurate (Stefan and Preudhomme 1993). As well, the linearity of this model breaks down at high and low temperatures (Mohseni and Stefan 1999). At low temperatures, the stream temperature goes to zero as an asymptote, and at high temperatures elevated evaporation rates increase cooling, and thus the relationship between stream temperature and air temperature has sigmoid characteristics (Mohseni and Stefan 1999). While the sigmoid relationship is not seen clearly in the China Creek data set, a decrease in strength of the relationship between stream temperature and maximum air temperature is seen above 15°C.

Stream temperature models can indicate if a change in temperature has occurred and some of the processes that seem to be driving the change. In addition to this, models between stream temperature and maximum air temperature can be used as an indicator of thermal recovery following disturbance (Gomi *et al.* 2006). Thermal recovery is expected between 5-15 years, depending on the type of harvest treatments used (Moore *et al.* 2005a). Thus, as the monitoring of China Creek continues, models from this study can be run for post-disturbance years to determine if the relationships between stream temperature and air temperature and specific conductance have returned to pre-disturbance conditions.

Conclusion

For China Creek, Vancouver Island, the data were insufficient data to conclude whether significant changes in chemical or biological water quality measures occurred after disturbance in the watershed by timber harvest and a power plant weir construction. However, the levels remained largely below BC Water Quality Guidelines (BC Ministry of Environment 2010).

Modelling the maximum daily stream temperature (Tw_{max}) using the continuous water monitoring measures of maximum daily air temperature (Ta_{max}) showed an increase of approximately 1°C in stream temperatures during low flows following disturbance. There were also changes in stream temperature following disturbance for the full, summer and winter data sets. How stream temperature changed in these cases was not determined because of the complex interactions between the two predictor variables, Ta_{max} and average daily specific conductance (SC_{mean}). The results were limited by the auto- and cross-correlation of the variables which may bias standard error estimates and thus, F- and partial F-tests.

Modelling maximum stream temperature changes in China Creek is valuable for detecting changes following disturbance, and especially for exploring the processes driving this change. This understanding can be used in monitoring the recovery of temperature and thermal processes following disturbance.

References

BC Hydro. *China Creek hydroelectric project* in BC Hydro [database online]. 2009 [cited 18 March 2010]. Available from www.bchydro.com/planning_regulatory/acquiring_power/green_ipps/project_updates/china_creek.html.

BC Ministry of Environment. *Fisheries information summary system (FISS) database* in Government of British Columbia [database online]. 2008 [cited 18 March 2010]. Available from www.env.gov.bc.ca/fish/fiss/index.html.

———. *Water quality guidelines (criteria) reports* in Government of BC [database online]. 2010 [cited 11 April 2010]. Available from http://www.env.gov.bc.ca/wat/wq/wq_guidelines.html.

Carmanah Research Ltd. 1997. *Work plan for a water quality program for community watersheds vancouver island region, british columbia.* Nanaimo, BC: Prepared for Ministry of Environment, Land and Parks.

Epps, D., R. Barlak, and B. Phippen. 2010. *Water quality assessment and objectives for the China Creek community watershed.* Victoria: BC Ministry of Environment, Water Quality Branch.

Feller, M. C. 1981. Effects of clearcutting and slashburning on stream temperature in Southwestern British Columbia. *Water Resources Bulletin* 17, (5): 863-867.

———. 2005. Forest harvesting and stream water inorganic chemistry in Western North America: A review. *Journal of the American Water Resources Association* 41, (4): 785-811.

Gomi, T., R. D. Moore, and M. A. Hassan. 2005. Suspended sediment dynamics in small forest streams of the Pacific Northwest. *Journal of the American Water Resources Association* 41, (4): 877-898.

Gomi, T., R. D. Moore, and A. S. Dhakal. 2006. Headwater stream temperature response to clear-cut harvesting with different riparian treatments, Coastal British Columbia, Canada. *Water Resources Research* 42, W08437: 1-11.

Gravelle, J. A., and T. E. Link. 2007. Influence of timber harvesting on headwater peak stream temperatures in a Northern Idaho watershed. *Forest Science* 53, (2): 189-205.

Gravelle, J. A., G. Ice, T. E. Link, and D. L. Cook. 2009. Nutrient concentration dynamics in an inland Pacific Northwest watershed before and after timber harvest. *Forest Ecology and Management* 257, (8): 1663-1675.

