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Assessing Spatiotemporal Stream Temperature Trends and Drivers through Integrated Longitudinal Thermal Profiling and Stationary Data Logger Methodology on the Upper Chehalis River, WA

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by

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Abstract

This study encompasses 25 kilometers of the Chehalis River in Washington, USA that currently has sections under a Total Maximum Daily Load (TMDL) plan for stream temperature impairments that exceed 18°C, a regulatory standard set at the time of the listing to protect salmonid spawning, rearing, and migration. Using information integrated from stationary data loggers (n=22) that collected stream temperature information from August 4 – September 10, 2017, and longitudinal thermal profiling performed on July 29 –30, August 4 – 5, and September 9 – 10, 2017, this study aimed to quantify the spatial distribution of stream temperature, evaluate relative consistencies of the riverine thermal regime over time, and identify which independent variables (land cover, aspect, canopy cover, impervious surfaces, channel width, discharge and air temperature) are correlated with stream temperature metrics using Spearman's rank correlation and stepwise linear regression modeling. Stream temperature was found to be strongly correlated with all air temperature metrics. The strongest model from stepwise linear regression (R^2 = 0.711) found width, shrub/scrub, mixed forest, and cultivated crop land cover to be the strongest explanatory variables with the seven day average of the daily maximum stream temperatures (7DADMaxTw) at the 22 sites. Tributaries had overall cooler average maximum stream temperatures than main stem sites. Thermal profiling identified seven cold-water patches (defined as the cumulative stream temperature ≥ 1°C cooler than the surrounding water). Integrating longitudinal thermal profiling and stationary data loggers allows resource managers to understand

spatiotemporal stream temperature trends and influences and can assess more effective mitigation strategies to combat rising stream temperatures.

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Table of Contents

List of Tables

List of Figures

1. Introduction

Stream temperature is a primary factor in determining the health of aquatic ecosystems as well as the growth rate, abundance, and distribution of aquatic species (Caissie 2006, Isaak et al. 2012, Ficklin et al. 2014). Fish and other aquatic organisms are ectotherms, which means that they cannot regulate body temperature internally and must thermoregulate by seeking cooler patches of water when stream temperatures are elevated beyond physiological thresholds (Caissie 2006; Isaak et al. 2012). Stream temperature can affect all parts of the life cycle of salmonids which includes hatching and rearing of juvenile fish in freshwater streams, migrating to the marine environment until sexual maturity, and a migration back to freshwater habitats for spawning and mortality (Chang et al. 2018). Understanding the thermal regime of rivers as well as the key drivers of stream temperature are important for resource managers to determine appropriate placement and technique of restoration, enhancement, or protection of thermal habitats. This study focuses on understanding the thermal regime and key drivers of a 25 kilometer section of the upper Chehalis River in western Washington State.

Salmon have an important economic role in Washington State by contributing to the $1.1 billion sport fishing revenue and the $1.6 billion commercial fishing revenue (Anderson 2010). Additionally, jobs associated with sport fishing and commercial harvesting total nearly 30,000 in Washington State (Anderson 2010). Salmon fishing brings revenue to rural communities with lodging, dining, equipment, and gas purchases. Ensuring salmon survival is an economic gain for Washington State and enhances rural community economies. Salmon in the Chehalis River Basin also have a cultural significance for the Confederated Tribes of the Chehalis Reservation who historically relied on salmon for food and brought forth lasting traditions.

Since water temperature is essential to the health of aquatic species and ecosystems, water quality standards are set in place under the Clean Water Act of 1972 to regulate elevated stream temperature, which is considered nonpoint source pollutant. Under the Washington Administrative Code (WAC hereinafter) 173-201A-200, the freshwater uses and criteria standards that apply to the study area currently sets the highest 7-day average of the daily maximum temperature (7DADMaxTw) at 17.5°C for spawning, rearing, or migrating salmonids. Areas that are designated as core summer salmonid habitat have additional temperature standards set at 16°C from June15-September 15 (WAC 173-201A-200). When surface waters fail to meet water quality standards, a Total Maximum Daily Load (TMDL) plan is implemented and identifies pollutant sources, determines the amount of a pollutant that can be discharged while still meeting water quality standards, and identifies mitigation options.

To create effective stream restoration or enhancement plans aimed towards meeting these regulatory standards, this study aims to:

1) Quantify the spatial distribution of stream temperature.

2) Evaluate the relative consistency of the riverine thermal regime over time.

3) Identify independent variables that impact or contribute to the thermal regime and may be used in the future to identify potential sites and appropriate techniques for protection, restoration, or enhancement that will be most effective.

1.1 Stream Temperature Effects on Salmonids

Metabolic rates of aquatic organisms increase with water temperatures, which subsequently alters the timing of transitions from egg hatching and fry emergence (Steel et al. 2012). In a study on a small drainage basin in British Columbia, Scrivener and Andersen (1984) found that Coho salmon fry emerged six weeks earlier and moved downstream more quickly following clear-cut logging, attributing the early emergence to warmer winter water temperatures. Johnson (1997) monitored downstream movements of salmon in two streams in New Brunswick, Canada and found that while salmon used both streams for spawning and rearing habitat, salmon fry located in the cooler of the two streams grew more rapidly in length and were in better condition than those in the warmer streams.

Stream temperature not only influences the rate of growth of juvenile salmonids, but the timing of migration to and from the marine environment. Goniea et al. (2006) found that migration rates of fall Chinook salmon returning to the Columbia River for spawning were significantly slowed when water temperatures were above 20°C. Salmonids such as Chinook salmon, stop feeding upon entering freshwater in spring and rely on energy reserves for gametes to mature prior to spawning in autumn (Ebersole et al. 2014). Excessive energy expenditures and stress during periods of warm water deplete energy reserves more quickly, reduce gamete viability, and lead to increased pre-spawning mortality (Ebersole et al. 2014). Having cool patches of water where salmonid species can temporarily reside during elevated summer temperatures during spawning migrations is crucial in mitigating rising stream temperatures.

Stream temperature is an important determinant of the distribution of salmonids. The Washington State Department of Ecology (DOE) have found that temperatures between 21-24°C creates avoidance behavior and migration barriers in steelhead (Washington Department of Ecology 2001). The Environmental Protection Agency (EPA) concluded that stream temperatures between 22 – 24°C may limit or eliminate salmonids from a location (Torgersen et al. 2012). While not a requirement, the WAC 173-201A-200 sets guidelines to prevent acute lethality and barriers to migration of salmonids, which are set at 7DADMaxTw at or below 22°C for adult and juvenile salmonids and the 1-day maximum (MaxTw) at or below 23°C. These guidelines are not a standard but are intended to be used as a consideration by the DOE in determinations of compliance and do not override temperature criteria established for surface waters (WAC 173-201A-200).

Salmonids are very sensitive to stream temperatures and can detect differences of less than 0.1°C and respond by temporarily moving to favorable areas until stream temperatures cool enough to continue migrating or to seek other refuges (Torgersen et al. 2012). The significant positive association between salmon density and cool-water reaches is well documented (Torgersen et al. 1999; Ebersole et al. 2006). Torgersen et al. (1999) found that Chinook salmon on the Middle Fork John Day River in Oregon sought cover in thermal refugia created by pools and undercut banks during times of elevated stream temperatures. Ebersole et al. (2003) also found an increased abundance of Chinook salmon and rainbow trout located near cold water patches formed by cold-water inflow from groundwater sources in northeastern Oregon streams. Methods that can locate cold water refugia or thermal patchiness at a fine spatial scale, along with the ability to monitor changes over time, can be beneficial to watershed managers in identifying sites to focus protection or restoration.

1.2 Climate Change Implications for Stream Temperature

Increases in stream temperature and flooding due to climate change is projected to decrease suitable habitat for trout and salmon and exceed physiological thresholds. Stream temperature has already increased approximately 0.1 – 0.2°C per decade in the neighboring Columbia River Basin between 1980-2009, and rising air temperature may increase stream temperature 1 – 4°C by the 2080s (Isaak et al. 2012, Chang et al. 2018). Wenger et al. (2011) projected a 47% decline in suitable trout habitat across the country based on projections under the 2080s A1B emissions scenario forecast.

Hydrologic models based on climate change scenarios have projected wetter winters with the shift from snow to rainfall, warmer summers, increasing stream temperatures, and decreasing flows in the Pacific Northwest which threatens not only adult salmonids and fry but also to eggs that incubate through winter months and can be destroyed or displaced with flooding (Mantua et al. 2010; Wenger et al. 2011; Beechie et al. 2013; Ficklin et al. 2014). As average temperatures increase due to climate change during the summer months when salmon species are migrating, spawning may be interrupted, delayed, or eliminated when thermal tolerances are exceeded (Goneia et al. 2006; Isaak et al. 2012). Habitat will also be impacted as thermal boundaries for fish will gradually shift upstream towards cooler waters sourced from tributaries and headwaters, increasing competition among aquatic species and reducing habitat available for fish species that are cold water adapted (Isaak 2010; Isaak et al. 2012).

Different location and environmental factors make certain streams and rivers more susceptible to the harmful impacts of climate change. Isaak et al. (2012) found that streams that are flattest (which also are the most biodiverse), have east-west orientations, and are fragmented will be the most impacted by climate change. Lowland streams that are surface water-fed and lack riparian vegetation are also expected to be most vulnerable to climate change impacts (Chang et al. 2018). The Upper Chehalis River study section is a lowland stream, fed predominantly by precipitation, is generally flat, and flows from west to the east before turning back west, making it particularly vulnerable to the effects of climate change. Identifying landscape and meteorological variables that strongly correlate with stream temperature on a reach-scale can help identify appropriate sites for restoration or protection and effective strategies to ameliorate climate change impacts.

2. Literature Review

This literature review analyzes research papers pertaining to data collection methods that can quantify the spatiotemporal distribution of stream temperature. Landscape metrics that were identified as having a correlation with stream temperature were also analyzed to select appropriate independent variables in determining key drivers of stream temperature. A full review of the literature, methods, and findings can be found in Table 1.

2.1 Landscape Metrics

While stream temperature is primarily driven by solar radiation (Caissie 2006), landscape variables such as stream width, vegetative cover, and land uses contribute to the thermal regime, but the degree of influence varies by location. Woltemade and Hawkins (2016) stated that "the wide range of predictor variables identified in stream temperature research suggests that further work should better define specific influence of landscape and microclimate on streams….Place-based approaches emphasizing local environmental conditions might help improve our understanding." Understanding the general longitudinal thermal regime of a river is important in identifying potential restoration or protection sites but understanding the drivers of stream temperature for a river reach is also important to determine where to focus efforts and what methods will be most effective.

In this study, I considered channel width, discharge, aspect, air temperature, canopy cover, percent of impervious surfaces, and land use cover as potential predictor variables of stream temperature. Channel width controls surface area available for energy exchanges and are sensitive to solar inputs (Chang and Psaris 2013; Jackson et. al 2016; Woltemade and Hawkins 2016). Channel orientation affects the amount of solar radiation reaching the stream and the shading effects (Jackson et al. 2016). Dick et al. (2015) found south and east facing streams showed higher maximum stream summer temperatures and that spatial variability in temperature primarily reflects aspect. Vegetative cover to create shading has been found to have a profound impact on stream temperature, but largely depends on the placement of the shading. Jackson et al. (2017) found a negative correlation between stream temperature and the percentage of range woodland cover, whereas Johnson and Wilby (2015) found that tree canopy cover only affected short river reaches and had a greater effect where water volumes are low. Loicq et al. (2018) found that vegetative cover is less effective where streams are wide and there is an increase in solar radiation. Land use practices have been found to have a direct impact on the health of streams (Johnson 2004). Disturbances such as the removal of vegetation for forest harvest or agricultural operations have an impact on rising stream temperatures, while forest land cover has been found to protect thermal habitats (Johnson 2004, Caissie 2006). While maximum stream temperatures have been found to decrease as elevation increases (Chang and Psaris 2013; Jackson et al. 2016) and increases in channel gradient have been found to have cooler stream temperatures (Fullerton et al. 2015, Jackson et al. 2016), slope and elevation were found to be relatively static amongst sites due to the relatively flat nature of the river (~67.4 meters to 68.58 meters elevation range for all sites) and were not included in this analysis.

2.2 Stream Temperature Data Collection Methods

Stream temperature data is commonly collected through four technologies: remotely sensed thermal infrared (TIR), stationary data loggers placed throughout the stream, distributed fiber-optic temperature sensors (DTS), and towing a temperature probe near the streambed (referred to as longitudinal thermal profiling or thermal profiling here on out). Capturing relatively fine spatial and temporal temperature information across large reaches of river is challenging and each method has limitations. A comparison of these four data collection methods can be found in Table 2.

Vatland et al. (2015) attempted to overcome the spatiotemporal limitations of stream temperature data collection methods by combining TIR, stationary data logger, and longitudinal thermal profiling data into a new dataset and performed statistical modeling, revealing "considerable spatial and temporal heterogeneity in summer stream temperatures and highlighted the value of assessing thermal regimes at relatively fine spatial and temporal scales". This study seeks to assess the thermal regime of the study area at a relatively fine spatial and temporal scale by integrating longitudinal thermal profiling methods with stationary data loggers.

2.3 Longitudinal Thermal Profiling

Longitudinal thermal profiling is an inexpensive method of mapping sections of the stream thermal regime at a fine spatial and temporal scale and has been found to be effective at detecting groundwater inputs (Vacarro et al. 2006). One temperature probe is towed behind a kayak or boat on or near the streambed and collects temperature at specified intervals of time. This can be done throughout the year which allows for the monitoring of the thermal regime over time but does have temporal limitations as stream temperature rises throughout the day and kayaks or boats must move downstream to continually collect data. Longitudinal thermal profiling is more effective with the placement of stationary data loggers to account for diurnal and seasonal temperature changes (Vatland et al. 2015).