Hartman, G. F., J. C. Scrivener, and M. J. Miles. 1996. Impacts of logging in Carnation Creek, a high-energy coastal stream in British Columbia, and their implication for restoring fish habitat. *Canadian Journal of Fisheries and Aquatic Sciences* 53: 237-251.

Holtby, L. B. 1988. Effects of logging on stream temperatures in Carnation Creek, British Columbia, and associated impacts on the coho salmon (*oncorhynchus kisutch*). *Canadian Journal of Fisheries and Aquatic Sciences* 45, (3): 502-515.

Holtby, L. B., T. E. McMahon, and J. C. Scrivener. 1989. Stream temperatures and inter-annual variability in the emigration timing of coho salmon (*oncorhynchus kisutch*) smolts and fry and chum salmon (*O. keta*) fry from Carnation Creek, British Columbia. *Canadian Journal of Fisheries and Aquatic Sciences* 46, (8): 1396-1405.

Hubbart, J. A., T. E. Link, J. A. Gravelle, and W. J. Elliot. 2007. Timber harvest impacts on water yield in the continental/maritime hydroclimatic region of the United States. *Forest Science* 53, (2): 169-80.

Karwan, D. L., J. A. Gravelle, and J. A. Hubbart. 2007. Effects of timber harvest on suspended sediment loads in Mica Creek, Idaho. *Forest Science* 53, (2): 181-188.

Kiffney, P. M., J. P. Bull, and M. C. Feller. 2002. Climatic and hydrologic variability in a coastal watershed of Southwestern British Columbia. *Journal of the American Water Resources Association* 38, (5): 1437-1451.

Mohseni, O., and H. G. Stefan. 1999. Stream temperature air temperature relationship: A physical interpretation. *Journal of Hydrology* 218: 128-141.

Moore, R. D. 2005. Small stream channels and their riparian zones in forested catchments of the Pacific Northwest: Introduction. *Journal of the American Water Resources Association* 41, (4): 759-761.

Moore, R. D., G. Richards, and A. Story. 2008. Electrical conductivity as an indicator of water chemistry and hydrologic process. *Watershed Management Bulletin* 11, (2): 25-29.

Moore, R. D., D. L. Spittlehouse, and A. Story. 2005a. Riparian microclimate and stream temperature response to forest harvesting: A review. *Journal of the American Water Resources Association* 41, (4): 813-834.

Moore, R. D., P. Sutherland, T. Gomi, and A. Dhakal. 2005b. Thermal regime of a headwater stream within a clear-cut, coastal British Columbia, Canada. *Hydrological Processes* 19, (13): 2591-2608.

Moore, R. D., and S. M. Wondzell. 2005. Physical hydrology and the effects of forest harvesting in the Pacific Northwest: A review. *Journal of the American Water Resources Association* 41, (4): 763-784.

Olden, J. D., and R. J. Naiman. 2010. Incorporating thermal regimes into environmental flows assessments: Modifying dam operations to restore freshwater ecosystem integrity. *Freshwater Biology* 55, (1): 86-107.

Quinn, J. M., and A. E. Wright-Stow. 2008. Stream size influences stream temperature impacts and recovery rates after clearfell logging. *Forest Ecology and Management* 256, (12): 2101-2109.

Richardson, J. S., R. E. Bilby, and C. A. Bondar. 2005. Organic matter dynamics in small streams of the Pacific Northwest. *Journal of the American Water Resources Association* 41, (4): 921-934.

Scrivener, J. C., and B. C. Andersen. 1984. Logging impacts and some mechanisms that determine the size of spring and summer populations of coho salmon fry (O*ncorhynchus kisutch*) in Carnation Creek, British Columbia. *Canadian Journal of Fisheries and Aquatic Sciences* 41, (7): 1097-1105.

Stefan, H. G., and E. B. Preudhomme. 1993. Stream temperature estimation from air-temperature. *Water Resources Bulletin* 29, (1): 27-45.

Streamline Environmental Consulting Ltd. and Ostapowich Engineering Services Ltd. 2005. *Watershed assessment – China Creek watershed*. Prepared for Weyerhaeuser South Island Timberlands West Island Timberlands.

Tremblay, Y., A. N. Rousseau, A. P. Plamondon, D. Levesque, and M. Prevost. 2009. Changes in stream water quality due to logging of the boreal forest in the Montmorency Forest, Quebec. *Hydrological Processes* 23, (5): 764-776.

Zhu, J. Z., and A. Mazumder. 2008. Estimating nitrogen exports in response to forest vegetation, age and soil types in two coastal-forested watersheds in British Columbia. *Forest Ecology and Management* 255: 1945-1959.

Appendices

A. Graphs of Discrete Water Samples from 2001-2009

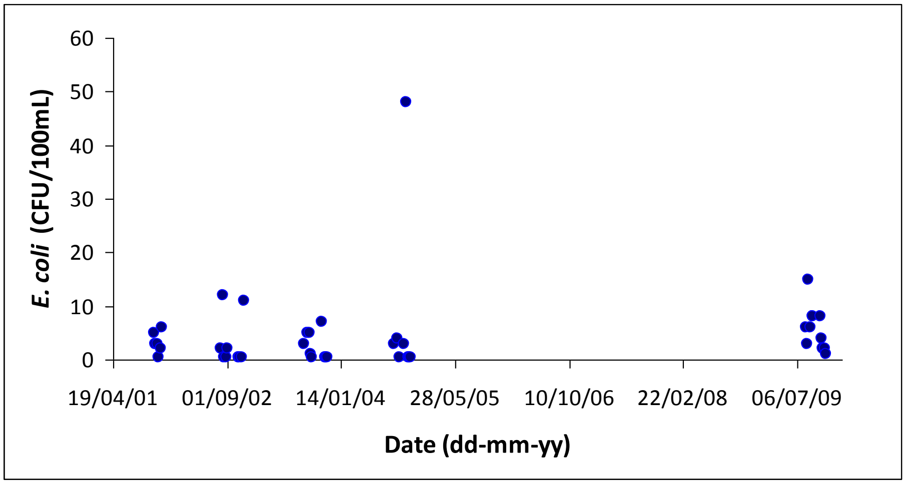

Figure 12: Escherichia coli *concentrations in China Creek between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.*

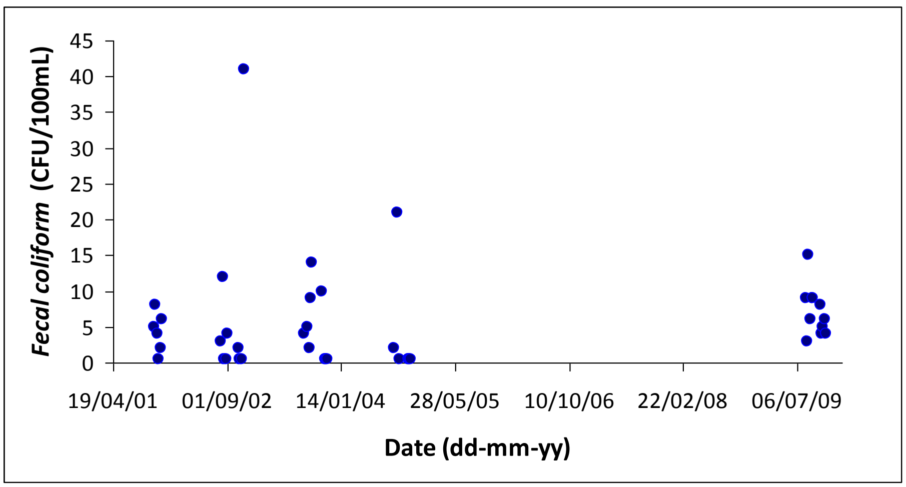

Figure 13: Fecal coliform concentrations in China Creek, between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