There have been three USGS studies using longitudinal thermal profiling methods in Washington State, used largely the locate groundwater inputs and capture stream temperature variability. Vaccaro et al. (2006) conducted a stream temperature profiling study across 20 km of the Yakima River, Washington in an extreme drought year (2001) by towing a temperature probe near the streambed and one near the surface, collecting temperature every 1-to-3 seconds and synced with a GPS unit programmed to collect a coordinate at the same time. The purpose was to identify a viable method to thermally profile long (5-25 km) river reaches and to identify areas of ground-water discharge and was found to be effective at doing so. Appel et al. (2011) used similar methods to identify cold water inputs from groundwater sources on the Lower Yakima River, but used three boats each towing a data logger near the surface and near the streambed. Similarly, Gendaszek (2011) conducted longitudinal thermal profiles of near-streambed temperature for eight reaches of the Stillaguamish River, Washington in August of 2011 by towing one temperature logger near the streambed and synced with a GPS unit. Graphs and thermal maps were produced from all studies showing the spatial distribution of stream temperature and identifying groundwater inputs, but areas where resource managers could focus restoration efforts that will have the most impact on reducing stream temperatures or preserving existing cold water refugia were never identified.

This study uses longitudinal thermal profiling to quantify the spatial distribution of near-surface and near-bottom stream temperature of a 25-kilometer section of the Upper Chehalis River, WA in conjunction with stationary data logger information to assess the spatial and temporal changes as well as the correlation of key landscape contributors on stream temperature. Longitudinal thermal profiling was determined to be an appropriate data collection method since it has been found to be effective in locating groundwater inputs and the Chehalis River is precipitation and groundwater fed (Appel et al. 2011; Vacarro et al. 2006; Washington Department of Ecology 2001). From this literature review, a study using only longitudinal thermal profiling in conjunction with stationary data logger methods to quantify the riverine thermal regime and identify environmental influences on stream temperature has not been identified.

3. Study Area

This study encompasses 25 kilometers of the Upper Chehalis River (see Figure 1) in western Washington, USA. The Chehalis River flows approximately 200 km and drains approximately 1093 hectares (Ruckelshaus Center 2014). It is the second largest watershed in Washington State, behind the Columbia River Basin (Ruckelshaus Center 2014). Land cover calculations extracted from 2011 National Land Cover Database information (Homer et al. 2015) in the Upper Chehalis River Basin is comprised of 35% forested lands, 13% agricultural, 8% wetlands, and 18% developed land (see Figure 2). Within 1 km of the study area, land cover is composed of 9% developed, 31% forested, 32% agricultural, and 7% wetlands. Approximately 70% of soils within the study area are silty clay loam varieties, with the remaining 30% being comprised of varieties of just clay, loam, silt, and cobbly silt loam (Soil Survey Staff 2018). Geology in the Chehalis River Basin is comprised primarily of basalt flows that have been overlain by marine and non-marine sedimentary deposits or glacial material (Chehalis River Basin Flood Authority 2010).

The Chehalis River Basin does have groundwater inputs, but is largely rain-fed with an average annual precipitation amount of 145 centimeters but varies with 76 centimeters near the city of Chehalis and 305 centimeters towards the headwaters of the Chehalis River (Washington Department of Ecology 2001). While the Chehalis Basin has experienced historical minor flooding every 2 to 5 years and major flooding every 10 years, major flooding has increased in frequency and intensity over the last 30 years and is expected to increase with climate change (Ruckelshaus Center 2014). Discharge data for USGS station 12021800 located near Adna, WA within the study area is only available from October 1, 2015 – June 10, 2018 at the time of this study but shows considerable discharge extremes with an average maximum of 628.64 cubic meters per second (CMS) in November and December and an average minimum of .985 CMS in August and September (U.S. Geological Survey 2018).

Flooding has been so problematic that a flood control dam has been proposed in the main stem Chehalis River at river kilometer 174 (Ashcroft et al. 2017), upstream of the study area. A study conducted by the Washington Department of Fish and Wildlife near the site of the dam location revealed spring Chinook, fall Chinook, Coho salmon, and winter steelhead spawning activities take place in this area and primarily in the main stem river (Ashcroft et al. 2017). Chinook spawning activity occurs between September and November upstream near the proposed dam site location (Ashcroft et al. 2017), making the study area a thoroughfare for spawning salmonids attempting to reach their upstream destination, at least during the August and September months that data was collected in this study.

Within Washington State, the Chehalis Basin boasts the highest amphibian diversity and is the only basin without an Endangered Species Act (ESA) listing for salmonids (Ruckelshaus Center 2014). An estimated 94,000 Chinook, Coho, and steelhead return to the Chehalis Basin annually (Ruckelshaus Center 2014). While salmon are not listed as endangered or threatened in the Chehalis River, populations have been seriously degraded in the last 100 years due to channel incision, sedimentation, riparian loss, a reduction in streamflow, and water quality problems such as high water temperatures and low dissolved oxygen levels (Smith and Wenger 2001). Compared to historic levels, it is estimated that Spring-run Chinook populations have been reduced by 78%, Fall-run Chinook by 45%, Coho by 69%, and steelhead by 44% (Ruckelshaus Center 2014). If no action is taken to restore physical and ecological processes and habitat, it is predicted that the effects from habitat degradation and climate change will eliminate Spring-run Chinook and reduce Coho populations by 70% by the end of the century (Ruckelshaus Center 2014).

In 1998, nine streams of the Upper Chehalis River Basin (representing 19 segments) were listed under Section 3030(d) of the Clean Water Act for stream temperature impairments that exceed 18°C, a standard set by the WAC at that time (Washington Department of Ecology 2001). In 1999, the Upper Chehalis River Basin TMDL was completed to address temperature impairments separately from the TMDLs for dissolved oxygen and fecal coliform bacteria (Washington Department of Ecology 2001). Inadequate in-stream flows from water withdrawals, altered channel morphology, and over 30% of basin-wide riparian vegetation loss were identified in the TMDL as human causes of temperature impairment (Washington State Department of Ecology 2001). In 2004, a detailed implementation plan was released to mitigate stream temperatures that rise above water quality standards, primarily by using shade target percentages along impaired stream segments (Washington Department of Ecology 2004).

The study area has designated uses for water supply, recreation, core summer salmonid habitat, and salmonid rearing and migration. Each designated use has a temperature criteria using the 7DADMaxTw temperature metric. The highest

7DADMaxTw under WAC 173-201A-602 for stream sections designated as core summer salmonid habitat is 16°C from June 15 – September 15. Sections designated for the freshwater use of salmonid rearing and migration are set at a highest 7DADMaxTw of 17.5°C year-round. Additionally, sections that have been identified as impaired and placed under a TMDL (see Figure 1) are still held to a temperature criterion not to exceed 18°C, a standard that was in place at the time of the listing. If the TMDL is achieved, a potential analysis would then be completed to determine if additional actions can be taken to meet the current 17.5°C criteria (Finch 2018). Any new actions to achieve the temperature water quality standards will be held at the current 17.5°C standard (Finch 2018).

A report submitted by the Grays Harbor College on the state-of-the-river for the Chehalis River Basin from 2006-2009 found that stream temperatures frequently rose above the 16°C summer salmonid habitat use criteria during July and August (Green et al. 2009). A survey published in 2010 by the DOE found that temperature continued to be problematic and that based on single-sample measurements, additional stream reaches would be listed as impaired on Washington's 303(d) list (Washington Department of Ecology 2010). Data from two ambient monitoring stations upstream from the study area showed an increase in average monthly maximum stream temperatures from 2000-2008 (Washington Department of Ecology 2010). Based on the results of this study, DOE recommended assessing percent shade targets, continuing ambient monitoring stations, and implementing best management practices (BMPs) on impaired stream reaches with low riparian vegetation buffer percentages

4. Data and Methods

4.1 Stationary Temperature Data Collection

Twenty temperature data loggers (HOBO U22-001, Bourne, MA, USA) with an accuracy of ±0.2°C were placed throughout the study area, programmed to take a temperature reading every five minutes from August 4 – September 10, 2017. During the August 4 – 5 float, 17 temperature data loggers were placed throughout the study area during a heat wave and following the warmest day of the season on August 3, 2017 according to air temperature data taken from the DOE's Station 23K060 on the South Fork Chehalis, located within the study area. An additional three data loggers were placed on August 11, 2017. One data logger was placed in tributary Garret Creek (site three), one in the confluence of Garret Creek and the Chehalis River (site four), and another near the mouth of the South Fork Chehalis River (site 11). Bunker Creek was not able to have a data logger placed due to a beaver dam blocking the entrance, but water temperature data taken every 15 minutes was retrieved from DOE's water quality monitoring station 23I070 on Bunker Creek at Ceres Hills Road (site18). Water temperature data was also retrieved from station 23K060 on the South Fork Chehalis River at Highway 6 (site 12), making it an additional stream temperature monitoring site within the South Fork Chehalis River (additional to site 11). Since tributaries have been found to decrease water temperatures through inputs of cooler water (Fullerton et al. 2015) and Chinook salmon have been found to occupy tributaries on the Chehalis River to escape elevated main stem stream temperatures (Liedtke et al. 2017), these were selected as sites to identify potential cold-water inputs and evaluate differences from main stem temperatures. The locations of stream temperature monitoring sites on the South Fork Chehalis River and Bunker Creek are also within areas under a TMDL for stream temperature impairments, so an evaluation as to whether or not these areas are still impaired was deemed useful. Data loggers were retrieved on the September 9-10 float. Figure 3 shows the placement of stationary data loggers, the DOE air temperature monitoring station, and the USGS stream gauge used in this study.

4.2 Longitudinal Thermal Profiling Data Collection

Two temperature probes (HOBO U12-015-02, Bourne, MA, USA) with an accuracy of ± 0.25°C and a response time of 20 seconds or less were used in this study for longitudinal thermal profiling. Probes were encased in PVC pipes for protection with holes drilled throughout to allow for adequate water flow and accurate water temperature readings. Temperature probes were towed behind a kayak, with one probe weighted to collect temperature readings near the streambed and one floated to collect near-surface water temperature. Temperature probes were programmed to collect a reading every 10 seconds. A GPS unit (Trimble Juno 3B, Westminster, CO, USA) was programmed to collect a position coordinate every five seconds. Position coordinates were later matched up with temperature readings by time, so a location could be matched with a corresponding water temperature reading.

Data was collected three times across 25 km of the Chehalis River during the 2017 summer season: July 29 – 30, August 4 – 5, and September 9 – 10, 2017. Since the study area is relatively long (25 km), it was divided into two sections, with the first section being approximately 10 km and the second section approximately 15 km in length. Launch times for the floats occurred in the 10 A.M. (PDT) hour, based on historical water temperature data that indicated the Chehalis River begins to warm after 10 A.M. during July, August, and September. Temperature data was collected in a Langrangian framework (meaning at the velocity of the river) when possible, but light paddling was required in areas where river flows were low, and the temperature probe acted as an anchor.

4.3 Independent Variable Data Collection

Width, aspect, land cover, impervious surfaces, canopy cover, air temperature, and flow were selected independent variables for this study. Land cover, impervious surfaces, and canopy cover information were derived from the Multi-Resolution Land Characteristics (MRLC) 2011 National Land Cover Database (NLCD), the most recent land cover data available at the time of this study and at a 30-meter pixel resolution (Homer et al. 2015). Percent of land cover type was broken down for each buffered area by individual land cover class. Land cover classes included: developed open space, developed low intensity, developed medium intensity, developed high intensity, barren land, deciduous forest, evergreen forest, mixed forest, shrub/scrub, grassland/herbaceous, pasture/hay, cultivated crops, woody wetlands, and emergency herbaceous wetlands. These classes were also combined to represent agriculture, wetlands, forests, and developed land to compare overall land cover trends with overall stream temperature trends from upstream to downstream.

Using ArcGIS 10.5 (ESRI 2016), all stationary data logger sites had width measured manually using 2012 DRM Grays Harbor LiDAR datasets that were converted to a Digital Terrain Model (DTM). Aspect information was gathered by extracting multi-values to points for each data logger location. Polylines were created 300 meters upstream from stream temperature monitoring sites, which was determined to be an appropriate length to reduce overlap where data loggers were placed more closely together. Reducing overlap avoids spatial dependence of explanatory variables for each site (Mainali and Chang, 2018; Pratt and Chang, 2012). However, other studies used a 1 km upstream buffer (Chang and Psaris 2013; Watson and Chang 2018) and determined this to be an appropriate buffer in correlation analyses between stream temperature metrics and landscape predictor variables. Subsequently, all data logger temperature sites were also buffered 1 km upstream, providing two scales of analysis- one at a more localized scale (300 m) where overlap is minimal, and another at a scale that captures more of the upstream relative contributing area (RCA) effects on stream temperature (1 km). All upstream polylines were buffered 100 m to evaluate the upstream and surrounding effects of land cover, percent of impervious surfaces, and canopy cover on stream temperatures. The 100-meter buffer was used based on the wide nature of the river, the large 30-meter pixel resolution of NCLD data being evaluated, the need to capture more of the surrounding contributing land uses aside from riparian vegetation, and was deemed an appropriate buffer width in a similar analysis comparing explanatory variables to water quality trends (Mainali and Chang, 2018).