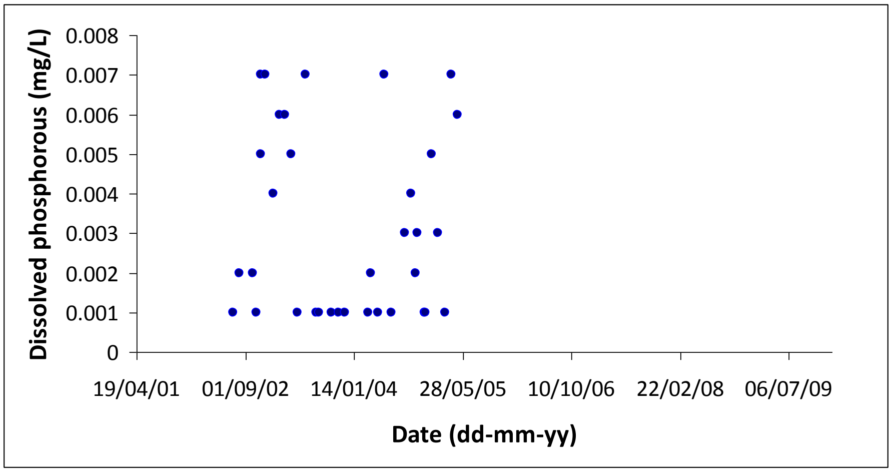

Figure 14: Concentrations of dissolved phosphorous in China Creek, 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

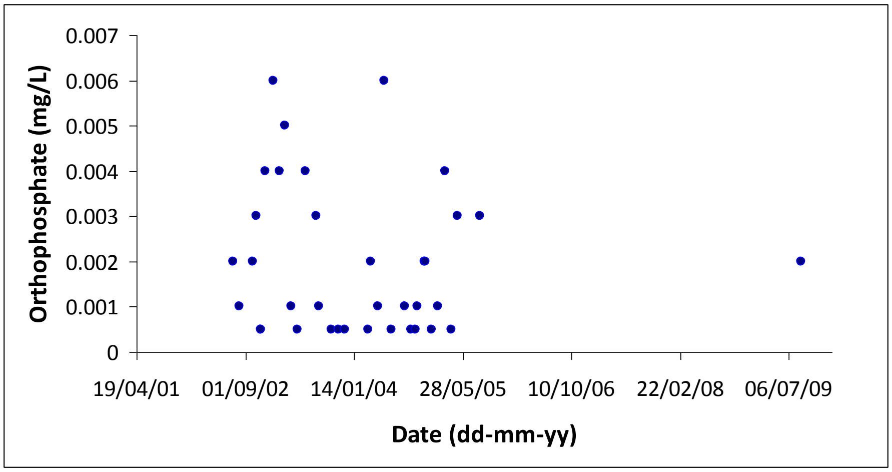

Figure 15: Concentrations of orthophosphate in China Creek, between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

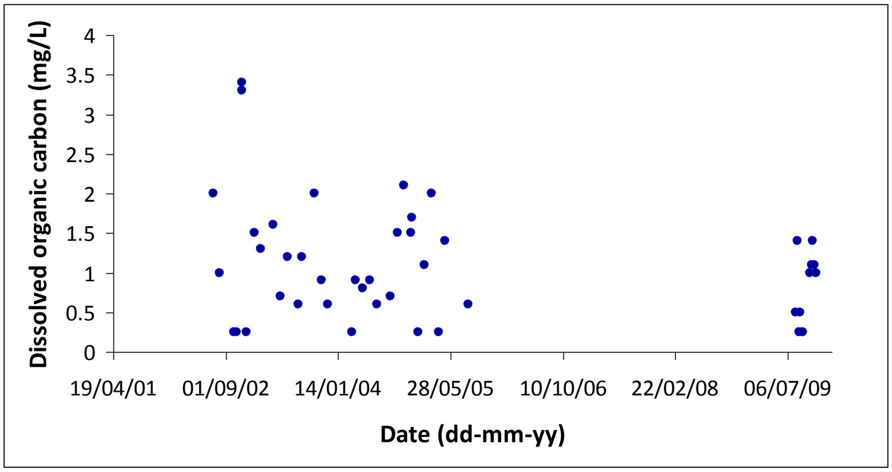

Figure 16: Dissolved organic carbon concentrations in China Creek, 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

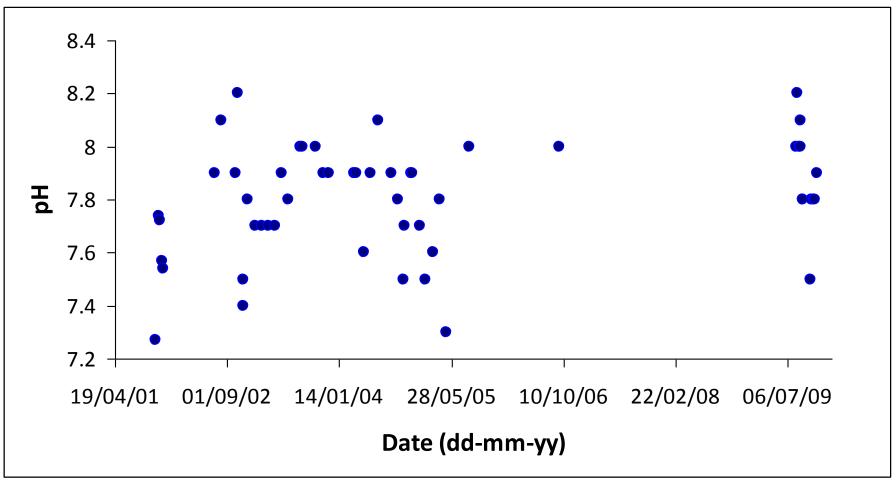

Figure 17: Hydrogen ion (pH) concentrations in China Creek, between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

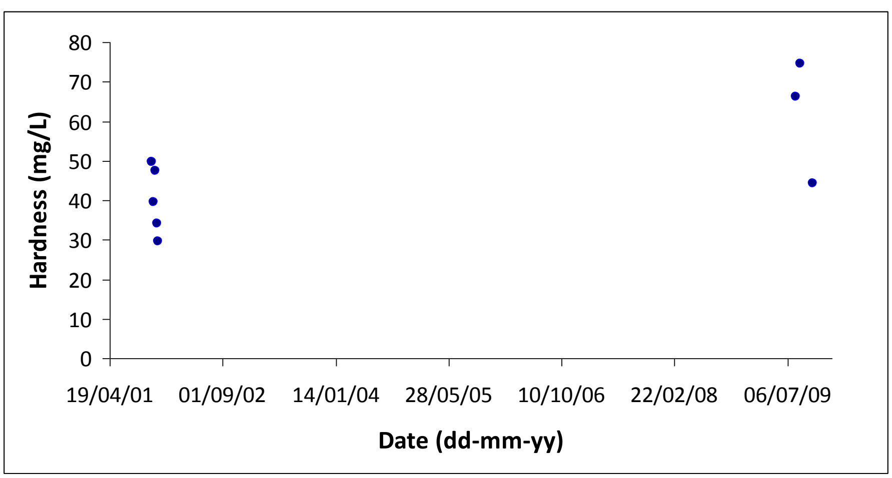

Figure 18: Hardness in China Creek, between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

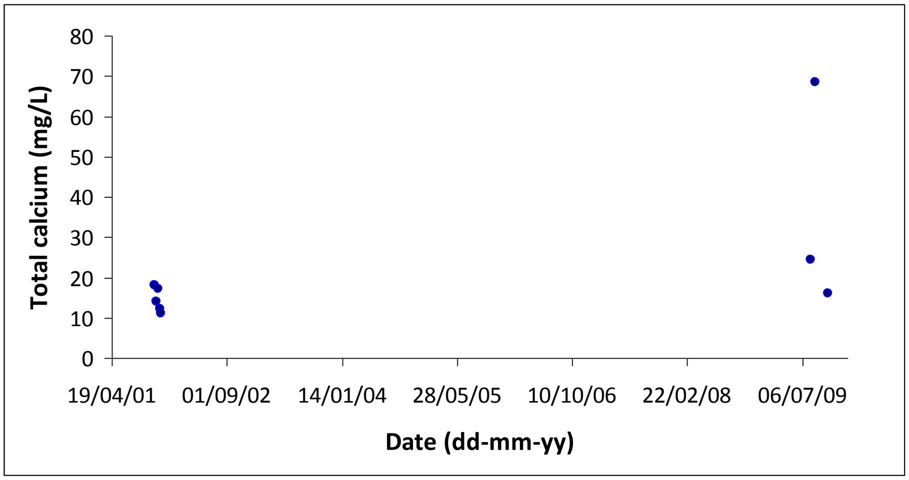

Figure 19: Total calcium concentrations in China Creek, between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