Data pertaining to air temperature was collected from DOE's station 23K060 on the South Fork Chehalis River from August 4, 2017 – September 10, 2017, which was the study period for stationary data logger stream temperature data collection. The air monitoring station is located within the study area and temperature was taken every 15 minutes. Flow information from August 4, 2017 – September 10, 2017 expressed as cubic feet per second (CFS) taken every 15 minutes was utilized from the USGS station 12021800 located on the Chehalis River near Adna, WA, located within the study area, and was converted to cubic meters per second (CMS). See Table 3 for detailed information pertaining to data and sources for variables examined in this study. Table 4 lists locations of stream temperature monitoring sites and information pertaining to width and aspect.

4.4 Stationary Data Logger Analysis Methods

I calculated maximum and minimum daily air (MaxTa and MinTA, respectively) maximum and minimum stream temperature (MaxTw and MinTw, respectively), as well as the seven-day moving average of daily minimum and maximum air temperature and stream temperature by averaging the maximum and minimum temperatures for a day, the three days prior, and the three days following (7DADMinTa, 7DADMaxTa, 7DADMinTa, and 7DADMaxTw). This was done for all days during the study period (August 4 – September 10, 2017). The 7DADMax temperature metric has been found to be a reliable buffered maxima of stream temperature (Grabowski et al. 2016) and is used in establishing regulatory thresholds and standards. Average range was also used as a dependent variable and was calculated by subtracting the minimum daily stream temperatures from maximum daily stream temperatures and averaging for each site. This metric was chosen because it captures daily variation for each site and has been used in a similar study determining landscape variable impacts on stream temperature (Watson and Chang 2018).

Since Washington state standards are based off 7DADMaxTw metrics under WAC 173-201A-200, this was selected as a dependent variable and was used in stepwise linear regression with independent variables including width, percent of canopy cover, percent of impervious surfaces, and percent of land cover in the 300 m and 1 km upstream buffered areas. A Pearson's correlation analysis between independent variables was conducted to determine correlations amongst independent variables (see Tables 9 and 10). Independent variables were first assessed for collinearity by calculating the variation inflation factor (VIF) and variables with a VIF $\geq$ 5 were removed. At the 300 m scale variables removed for collinearity with 7DADMaxTw being the dependent variable included: pasture/hay, evergreen forests, canopy cover, and developed open space. At the 1 km scale, variables removed when using 7DADMaxTw as a dependent variable included: cultivated crops, high intensity development, evergreen forests, pasture/hay, emergent herbaceous wetlands, and developed low intensity land uses covers. When using average range as a dependent variable at both the 300 m and 1 km upstream buffered scale variables removed due to collinearity included: cultivated crops, developed high intensity, evergreen forests, pasture/hay, emergent herbaceous wetlands, and developed low intensity land cover. A table summarizing collinearity through a

Pearson's correlation analysis for independent variables at the 300 m upstream buffered scale can be found in Table 9 and Table 10 for the 1 km upstream buffered scale. Removing variables that are highly correlated with one another reduces the risk of those variables being incorrectly interpreted as stream temperature contributors (Holgerson 2015). Remaining independent variables were then used in a stepwise multiple linear regression analysis using IMB SPSS Statistics 25 at a 95% confidence interval to obtain models with the independent variables that best explain the variation in 7DADMaxTw and average range dependent variables. Stepwise regression is a method of fitting regression models through an automated process that adds or subtracts explanatory variables, using R^2 as an indicator of best fit models. Stepwise multiple linear regression was chosen due to its use in other studies to model trends in water quality using land cover variables and landscape patterns in other studies (Mainhali and Chang 2018; Wang and Zhang 2018).

Maximum and minimum daily air and stream temperatures and 7DADMax and 7DADMin were correlated using the Spearman's rank correlation coefficient in IBM SPSS Statistics 25. The Spearman's rank correlation coefficient was selected due to its use in similar studies that determined relationships between water quality indicators and variables that drive change (Woltemade 2017; Diamantini et al. 2018), the sample size (n=22 for temperature sites), and because it does not assume a normal distribution (nonparametric). MaxTw, MinTw, 7DADMaxTw, and 7DADMinTw were also correlated with flow metrics (MaxCMS, MinCMS, 7DADMaxCMS, 7DADMinCMS) using the Spearman's rank correlation coefficient to determine what impacts flow has on maximum and minimum stream temperatures, both on a daily and weekly scale.

4.5 Thermal Profiling Analysis Methods

Stream temperature readings taken near the streambed and coordinate location points were matched up by time, so a temperature is associated with a location. Temperature points were plotted using ArcGIS 10.5 (ESRI 2016). Basic statistics pertaining to thermal profile information (minimum, maximum, mean, and standard deviation) for near-streambed temperatures were also gathered using ArcGIS 10.5 to assess overall trends. Standard deviation was used as an indicator of stream temperature variability for thermal profiles. Stream temperature readings for near-streambed conditions are mapped in Figure 6 for the first segment profiles that occurred on July 29, August 4, and September 9, 2017 and Figure 7 for the second segment for profiles conducted on July 30, August 5, and September 10, 2017. Graphs were produced to compare streambed temperatures and near-surface stream temperatures and basic statistics were compared to assess the variability and differences between the surface and streambed temperatures.

Thermal profile data was also evaluated to identify cold-water patches and possible explanations for their presence. The definition of cold-water patches or cold-water refugia varies, depending on the study. The EPA has defined cold water refuges as water that are 2°C colder than surrounding water (Torgersen et al. 2012). Some studies defined cool patches of water as areas ≥0.5 km long and ≥ 1°C cooler than adjacent water

(Fullerton et al. 2018) while other studies used a criterion of 3°C colder than adjacent ambient stream temperature (Ebersole et al. 2015, Ebersole et al. 2003). Other studies defined these areas as any discrete area 0.5°C cooler than ambient main stem temperatures (Dugadle et al. 2015). Due to the differing definitions of cold-water patches and since no areas of this study met the EPA's definition of a cold-water refuge (2°C cooler than surrounding waters), cold-water patches were defined as areas where water is ≥ 1°C cooler than surrounding water for the purposes of this study.

Cold-water patches were identified by taking a temperature point from profile data and subtracting the temperature of the previous point. Areas where temperature differences were found to be negative and in patches were summed to determine if the cumulative sum of these patches met the ≥ 1°C criterion. These areas were then identified and mapped. Average width was measured for these areas using ArcGIS 10.5 and the DNR 2012 Grays Harbor LiDAR derived digital terrain model. Upstream buffers 300 m in length were created stemming from the start of the cold-water patches, buffered 100 m out, and land cover data was extracted for each buffered area. This buffer was used to maintain a consistent scale with stationary data logger methods for extracting land use data. Additionally, the entire 25 km study area stretch of the Chehalis River was outlined, buffered 100 m, and land cover data was extracted to compare with that of cold-water patches. Width was measured manually for the entire study area using ArcGIS 10.5, at an interval of one temperature point per minute for the profiles that occurred on August 4 – 5, 2017. This information was extracted to compare to the width of cold-water patches to evaluate if this may be an explanatory variable. Since tributaries can be inputs of cool water, distance from a tributary (upstream) was also measured from each cold-water patch, assuming all tributaries provide cooler temperature inputs than the main stem of the river.

5. Results

5.1 Stationary Data Logger Stream Temperature Results

At no point during the study did any stream temperature data collection site have 7DADMaxTw values at or below the freshwater designated use standards set by the WAC 173-201A-200 for any aquatic use category in this area (7DADMaxTw < 16°C for salmonid summer salmonid habitat and 7DADMaxTw < 17.5°C for rearing and migration) for the days 7DADMaxTw temperatures were calculated (30 days for most sites taken within the August 7 – September 6, 2017 time period). No site under a TMDL for temperature impairments exceeding 18°C (sites 11, 12, 18, and 22) had maximum temperatures below this criterion.

Table 5 summarizes average MaxTw, MinTw, 7DADMaxTw, and 7DADMinTw for each data logger site along with the percent of MaxTw days that exceeded the recommended guideline ≤ 23°C, and the percent of 7DADMaxTw values that exceeded the recommended ≤ 22°C for avoiding acute lethality in salmonids recommended under WAC 173-201A-200. All sites exceeded the 7DADMaxTw ≤ 22°C recommendation for avoiding acute lethality in salmonids 74.6% of the time (30 days for most sites taken within the August 7 – September 6, 2017 time period). All sites exceeded the MaxTw recommendation of ≤ 23°C 42% of the time during the study period (36 days for most sites taken from August 4 – September 10, 2017 time period). Data loggers number 3, 4, 10, and 18 which were placed in tributaries, tributary confluences, and an apparent groundwater input zone (site 10) had most or all 7DADMaxTw and MaxTw values below the recommended acute lethality temperatures with an average of 8% of 7DADMaxTw values ≥ 22°C and an average of 5.5% of MaxTw ≥ 23°C. Bunker Creek (site 18) had an average MaxTw 2.92° cooler, and Garret Creek (site 3) had average MaxTw 4.39°C cooler than the average MaxTw of all other stream temperature monitoring sites. Data logger number four placed at the confluence of Garret Creek and the Chehalis River was found to be influenced by cooler temperatures from Garret Creek with an average MaxTw difference of 1.42°C between the nearest upstream and downstream sites (sites 2 and 5).

Overall average MaxTw temperatures were found to have a difference of 0.45°C from site 1 to site 22. Coolest 7DADMaxTw and MaxTw temperatures were found in tributaries and an apparent groundwater input at site 10 (see figure 4). Temperature loggers 1 – 8 (representing the first segment of the thermal profiles conducted on July 29, August 4, and September 9, 2017) did reveal an overall 0.87°C decrease in average MaxTw temperatures compared to data loggers 9 – 22 (representing the second segment of thermal profiles conducted on July 30, August 5, and September 10, 2017), indicating an overall warming trend from upstream to downstream. The increases in average MaxTw from upstream to downstream coincided with a 41% reduction of the average percent of forested land cover (defined as evergreen forest, mixed forest, and deciduous forest land cover) from sites 1 – 8 to sites 9 – 22 and a 43% increase in average agricultural land cover (defined as cultivated crops and pasture/hay land cover). Figure 5 summarizes land cover for each of the 22 stream temperature monitoring sites.

5.2 Statistical Analysis Results

Four models were produced from stepwise multiple linear regression and one significant regression equation was found ($F(4, 16) = 9.862$, $p < .000$), with an R^2 of .711. Width, percent of shrub/scrub, percent of mixed forest, and percent of cultivated crops were found to be significant predictors of 7DADMaxTw ($p < .05$). Table 6 summarizes model results pertaining to this analysis. Dependent variable 7DADMaxTw was equal to 20.312 + .033 (width) + .083 (shrub/scrub) - .132 (mixed forest) + .032 (cultivated crops). 7DADMaxTw increased .033°C for each meter of width within upstream buffered areas, .083°C for each percent of shrub/scrub, decreased -.132°C for each percent of mixed forest, and increased .032°C for each percent of cultivated crops within 300 m upstream buffered areas from stationary data logger sites. Width was found to be the strongest predictor variable of 7DADMaxTw variability in model 4 for the 300 m upstream buffered scale (see Table 6) with ß = 0.728, followed by shrub/scrub with ß = 0.58, mixed forest ß = - 0.39, and cultivated crops ß= 0.292.

At the 1 km upstream buffered scale, only one model was produced. Six variables were not included in the stepwise regression (cultivated crops, developed high intensity, evergreen forests, pasture/hay, emergent herbaceous wetlands, and developed low intensity) due to collinearity issues. The regression equation found was ($F(18, 1) = 5.346$, $p < .033$), with an R^2 of .229. The predicted 7DADMaxTw dependent variable is equal to 21.347 + .022 (width). 7DADMaxTw increased .022°C for every meter of width. Only width was a significant predictor of 7DADMaxTw ($p = .033$).

No predictor variables were determined to be significant enough to include in models when using range as the dependent variable at either the 300 m or 1 km upstream scale.

All four air temperature metrics (MaxTa, MinTa, 7DADMaxTa, and 7DADMinTa) were found to be highly positively correlated with all four stream temperature metrics (MaxTw, MinTw, 7DADMinTw, and 7DADMinTw) with highest correlation coefficients between 7DADMinTw and 7DADMinTa ($r_s = .883$) followed by 7DADMaxTw and 7DADMinTw ($r_s = .793$). These results are summarized in Table 7 and indicate that an increase in maximum and minimum air temperatures impact maximum and minimum stream temperatures, both on a weekly and daily scale. No flow metrics (MaxCMS, MinCMS, 7DADMaxCMS, 7DADMinCMS) were found to be correlated with any stream temperature metrics (see Table 8). Aspect as an independent variable also did not reveal any clear patterns or correlations with stream temperature.

5.3 Results of longitudinal thermal profiles

While thermal profiling revealed areas of thermal patchiness (Figures 6 and 7), none qualify as a cold-water refuge according to the EPA's definition as water that are 2°C colder than the surrounding water (Torgersen et al. 2012). Thermal variability (as indicated by the standard deviation of temperatures and temperature from start to finish) increased the most when maximum daily air temperature was greatest (Figures 6 and 7). MaxTa and MaxTw were found to be greatest on the August 4 – 5 thermal profiles, followed by July 29 – 30, and coolest stream and air temperatures occurred during the

September 9 – 10 thermal profiles. Cooler stream temperatures were present at the beginning of study sections, coinciding with cooler air temperatures earlier in the day. For study section one (thermal profiles that occurred on July 29, August 4, and September 9, 2017), there was a 4.88°C Tw difference from start to finish over the course of a four hour and twenty-minute float on July 29, a 4.082°C Tw difference from start to finish over an approximate five-hour float on August 4, and a 1.99°C Tw difference from start to finish over a four hour and forty-minute float on September 9, 2017. Air temperatures also increased by 4.8°C on July 29, 1.7°C on August 4, and decreased 1.4 °C on September 9, 2017 throughout the course of longitudinal thermal profiling periods. For the second segment (thermal profiles that occurred on July 30, August 5, and September 10, 2017), stream temperature had a 4.08°C difference over the course of a five hour and twenty-minute float on July 30, a 4.84°C difference over a about a six-hour float on August 5, and a 3.5°C difference over the course of a about a seven-hour float on September 10, 2017 from start to finish. Air temperatures increased by 2.6°C on July 30, 2.7°C on August 5, and 2.8°C on September 10, 2017 throughout longitudinal thermal profiling periods. Even though floats took longer as flows decreased through the summer, stream temperature differences from start to finish decreased as air temperatures decreased. Differences in temperatures between start to finish were typically greatest when differences in air temperature during the thermal profiles were greatest.

Graphs of near-surface temperature and near-streambed temperature for the study area segments (see Figures 8a – 8c for segment one and Figures 9a – 9c for segment two) reveal an overall well-mixed body of water with little differences between surface and streambed temperatures. Average differences between surface and streambed temperatures were 0.02°C on July 29, 0.004°C on July 30, 0.02°C on August 4, 0.06°C on August 5, 0.012°C on September 9, and 0.08°C on September 10, 2017. However, these differences in temperature between surface and streambed readings are well below the accuracy of the thermistors (± 0.25°C), so it cannot be accurately reported that there are overall differences between surface and streambed temperatures.

Overall, seven cold-water patches were identified and are presented in Figure 10 pertaining to floats conducted in the first section (July 29 and August 4, 2017) and Figure 11 for cold-water patches located within the second segment identified on August 5 and September 10, 2017. These cold-water patches are labeled 1 – 7 with patches 1 – 4 that were located on floats within the first study section (July 29 and August 4, 2017) and 5 – 7 located within the second segment of the study section (August 5 and September 10, 2017). Cold-water patches 1 – 4 occurred within a stretch of the Chehalis River approximately 2 km in length and while areas where these cold-water patches were identified in similar locations (site 1 on July 29 and site 4 on August 4 were located approximately 230 meters, for instance), they did not occur in the exact same locations over time. Cold-water patches 5 – 6 occurred in the South Fork Chehalis River and were the only patches identified as consistent for the two thermal profiles conducted to deploy and retrieve data logger number 11 in this area on August 5 and September 10, 2017. Cold-water patch number seven was detected on September 10, 2017 only.

Understanding what drives these areas may inform of appropriate restoration or protection methods. For sites 1 – 4, distance from a tributary (Garret Creek) ranged from

369 m – 2515 m, not signifying that distance to Garret Creek drives these cold-water patches. Sites 5 and 6 were directly related to distance from a tributary as they were located within the South Fork Chehalis River. Site 7 may have been influenced by distance from a tributary, being only 107 meters from Bunker Creek.

While width was found to be significantly correlated with 7DADMaxTw temperatures at the 300 m and 1 km upstream scale using stepwise multiple linear regression, average width in cold-water patches totaled 48.94 m while average width for the total study area was 47.81 m, indicating that width was not a driver of these cold-water patches.

Results from stepwise multiple linear regression showed that width, cultivated crops, and shrub/scrub had positive correlations with 7DADMaxTw temperatures while mixed forest had negative correlations with 7DADMaxTw. Figure 12 shows the land cover for 300 m upstream buffers for all seven cold-water patches. For sites 1 – 4 mixed forest land cover averaged 12.71% compared to this land cover type only making up 5.84% of the total 25 km study area that was buffered out 100 m. Total forested areas including deciduous, evergreen, and mixed forests averaged 18.97% compared to 8.99% for the total study area. Cultivated crops were not present in these areas compared to 7.92% contained in the total study area. However, these sites also had an average of 15.8% shrub/scrub, which was higher than the 10.03% for the total study area. The non-existence of cultivated crops and mixed forest land use types being more than double than that of the total area may counterbalance the increase in shrub/scrub by providing more shade for these stream reaches as compared to the rest of the study area. Cold-water patches 5 – 6 were comprised of 24.56% cultivated crops (as compared to 7.92% for the total area), 2.49% shrub/scrub (as compared to 10.03% for the total area), and 5.37% mixed forest (as compared to 5.84% for the total area). These cold-water patches can be explained by simply being located within a cool-water input tributary of the South Fork Chehalis River. Cold-water patch seven had no cultivated crops, 0.1% shrub/scrub, and 8.97% mixed forest land use types. Both cultivated crops and shrub/scrub which had positive correlations with 7DADMaxTw temperatures were low to non-existent, while mixed forests that were found to be negatively correlated were greater in comparison to the total study area.

6. Discussion

I found that stream temperature impairments are problematic and occur at more reaches than are currently listed under the TMDL, with 100% of all 22 stream temperature monitoring sites having exceeded 7DADMaxTw temperature criterion of 16°C for core summer salmonid habitat and the 7DADMaxTw criterion of 17.5°C for salmonid rearing and migration designated uses that have been applied to sections of the study area, for the entire study period (August 4 – September 10, 2017). Stream temperature monitoring sites within areas under a TMDL for stream temperatures that exceed 18°C (sites 11, 12, 18, and 22) violated this standard 100% of the time throughout the study period. Air temperature was highly positively correlated with all stream temperature metrics, and will likely continue to be problematic with climate change increasing air temperature throughout the 21st century (Isaak et al. 2012; Beechie et al. 2013). While it is not possible to cool an entire river, it is beneficial to understand the riverine thermal regime, what drives stream temperature to inform of appropriate restoration or protection efforts that will be most effective, and to identify cold-water patches that can be enhanced or protected to serve as thermal refugia for aquatic species.

Width was identified as a predictor variable and was strongly positively correlated with 7DADMaxTw at all scales, congruent with other studies that found width to be correlated with stream temperature (Justice et al. 2017; Woltemade 2017; Loicq et al. 2018). Model simulations have demonstrated that channel narrowing and a decreased width-to-depth ratio resulted in cooler water temperature (Justice et al. 2017). Studies have ascertained that areas where large woody debris and other in-stream features such as large rocks exist resulted in deeper pool volumes, narrower streams, lower stream temperatures, greater stream habitat complexity, and an increased abundance of salmonids (Fausch and Northcote 1992; Tan and Cherkauer 2013). Other techniques such as increasing woody bank vegetation have been found to be correlated with bank stabilization, and narrower stream widths (Anderson et al. 2004). Channel width reduction overall minimizes exposure to solar radiation inputs at the river surface through shading (Trimmel et al. 2018) and could be beneficial in reducing MaxTw in this study area, possibly through the methods identified above.

Results from stepwise multiple linear regression also indicate that shrub/scrub and cultivated crops had a positive correlation with 7DADMaxTw (ß = 0.58 and ß = 0.295, respectively) and that mixed forests had a negative correlation (ß = -0.39). The positive correlation with 7DADMaxTw and shrub/scrub and the negative correlation with mixed forests may be explained by a difference in canopy height. Shrub/scrub is defined as being less than 5 m tall while mixed forest is defined by trees generally greater than 5 m tall (Homer et al. 2015). Stream temperature modeling has revealed that increases in canopy height and density either lowers MaxTw or buffers stream temperatures during extreme heat waves (McHugh et al. 2017; O'Briain et al. 2017), while models that used inputs pertaining to a removal of riparian vegetation through activities such as logging or agriculture resulted in an increase in stream temperature (Trimmel et al. 2018). These findings are consistent with cultivated crop land cover increasing from upstream to downstream while mixed forested land cover decreasing, coinciding with an overall increase in average MaxTw within the study area. Additionally, the DOE found that effective shading declined when bankfull widths were 1.4 times the canopy height, regardless of canopy cover (Washington Department of Ecology 2007). Using these findings and the average width of the study area (47.81 m), effective shading would occur with tree height greater than 66.9 m on average, making the 5 m shrub/scrub land cover ineffective in stream shading and could explain the positive correlation with 7DADMaxTw and the negative correlation with the taller mixed forest land cover greater than 5 m in height. Shade effectiveness also tends to diminish as channel width and volume increases (Poole and Berman 2000), but modeling in studies that combined riparian planting with width reduction scenarios responded most strongly to a reduction in average MaxTw (Justice et al. 2017; Trimmel et al. 2018), and could be effective in the study area based on the strong predictor variables identified through stepwise linear regression.

Stream temperature monitoring sites in Garret Creek (site three), the confluence of Garret Creek and the Chehalis River (site four), and Bunker Creek (site 11) revealed lower MaxTw and 7DADMaxTw than surrounding sites and overall average MaxTw of the rest of the stream temperature monitoring sites. While the South Fork of the Chehalis River (sites 11 and 12) revealed higher average MaxTw than all other sites (23.34°C compared to 22.98°C for all other sites), this was identified as a consistent cold-water patch at a finer spatial scale through thermal profiling. The South Fork Chehalis River would have been overlooked with stationary data collection methods that are limited spatially, but augmenting data with fine-scale spatial thermal profiling was able to identify this site as a cold-water patch. The cold-water patch identified in this area did not reveal land cover consistent with model results from stepwise multiple linear regression, indicating that this tributary is a source of cool water independent of land use within the area. These results indicate that tributaries and tributary confluences would be appropriate sites for enhancement or protection techniques that aquatic species can use as temporary thermal refuges as well.

7. Conclusions

This study had three objectives: to identify a data collection method to quantify the spatial distribution of stream temperature, evaluate the relative consistency of the riverine thermal regime over time (July – September, 2017), and identify independent variables that impact or contribute to the riverine thermal regime. Integrating longitudinal thermal profiling can help to augment where stationary data loggers are spatially limited and can be conducted many times to assess where thermal patchiness remains consistent. Conversely, stationary data loggers can help to capture diurnal stream temperature trends where longitudinal thermal profiling is limited and can be used in statistical analysis to assess what independent variables drive stream temperature.

Stream temperature was highly responsive to air temperature, both on a daily and weekly scale. Cooling an entire stream is not practical but using stationary data logger information in analysis with landscape predictive variables can provide resource managers with insight into what correlations exist between land cover and can help to inform of where to best focus efforts and what techniques would be most effective. Overall, the findings from this study indicated that focusing restoration or protection efforts at tributaries and tributary confluences where cool water inputs already exist would be beneficial. Findings from modeling in other studies showed a reduction in width combined with the planting of tall, woody riparian vegetation to reduce maximum stream temperatures (Trimmel et al. 2018) and could be beneficial in this study area, since width was a strong predictor variable at all scales and shrub/scrub less than 5 m tall was not effective in shading (as indicated with the positive correlation with

7DADMaxTw), while mixed forest with heights greater than 5 m provided more effective shading and cooling indicated by the negative correlation with 7DADMaxTw. Predictive modeling in using vegetative height, channel width, and maximum stream temperatures could provide further insight on effective shading for this area.

Thermal profiling provides valuable information on what the overall thermal regime looks like at a fine spatial scale over time and can also assist in locating additional sites to focus protection efforts at existing cold-water patches. While sites 1 – 4 out of the seven cold-water patches identified in this study occurred within 2 km of each other, none were found to be consistent and in the same exact location over time. Only two sites were consistent over time, located in the mouth of the South Fork Chehalis River consistent with findings from stationary data logger information that showed tributaries to be cooler sources of water than main stem monitoring sites. While land cover in these cold-water patches does seem to coincide with model results (an increase in forested cover and decrease in cultivated crops), more research utilizing thermal profiling could be repeated in the study area to evaluate how and where these patches appear over time to assess whether these are groundwater driven or are purely influenced by landscape.

With natural resource agencies operating off of limited budgets, gathering stream temperature information at a fine spatial scale (such as thermal infrared) and over a long period of time can be challenging. Stationary data loggers are predominantly the method used for stream temperature studies due to the inexpensive nature and low maintenance needs (simply deploy and retrieve). However, combining the stationary data logger thermal profiling toolsets can be an effective method to assist resource managers with gaining a better understanding of the spatiotemporal stream temperature trends and contributing landscape characteristics that may be used to develop more effective site placement and restoration techniques.

Tables

Table 1. Overview of literature pertaining to landscape influences on stream temperature.

Author (year)	**Study Area**	**Study Period**	**Data Collection/Methodology**	**Relevant Findings**
Appel et al. (2011)	5 reaches of the Lower Yakima River, WA	Summer of 2008 and 2009	6 dipperLog probes- 3 near streambed, 3 near surface across the width of river synced with Lowrance HDS-5 Depthfinder/GPS Chartplotter unit.	Increase in flow did not correlate with a decrease in river temperature. River temperatures were correlated with ambient air temperatures. Decrease in temperature found to be greatest near seeps.
Bowler et al. (2012)	Worldwide studies- literature review	Varies- literature review	Systematic literature review of effects of wooded riparian zones on stream temperature	Riparian wooded zones lower spring and summer temperatures, less effect on mean temperature. No significant effect with buffer width and stream temperature found.
Chang and Psaris (2013)	Columbia River Basin, USA		Data from 74 stream temperature stations. Geographically weighted regression and ordinary least squares estimates.	Thermal sensitivity controlled by distance to the Pacific Coast, base flow index, and contributing area. Maximum stream temperatures controlled by base flow index, % forest land cover, and stream order.
Dick et al. (2015)	Cairngorms National Park, Scotland, UK	June 21,2012- September 21, 2013	Gemini data loggers, CTD divers, automatic weather station. Kruskall-Wallis test and Wilcoxon signed-rank test conducted to compare medians of non-normally distributed data sets.	Differences between sites become apparent in summer months only. South and east facing streams showed higher temperatures, shallow groundwater discharge most apparent in summer, deeper groundwater inputs apparent in winter.
Dugdale et al. (2013)	Rivière Ouelle catchment, Quebec, Canada	2009-2011	FLIR SC660 imaging camera, 16 stationary HOBO UA-002-64 temperature loggers. Coefficient of determination of regression used to quantify correlation of hydrometereological data and thermal refuge density.	Thermal refuges highly transient- temporal variability. Strong positive correlation with refuge density and mean discharge.