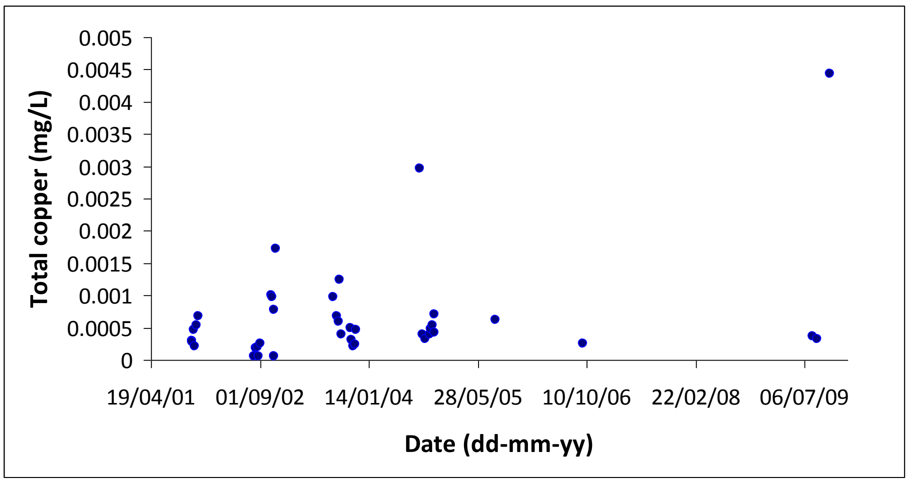

Figure 20: Total copper concentrations in China Creek, between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

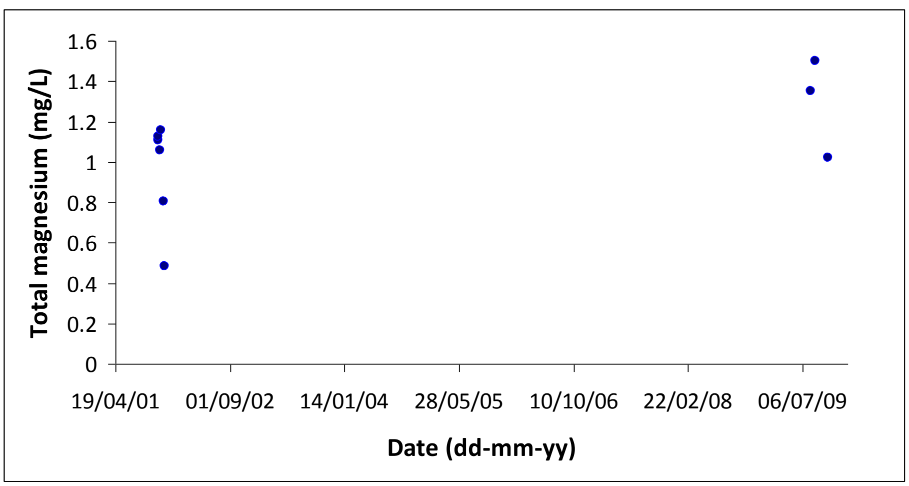

Figure 21: Total magnesium concentrations in China Creek, between 2001-2009. Water samples taken at the water intake for Port Alberni, BC by Ministry of Environment staff.