Dugdale et al. (2015)	~700 km of the Restigouche watershed, Canada	2011-2012 summer	Airborne TIR. Jacob's selectivity index and regression models to quantify and correlate thermal refuges and landscape variables.	Groundwater-driven thermal refuges varied by year. Thermal refuges correlated with river bends, proximity to tributary valleys, and moderate channel confinement
Ebersole et al. (2003)	37 study sites of the Grande Ronde basin, northeastern Oregon	July 1-September 1, 1997	Digital thermometers attached to probes while wading to detect cold patches. Experimentally manipulated shade cover on cold alcoves. ANOVA tests for results.	Cold water patches created by groundwater upwelling or intragravel flow. Experimental shading cooled daily maximum surface temperatures of cold water patches between 2-4°C, indicating strong influence of riparian vegetation on cold patches of water.
Fullerton et al. (2015)	53 rivers in the Pacific Northwest	July or August between 1994-2007	TIR data used to characterize rivers into 5 profile categories. Used root mean squared error, Nash-Sutcliffe model efficiency coefficient, Glejser test, and General Addictive Model to determine best model fit.	Rivers that originate at higher elevations with higher precipitation and flowed through arid areas were cool at headwaters and warmed rapidly downstream. Greater riparian shading and steeper gradients led to cooler stream temperatures.
Jackson et al. (2016)	25 sites part of Scotland River Temperature Monitoring Network	0/6/22/2015-08/31/2015	Gemini Tiny Tag Aquatic 2 (TG-4100) dataloggers. Used generalized additive models with smoothers to find relationship between maximum water temperature and landscape covariates.	Minimum and mean temperatures decreased with increasing elevation, riparian woodland percent, and channel gradient. Maximum temperatures increased with channel width. Lower order streams showed increased variability in all temperature metrics.
Johnson and Wilby (2015)	Dove and Manifold Rivers, England		37 paired air temperature and water temperature monitoring sites, 2003 aerial photographs to digitize woodland areas. Logistics regression models for analysis.	Shade most beneficial where discharge is modest, flow is dominated by near-surface groundwater exchanges, wide floodplains, and solar exposure is high. Approximately .5 km complete shade is necessary to reduce water temperatures by 1°C and 1.1 km required 25km downstream.

Loicq et al. (2018)	270 km of the Loir River, France	August 2007 to July 2014	T-NET to computer longitudinal water temperature, in stream temperature loggers for verification, LiDAR. Used riparian shading data in T-NET stream temperature model.	Vegetation decreases maximum stream temperature up to 3°C in the upstream part of the river and by 1.3°C in downstream reaches. Downstream reaches warm due to a reduction in riparian vegetation and increase in channel width.
Orr et al. (2015)	2773 data locations in England and Wales	1990-2006	Temperature information and flow taken from 2773 sites. Correlated using additive models.	No direct relationship between increasing trends in water temperature and flow. Rates of change in water temperature comparable to UK air temperatures.
Pratt and Chang (2012)	Portland Metro Region of Oregon and Clark County, WA	1998-2010/	USGS NHD, water quality data taken from 21 Portland sites and 30 Clark County sites. Ordinary least squares and geographically weighted multiple regression models for analysis.	Lower standard deviations of slope correlated with higher stream temperatures, percent single family residential land use positively correlated with temp,
Steel et al. (2016)	Snoqualmie River, Washington, USA	July 2011-September 2012	34 temperature monitoring sites and Tidbit loggers. Spatial stream network models for analysis.	Predictors of river thermal regime strongly correlated to elevation, mean annual discharge, and percent commercial area in summer months but less so in winter months.
Tan and Cherkauer (2013)	Green-Duwamish River, Washington, USA	August 25th and 27th, 2001	5-meter and 15-meter MODIS/ASTER imagery, thermal infrared. Image analysis/overlap of images performed, standard deviation and average used to create thermal profiles from TIR.	Average stream reach temperatures increased with urbanization and variability decreased. Riparian vegetation, and in-stream features such as rocks and woody debris affects stream temperature. An increase in solar radiation and warming throughout the day increased stream temperatures.
Woltemade (2017)	Navarro River watershed, California, USA	May 2014-September 2015	24 Onset "Tidbit" data loggers, Onset Hobo U23 data loggers for air temp and relative humidity, cup anemometers for wind speed, LI-COR LI-200 pyranometer, SonTek Doppler meter for	Contributing drainage area, channel width, land cover, channel shade, stream order, and diurnal temperature range found to have statistically significant correlations with stream temperature.

			discharge. Heat Source modeling, Spearman's rank correlation for analysis.	
Woltemade and Hawkins (2016)	Navarro River watershed, California, USA	Summer 2015	24 Onset "Tidbit" data loggers, Onset Hobo U23 data loggers for air temp and relative humidity, cup anemometers for wind speed, LI-COR LI-200 pyranometer, SonTek Doppler meter for discharge, 2012 NAIP imagery. Heat Source modeling for analysis.	Maximum weekly average temperatures (MWATs) influenced by flow and forest cover. Modelled MWATs increasing by 1.5-2.3°C in response to 3.5°C air temperature increases. Stream temperatures modeled under low flows showed sensitivity to changes in air temperature and shading.

Table 2. Analysis of stream temperature data collection methods, advantages, and limitations

Technology	Temporal Resolution	Pros	Cons
Stationary Temperature Data Loggers	Specified by brand and user (every 5, 15, 30 minutes, etc.)	Inexpensive, accurate, measures diurnal stream temperature changes	Limited spatially- cannot place throughout every stream reach.
Thermal Infrared (TIR)	Can collect images at specified intervals (IE 1 per 2 seconds) over hundreds of kilometers, pixel resolution of ~.6 meters or more.	Generates accurate, fine spatial stream temperature data over long stream reaches	Expensive which limits monitoring stream temperature over time. Measures surface temperature only. Limited where dense riparian vegetation exists.
Distributed Fiber Optic Temperature Sensor (DTS)	Detects 0.01°C temperature resolution every 1 meter within fractions of a minute, up to 3 kilometers	Relatively inexpensive fine spatial and temporal resolution data reported in near-real-time.	Spatially limited over long distances. Logistically challenging- cables drift or are exposed in shallow water and cannot withstand environmental severities or difficult terrain.
Longitudinal thermal profiling	Specified by brand and user (every 1, 10, 30 seconds, etc.)	Inexpensive, accurate, can be done over relatively long stream reaches, and repeated to monitor change. Can capture surface and streambed temperatures.	Not advised in deep rivers or where snagging hazards exist. Limited temporally with diurnal heating and movement downstream throughout the day.

Table 3. Data and sources for variables examined.

Variable	Source Agency	Source	Resolution
Air Temperature (°C)	Washington Department of Ecology	Station 23K060 South Fork Chehalis at Highway 6	°C every 15 minutes
Aspect	Washington State Department of Natural Resources (DNR)	2012 Grays Harbor LiDAR converted to Digital Surface Model	~1X1 meter
Canopy Cover (%)	United States Forest Service (USFS)	National Land Cover Database 2011 USFS Tree Canopy Analytical Layer	30X30 meter
Flow (Cubic Meters per Second)	United State Geological Survey (USGS)	Station 12021800 Chehalis River near Adna, WA	CFS every 15 minutes
Impervious Surface (%)	Multi-Resolution Land Characteristics	NLCD 2011 Percent Developed Imperviousness	30X30 meter
Land Cover (%)	Multi-Resolution Land Characteristics	National Land Cover Database 2011 (NLCD)	30X30 meter
Channel Width	Washington State Department of Natural Resources (DNR)	2012 Grays Harbor LiDAR converted to Digital Surface Model	~1X1 meter

Table 4. Site location information for stationary data logger information including latitude (LAT), longitude (LONG), width (m), and aspect.

SITE	NOTES	LAT	LONG	WIDTH (M)	ASPECT	ASPECT (ArcGIS DEGREE)
1	Before study area	46.634206	-123.206379	47.16	South	171.87
2	Thermal Profile Start	46.633598	-123.205269	46.63	North	18.43
3	Garret Creek	46.636162	-123.172527	5.83	South	164.74
4	Garret Creek confluence	46.63602778	-123.1722222	73.88	Southeast	148.63
5		46.635471	-123.169282	131.97	North	0.00
6		46.61871083	-123.17	60.41	East	82.30
7		46.597625	-123.1552778	47.84	North	14.30
8		46.60088889	-123.1472222	54.68	North	350.54
9		46.60793611	-123.1433333	58.94	South	178.60
10	Groundwater Input	46.60560556	-123.1366667	10.88	Southwest	222.14
11	South Fork Chehalis	46.604733	-123.123544	24.16	Southwest	245.17
12	South Fork Chehalis	46.603302	-123.123204	24.37	South	176.42
13		46.606799	-123.123725	85.64	North	15.75
14		46.6097075	-123.1194444	62.53	North	19.54
15		46.624722	-123.099559	89.79	South	195.73
16		46.633645	-123.109139	74.31	Southwest	206.03
17		46.640958	-123.110015	105.62	West	166.76
18	Bunker Creek	46.64458	-123.119317	16.47	Southwest	218.02
19		46.635826	-123.080614	57.91	West	248.75
20		46.641217	-123.089746	70.83	North	345.96
21		46.629532	-123.077236	55.47	Northwest	315.00
22	Adna, WA	46.628346	-123.061847	53.03	Northeast	45.00

Table 5. Stream temperature monitoring site information pertaining to stream temperature metrics and percent of violations of recommended temperatures to avoid acute lethality of salmonids according to WAC 173-201A-200.

SITE	NOTE	MaxTw	MinTw	7DADMaxTw	7DADMinTw	Percent of 7DADMaxTw ≥22°C	Percent of MaxTw ≥23°
1		22.21	18.91	22.19	18.91	52.2	28.6
2		22.67	19.38	22.51	19.19	63.3	41.7
3	Garret	18.60	16.03	18.41	15.84	0	0
4		21.17	17.60	20.95	17.38	12	10
5		22.50	19.74	22.33	19.55	56.7	22.2
6		23.27	19.85	23.08	19.65	100	61.1
7		23.60	19.37	23.42	19.16	83.3	58.3
8		24.17	19.30	24.03	19.13	100	61.1
9		23.48	19.81	23.33	19.61	100	58.3
10		21.66	20.79	21.47	20.60	22.2	10
11	S. Fork	23.17	20.73	22.98	20.52	100	36.2
12	S. Fork	23.50	20.55	23.27	20.25	100	58.3
13		23.80	20.70	23.67	20.46	100	66.7
14		24.01	20.32	23.89	20.12	100	69.4
15		23.08	20.92	22.93	20.72	100	38.9
16		23.42	21.31	23.25	21.11	100	61.1
17		24.15	20.87	24.01	20.64	53.3	27.8
18	Bunker	19.97	17.70	19.75	17.43	0	0
19		24.36	21.03	24.22	20.80	100	69.4
20		23.01	20.75	22.95	20.70	100	36.7
21		23.81	21.47	23.63	21.28	100	72.2
22		22.65	20.47	22.62	20.39	100	33.3

Scale	Model	R^2	*SE*	Predictor Variables	*B*	ß	*p*	*SE B*	*t*	Equation
300 m upstream	1	0.233	1.288	Width	0.022	0.483	0.027*	0.01	2.404	21.342 + .022 (width)
	2	0.472	1.098	Width	0.027	0.589	0.003*	0.01	3.364	20.331 + .027 (width) + .071 (shrub/scrub)
				Shrub/scrub	0.071	0.501	0.01**	0.03	2.857	
	3	0.629	0.947	Width	0.031	0.687	0**		4.416	20.740 + .031 (width) + .078 (shrub/scrub) - .137 (mixed forest)
				Shrub/scrub	0.078	0.546	0.002**	0.02	3.592	
				Mixed Forest	-0.14	-0.41	0.016*	0.05	-2.68	
	4	0.711	0.861	Width	0.033	0.728	0**	0.01	5.102	20.312 + .033 (width) + .083 (shrub/scrub) - .132 (mixed forest)
				Shrub/scrub	0.083	0.58	0.001**	0.02	4.167	+ .032 (cultivated crops)
				Mixed Forest	-0.13	-0.39	0.012*	0.05	-2.84	
				Cultivated crops	0.032	0.292	0.048*	0.02	2.137	
1 km upstream	1	0.229	1.345	Width	0.022	0.479	0.033	0.01	2.312	21.347 + .022 (width)

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6. Stepwise multiple linear regression results using 7DADMaxTw as the dependent variable and landscape predictor variables including land use, width, percent of canopy cover, and percent of impervious surface variables at the 300 m and 1 km upstream for stream temperature monitoring sites (n=22). Confidence interval at 95%.

Figures

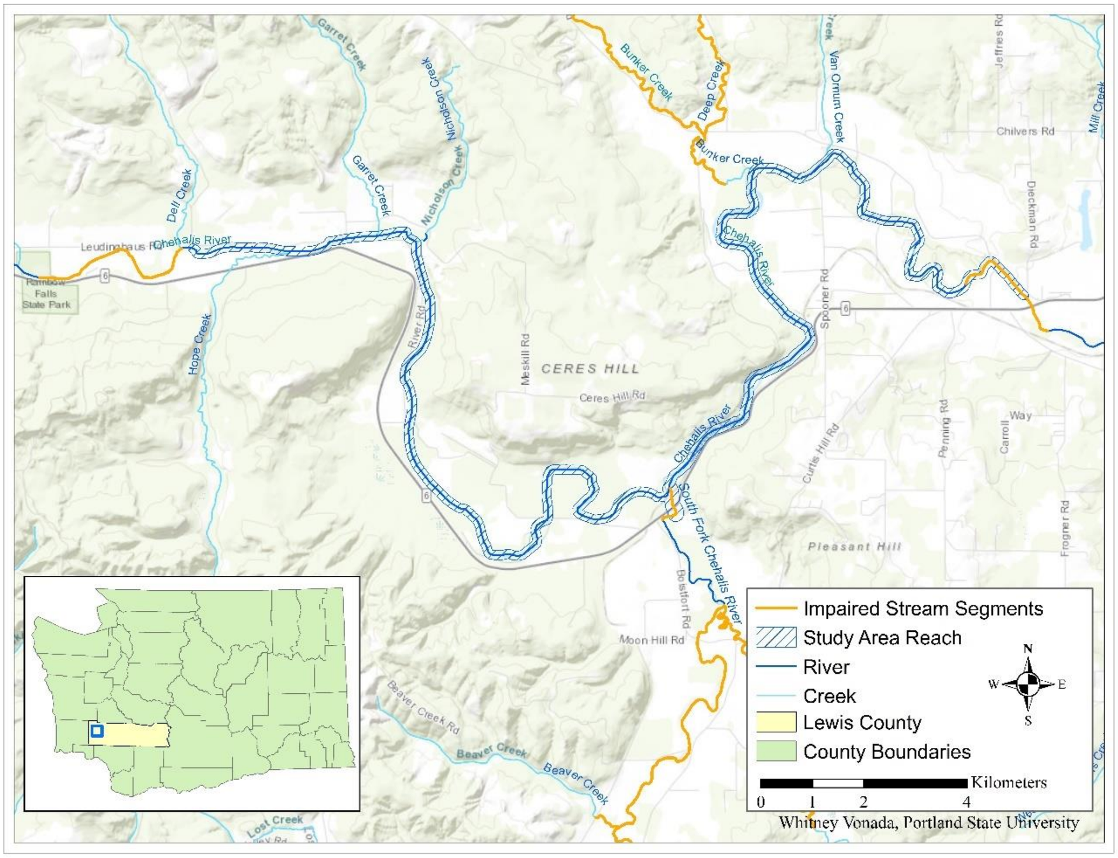

Figure 1. Map of the study area encompassing 25 km of the Chehalis River, WA and a small portion of the South Fork Chehalis River that was used in longitudinal thermal profiling. Orange sections represent impaired segments currently listed under the Upper Chehalis River Basin TMDL. Impaired areas that were studied using stationary stream temperature monitoring occurred in Bunker Creek, the South Fork of the Chehalis River, and the eastern most section of the study area.

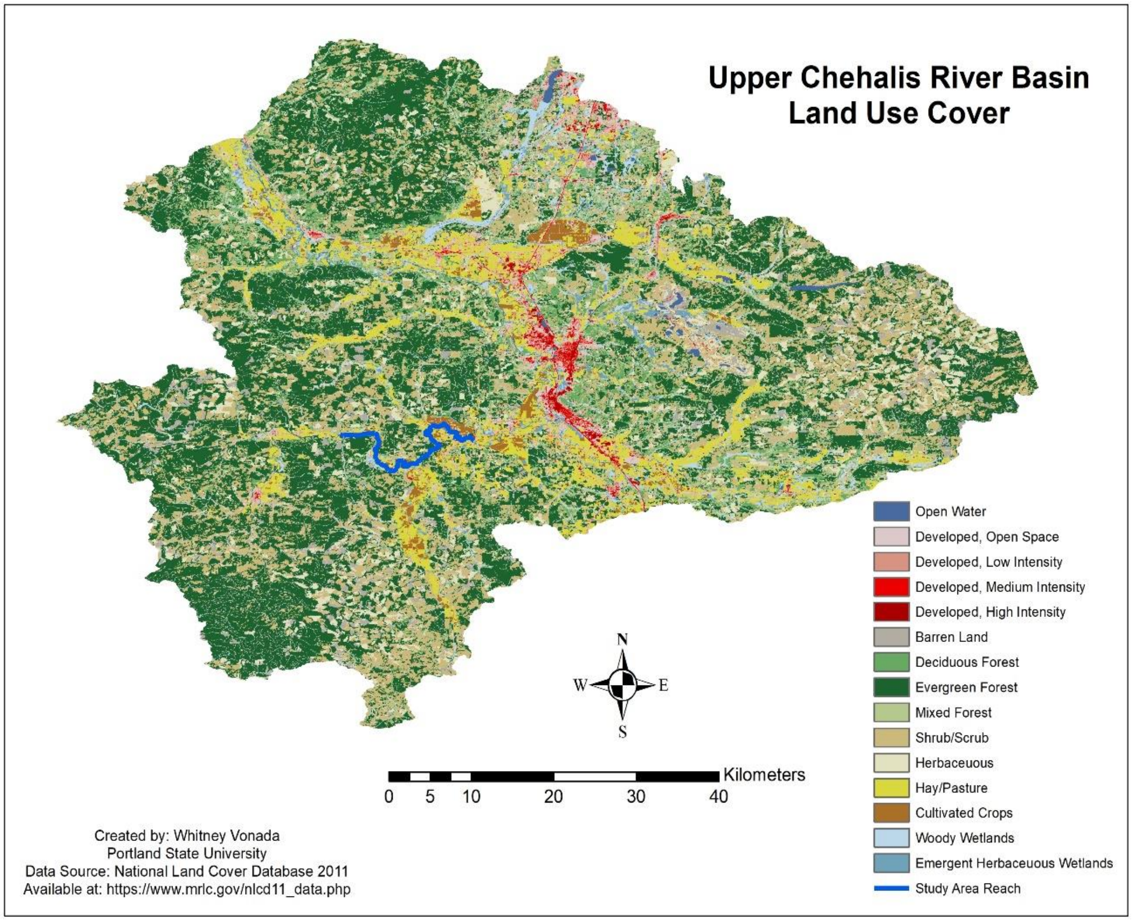

Figure 2. Land use cover for the Upper Chehalis Basin, 2011 National Land Cover Dataset.

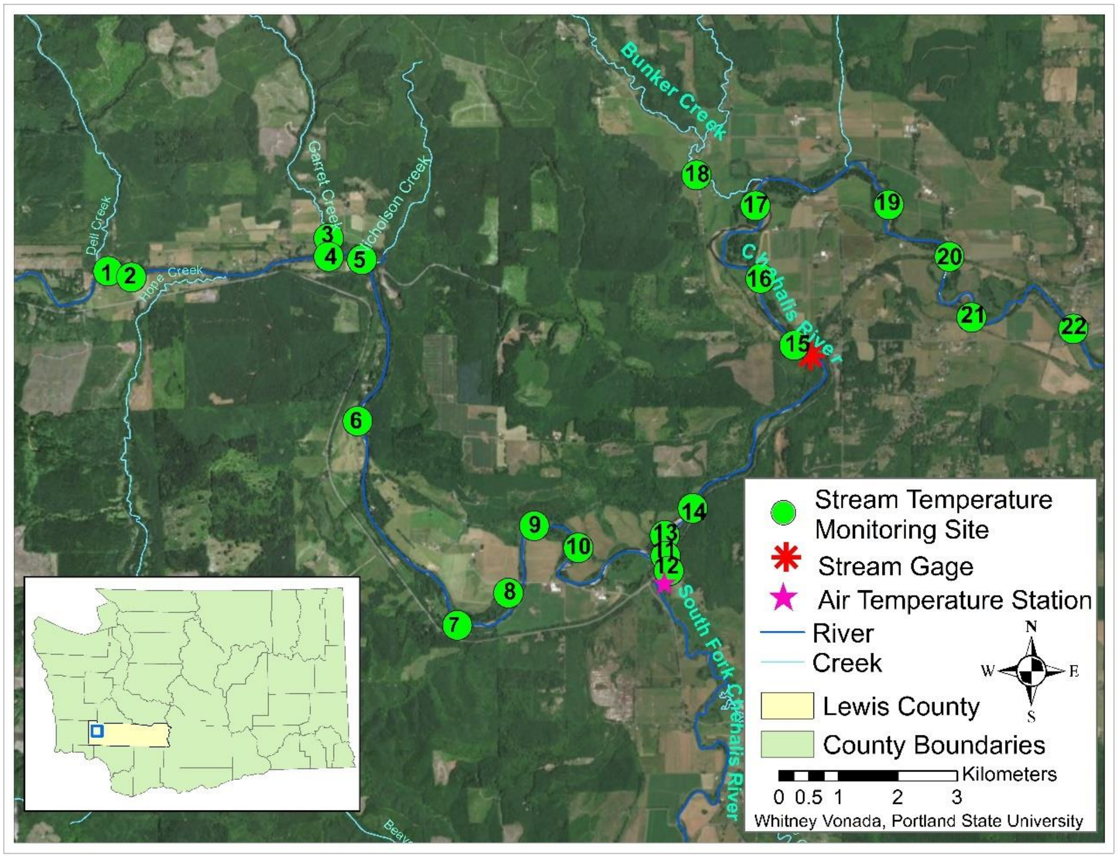

Figure 3. Locations and number for stream temperature monitoring stations and the DOE air temperature station and USGS stream gage used.

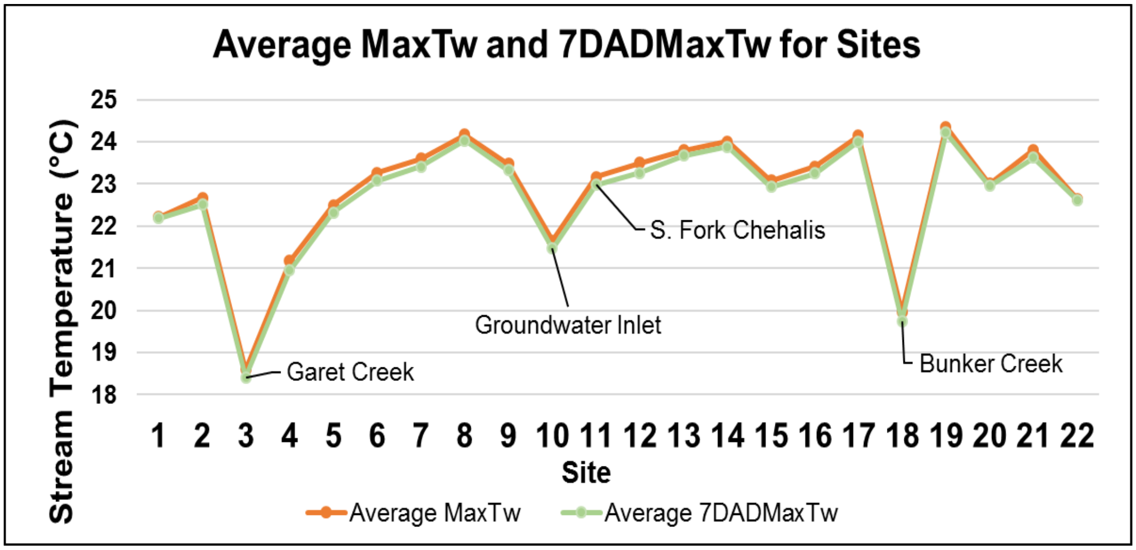

Figure 4. Graph summarizing MaxTw and 7DADMaxTw for all stream temperature monitoring sites (n=22).

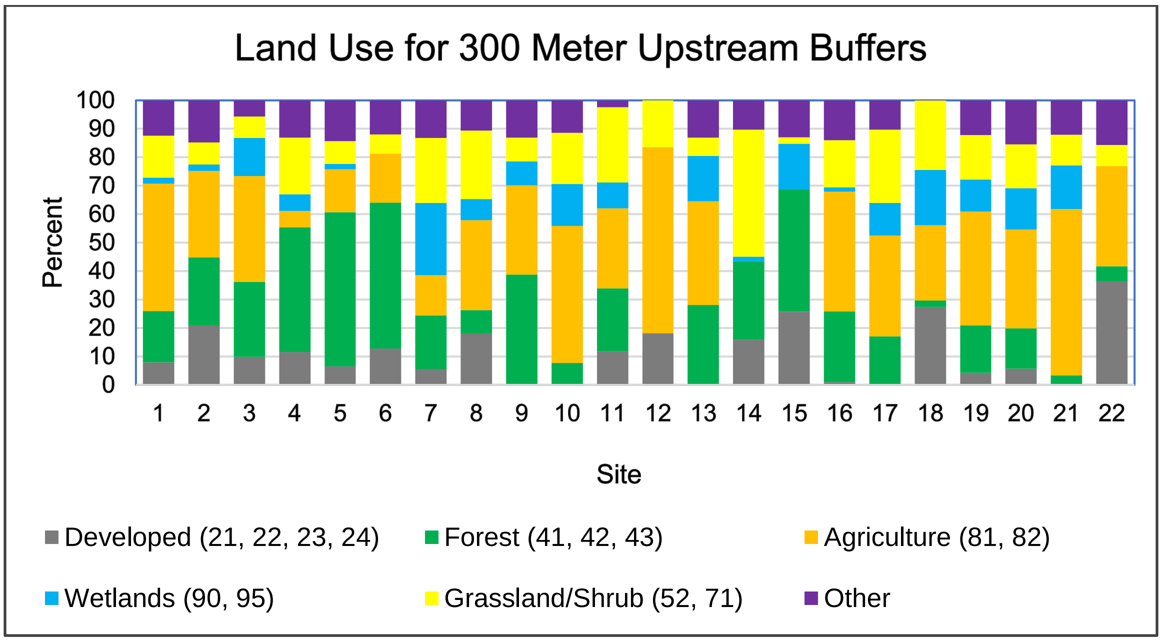

Figure 5. Bar chart summarizing grouped land use types for 300m upstream buffered sites. Land cover classes align with the 2011 NLCD legend (Homer et al. 2015) where 21=developed open space, 22= developed low intensity, 23= developed medium intensity, 24= developed high intensity, 41= deciduous forest, 42= evergreen forest, 43= mixed forest, 52= shrub/scrub, 71= grassland/herbaceous, 81= pasture/hay, 82= cultivated crops, 90= woody wetlands, 95= emergent herbaceous wetlands.