B. R Script for Data Analysis

```
setwd("c:/Users/Catherine/Desktop/Final Thesis/")

dfmw = read.csv("dfmw1.csv")

### Part 1: Model for max stream temp with air temp predictor
### using all data

mod1a = lm( Tmax ~ MaxAirTemp, data = dfmw )
summary(mod1a)

par(mfrow=c(2,2))
plot(dfmw$MaxAirTemp,dfmw$Tmax,pch=19,col="dark blue",
     xlab="Maximum Air Temperature (degrees Celsius)",
     ylab="Maximum Water Temperature (degrees Celsius)")
abline( mod1a, col="red")

plot( fitted( mod1a ), residuals( mod1a ),pch=19,col="dark blue",
     xlab="Fitted Values", ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod1a ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod1a ))
qqline(residuals( mod1a, col=2 ))

### Part 2: Model for max stream temp with air temp and SC predictors
### using all data

mod1c = lm( Tmax ~ MaxAirTemp + SCmean, data = dfmw )
summary(mod1c)

par(mfrow=c(2,2))
plot( fitted( mod1c ), residuals( mod1c ),pch=19,col="dark blue",
     xlab="Fitted Values", ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod1c ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod1c ))
qqline(residuals( mod1c, col=2 ))

### Part 3: Model for max stream temp with air temp predictor using
### low flow data

ss1 = subset(dfmw, SCmean > 75)
```

```
mod2a = lm( Tmax ~ MaxAirTemp, data = ss1 )
summary(mod2a)

par(mfrow=c(2,2))
plot(ss1$MaxAirTemp, ss1$Tmax,pch=19,col="dark blue",
      xlab="Maximum Air Temperature (degrees Celsius)",
      ylab="Maximum Water Temperature (degrees Celsius)")
abline( mod2a, col="red")

plot( fitted( mod2a ), residuals( mod2a ),pch=19,col="dark blue",
      xlab="Fitted Values",ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod2a ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod2a ))
qqline(residuals( mod2a, col=2 ))

### Part 4: Model for max stream temp with air temp and SC predictors
### using low flow data

mod2c = lm( Tmax ~ MaxAirTemp + SCmean, data = ss1 )
summary(mod2c)

par(mfrow=c(2,2))
plot( fitted( mod2c ), residuals( mod2c ),pch=19,col="dark blue",
      xlab="Fitted Values",ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod2c ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod2c ))
qqline(residuals( mod2c, col=2 ))

### Part 5: Model for max stream temp with air temp predictor
### using summer data

ss2 = subset(dfmw, dfmw$Month > 5 & dfmw$Month < 9)

mod3a = lm( Tmax ~ MaxAirTemp, data = ss2 )
summary(mod3a)

par(mfrow=c(2,2))
plot(ss2$MaxAirTemp, ss2$Tmax,pch=19,col="dark blue",
      xlab="Maximum Air Temperature (degrees Celsius)",
      ylab="Maximum Water Temperature (degrees Celsius)")
abline( mod3a, col="red")

plot( fitted( mod3a ), residuals( mod3a ),pch=19,col="dark blue",
```

```
      xlab="Fitted Values",ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod3a ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod3a ))
qqline(residuals( mod3a, col=2 ))

### Part 6: Model for max stream temp with air temp and SC predictors
### using summer data

mod3c = lm( Tmax ~ MaxAirTemp + SCmean, data = ss2 )

summary(mod3c)

par(mfrow=c(2,2))
plot( fitted( mod3c ), residuals( mod3a ),pch=19,col="dark blue",
      xlab="Fitted Values",ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod3c ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod3c ))
qqline(residuals( mod3c, col=2 ))

### Part 7: Model for max stream temp with air temp predictor
### using winter data

ss3 = subset(dfmw, dfmw$Month < 4 | dfmw$Month > 9)

mod4a = lm( Tmax ~ MaxAirTemp, data = ss3 )

summary(mod4a)

par(mfrow=c(2,2))
plot(ss3$MaxAirTemp, ss3$Tmax,pch=19,col="dark blue",
      xlab="Maximum Air Temperature (degrees Celsius)",
      ylab="Maximum Water Temperature (degrees Celsius)")
abline( mod4a, col="red")

plot( fitted( mod4a ), residuals( mod4a ),pch=19,col="dark blue",
      xlab="Fitted Values",ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod4a ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod4a ))
qqline(residuals( mod4a, col=2 ))
```

```
### Part 8: Model for max stream temp with air temp and SC predictors
### using winter data

mod4c = lm( Tmax ~ MaxAirTemp + SCmean, data = ss3 )
summary(mod4c)

par(mfrow=c(2,2))
plot( fitted( mod4c ), residuals( mod4a ),pch=19,col="dark blue",
      xlab="Fitted Values",ylab="Residuals")
abline(h=0,col="red")

hist(residuals( mod4c ),xlab="Residuals",col="light blue",main="")