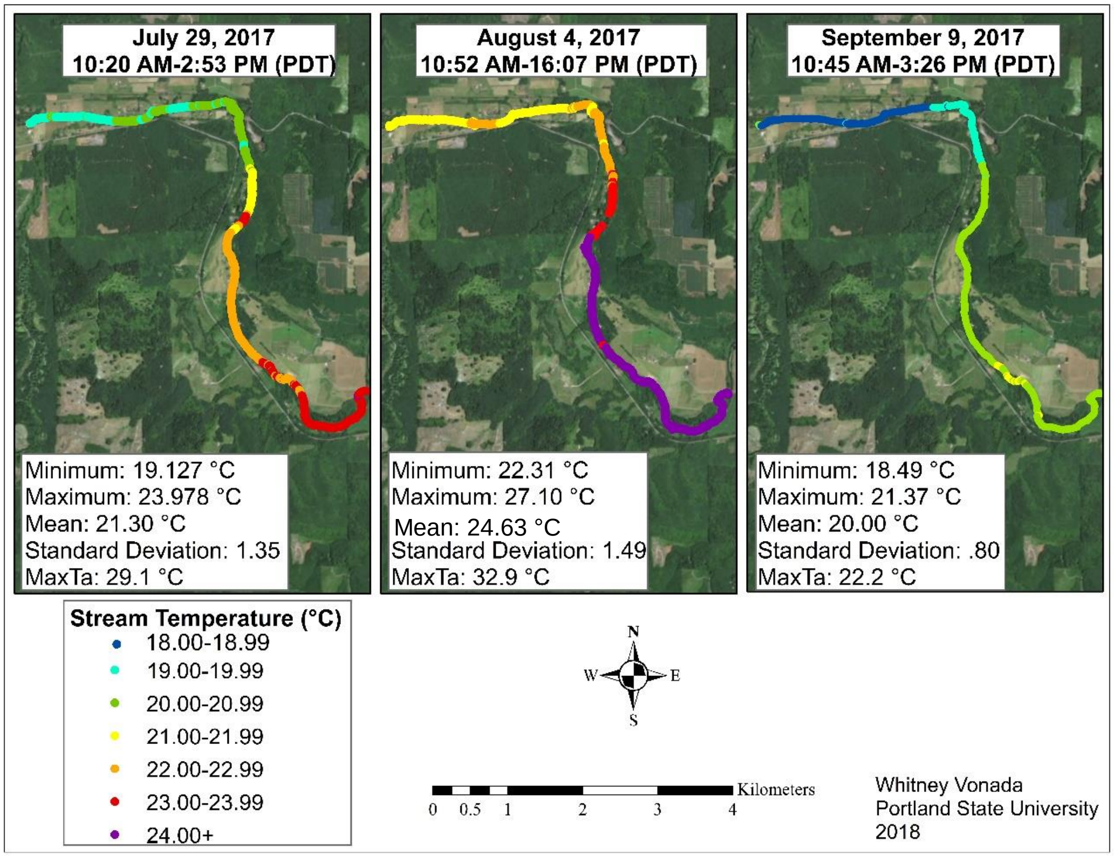

Figure 6. Longitudinal thermal profile results for study section one on July 29, August 4, and September 9 of 2017.

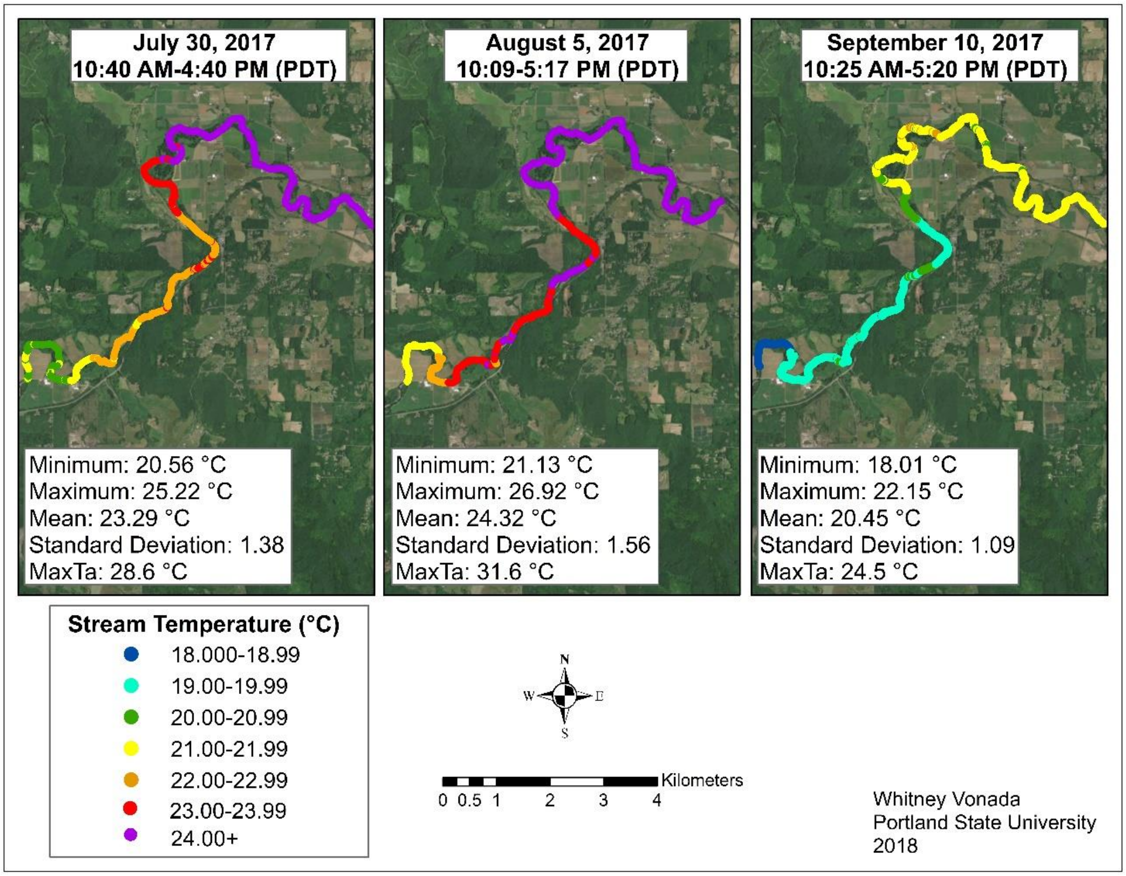

Figure 7. Longitudinal thermal profile results for study section two on July 30, August 5, and September 10 of 2017.

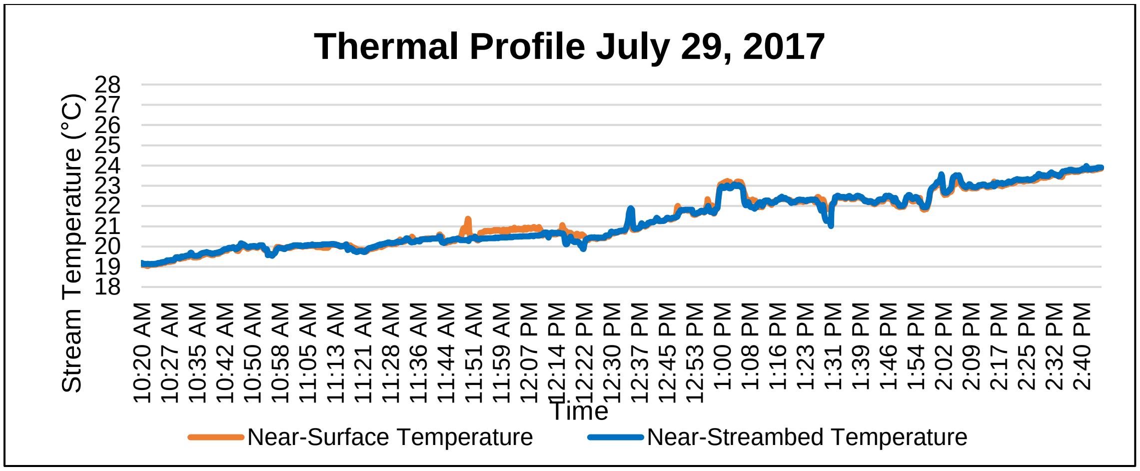

Figure 8a. Thermal profile data for segment one, July 29, 2017

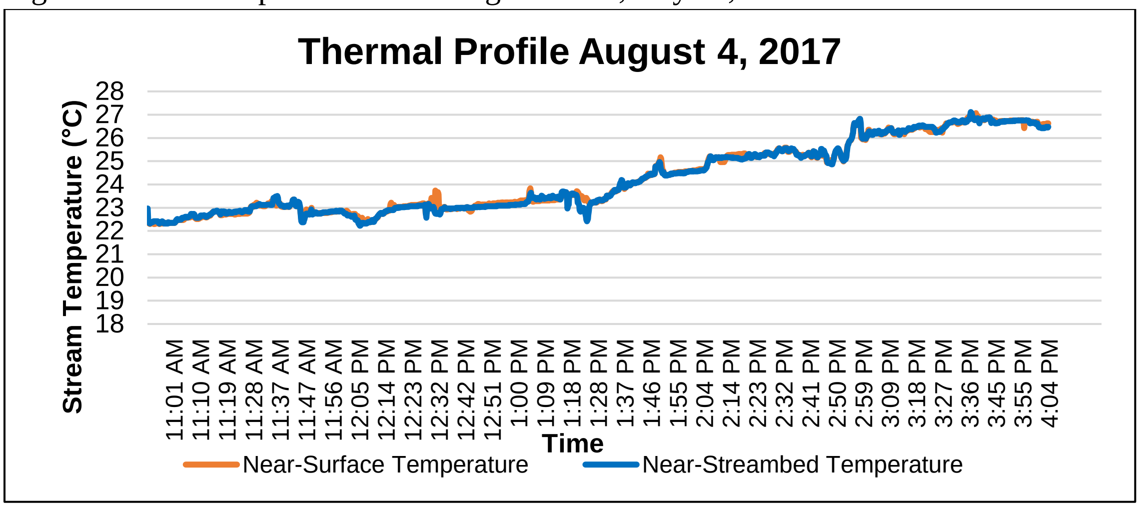

Figure 8b. Thermal Profile data for segment one, August 4, 2017.

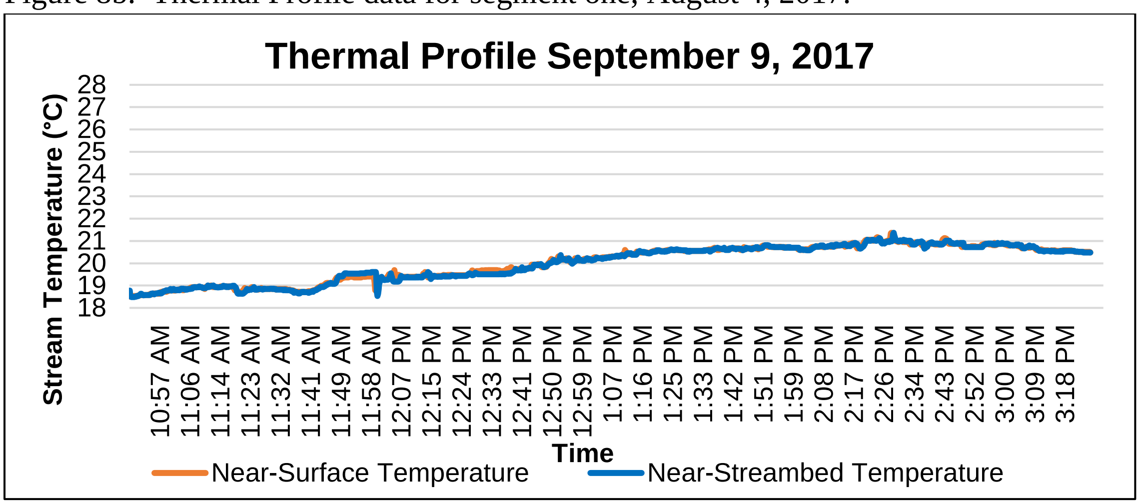

Figure 8c. Thermal profile data for segment one, September 9, 2017.