title(main="Histogram")

qqnorm(residuals( mod4c ))
qqline(residuals( mod4c, col=2 ))

### Part 9: Model for max stream temp with air temp predictor using
### all data with pre and post dummy variables

end.pre = ISOdate(2004, 5, 6)
begin.post = ISOdate(2004, 5, 7)

dfmw$tiso = ISOdate(dfmw$Year, dfmw$Month, dfmw$Day)
dfmw$period = 0*(dfmw$tiso <= end.pre) + 1*(dfmw$tiso >= begin.post)

mod1b = lm( Tmax ~ MaxAirTemp*period, data = dfmw )
summary(mod1b)

par(mfrow=c(1,1))
colour = c("blue", "red")
symbol = c(1, 2)
plot( dfmw$MaxAirTemp, dfmw$Tmax, pch = symbol[1+dfmw$period], col =
colour[1+dfmw$period],
      xlab="Maximum Air Temperature (degrees Celsius)",
      ylab="Maximum Water Temperature (degrees Celsius)")
legend( "topleft", c("pre","post"), bty = "n", pch = symbol, col =
colour )
abline(a = 3.102419, b = 0.304680, col = "blue")
abline(a = (3.102419-0.120268), b = (0.304680+0.005431), col = "red")

### Part 10: Model for max stream temp with air temp and SC predictors
using
### all data with pre and post dummy variables

mod1d = lm( Tmax ~ MaxAirTemp*period + SCmean*period, data = dfmw )
summary(mod1d)

### Part 11: Model for max stream temp with air temp predictor using
### low flow data with pre and post dummy variables

mod2b = lm( Tmax ~ MaxAirTemp*period, data = ss1 )
```

```
summary(mod2b)

par(mfrow=c(1,1))
colour = c("blue", "red")
symbol = c(1, 2)
plot( ss1$MaxAirTemp, ss1$Tmax, pch = symbol[1+ss1$period], col =
colour[1+ss1$period],
      xlab="Maximum Air Temperature (degrees Celsius)",
      ylab="Maximum Water Temperature (degrees Celsius)")
legend( "topleft", c("pre","post"), bty = "n", pch = symbol, col =
colour )
abline(a = 2.98591, b = 0.28173, col = "blue")
abline(a = (2.98591+1.08834), b = (0.28173+0.00499), col = "red")

### Part 12: Model for max stream temp with air temp and SC predictors
using
### low flow data with pre and post dummy variables

mod2d = lm( Tmax ~ MaxAirTemp*period + SCmean*period, data = ss1 )
summary(mod2d)

### Part 13: Model for max stream temp with air temp predictor using
### summer data with pre and post dummy variables

mod3b = lm( Tmax ~ MaxAirTemp*period, data = ss2 )
summary(mod3b)

par(mfrow=c(1,1))
colour = c("blue", "red")
symbol = c(1, 2)
plot( ss2$MaxAirTemp, ss2$Tmax, pch = symbol[1+ss2$period], col =
colour[1+ss2$period],
      xlab="Maximum Air Temperature (degrees Celsius)",
      ylab="Maximum Water Temperature (degrees Celsius)")
legend( "topleft", c("pre","post"), bty = "n", pch = symbol, col =
colour )
abline(a = 6.17327, b = 0.2144, col = "blue")
abline(a = (6.17327+0.14667), b = (0.2144-0.02662), col = "red")

### Part 14: Model for max stream temp with air temp and SC predictors
using
### summer data with pre and post dummy variables

mod3d = lm( Tmax ~ MaxAirTemp*period + SCmean*period, data = ss2 )
summary(mod3d)

### Part 15: Model for max stream temp with air temp predictor using
### subset of winter months with dummi variables for pre and post

mod4b = lm( Tmax ~ MaxAirTemp*period, data = ss3 )
summary(mod4b)
```

```
par(mfrow=c(1,1))
colour = c("blue", "red")
symbol = c(1, 2)
plot( ss3$MaxAirTemp, ss3$Tmax, pch = symbol[1+ss3$period], col =
colour[1+ss3$period],
     xlab="Maximum Air Temperature (degrees Celsius)",
     ylab="Maximum Water Temperature (degrees Celsius)")
legend( "topleft", c("pre","post"), bty = "n", pch = symbol, col =
colour )
abline(a = 3.20425, b = 0.31568, col = "blue")
abline(a = (3.20425-0.62270), b = (0.31568-0.02846), col = "red")

### Part 16: Model for max stream temp with air temp and SC predictors
using
### winter data with pre and post dummy variables

mod4d = lm( Tmax ~ MaxAirTemp*period + SCmean*period, data = ss3 )
summary(mod4d)

### Part 17:  Partial F tests comparing models with air temp predictor

anova( mod1a, mod1b )
anova( mod2a, mod2b )
anova( mod3a, mod3b )
anova( mod4a, mod4b )

### Part 18:  Partial F tests comparing models with air temp and SC
predictors

anova( mod1c, mod1d )
anova( mod2c, mod2d )
anova( mod3c, mod3d )
anova( mod4c, mod4d )
```

C. Photos of Ministry of Environment Water Monitoring Site at China Creek

Figure 25: Looking downstream towards weir for Port Alberni intake and site of Ministry of Environment sonde (left), with a close up of the sonde location (right). (Source: Rosie Barlak).