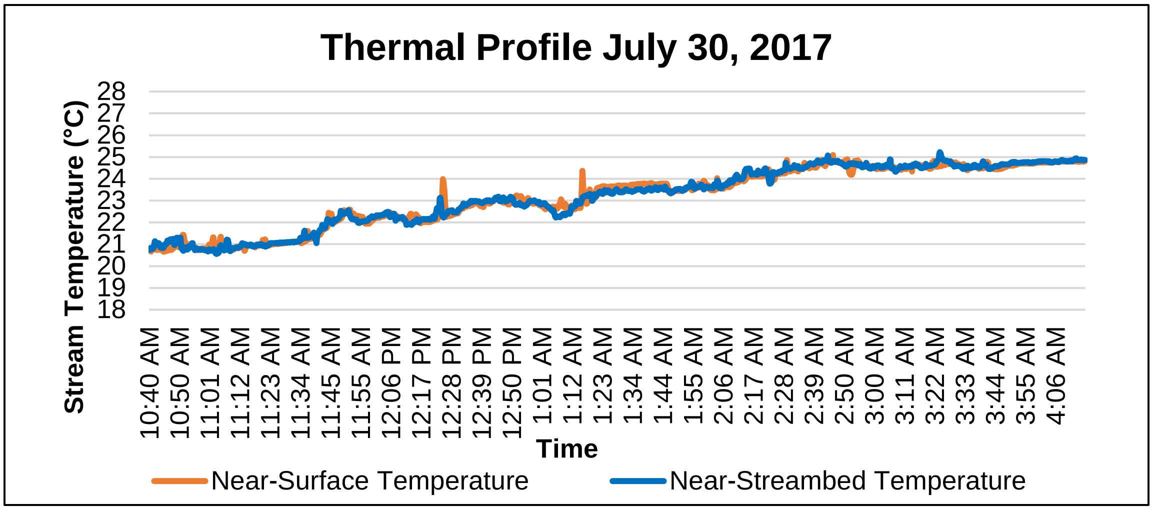

Figure 9a. Thermal profile data for segment two, July 30, 2017

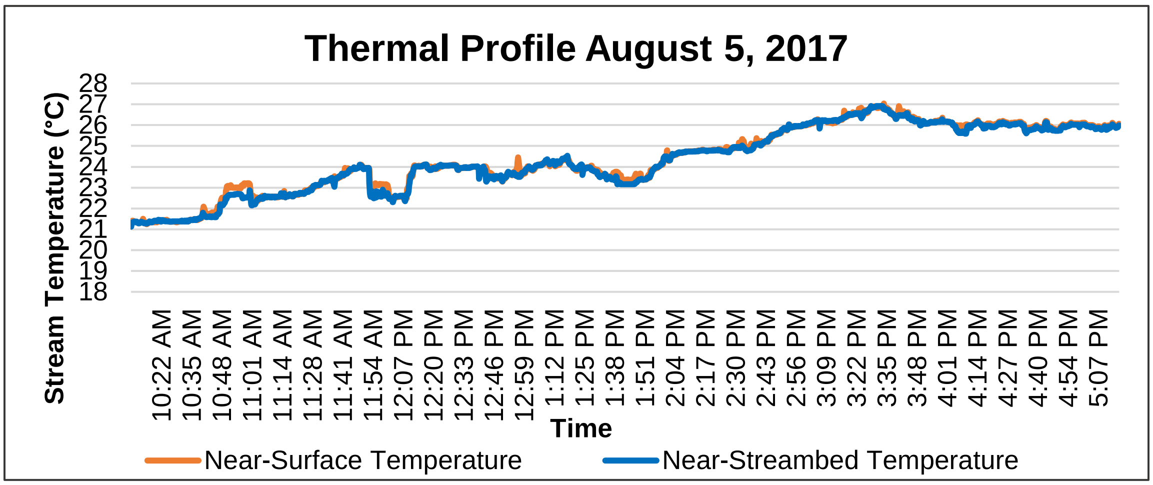

Figure 9b. Thermal profile data for segment two, August 5, 2017

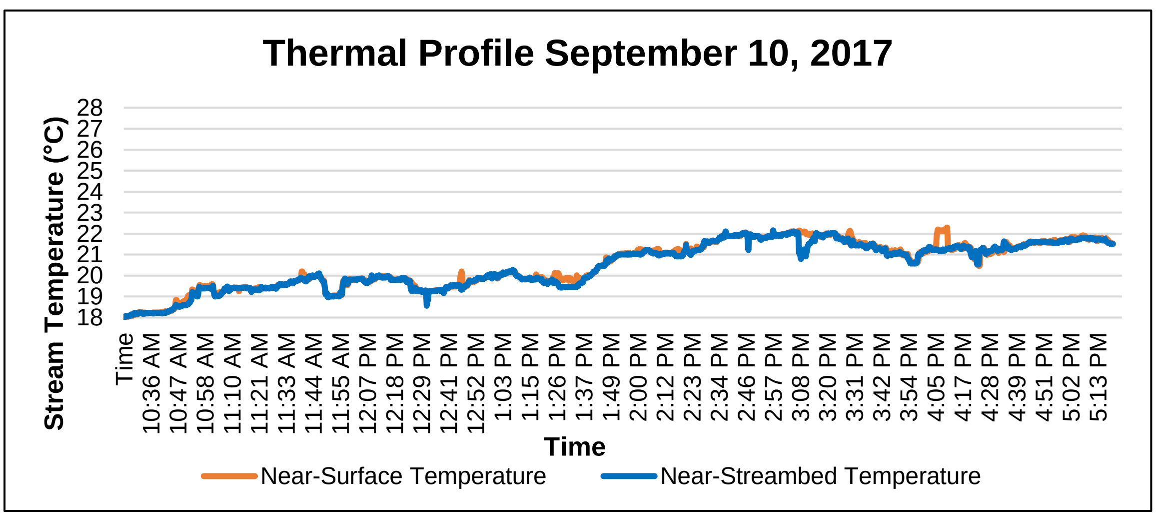

Figure 9c. Thermal profile data for segment two, September 10, 2017

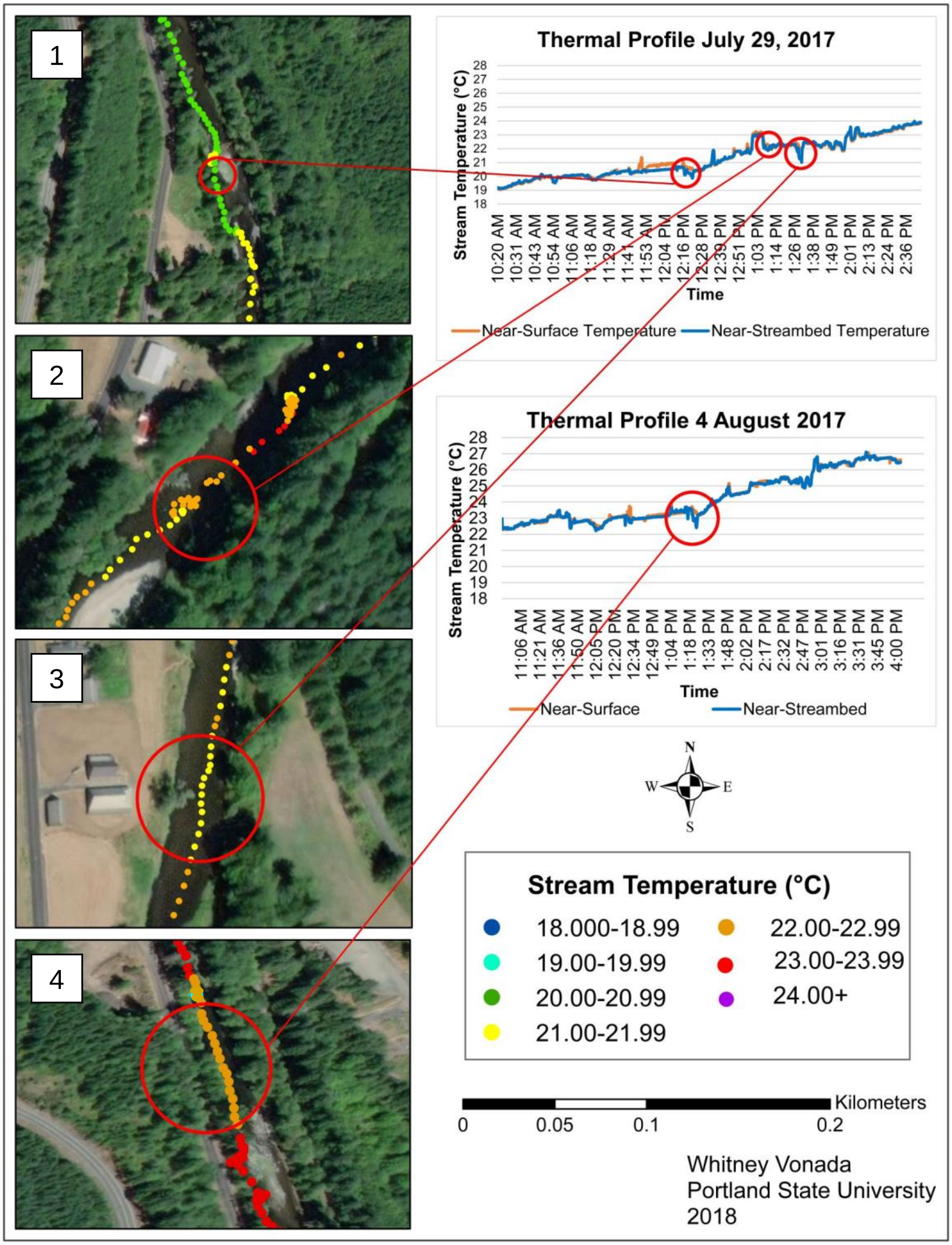

Figure 10. Areas where cold-water patches were found on thermal profiles for section one, located on July 29 and August 4, 2017.

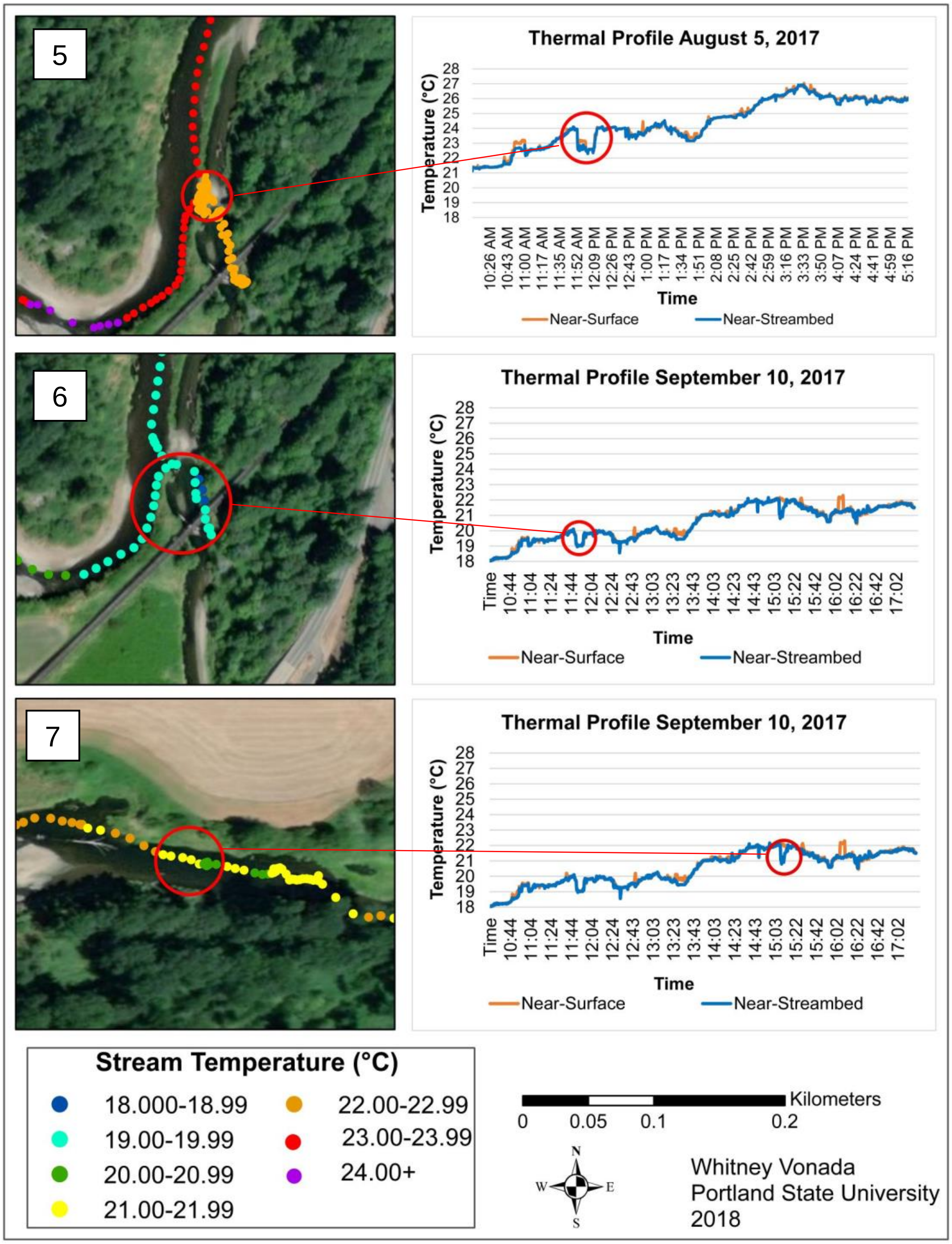

Figure 11. Areas of cold-water patches for thermal profiles pertaining to section two of the study area, located on August 5 and September 10, 2017. Cold-water patches 5 and 6 are located within the South Fork Chehalis River.

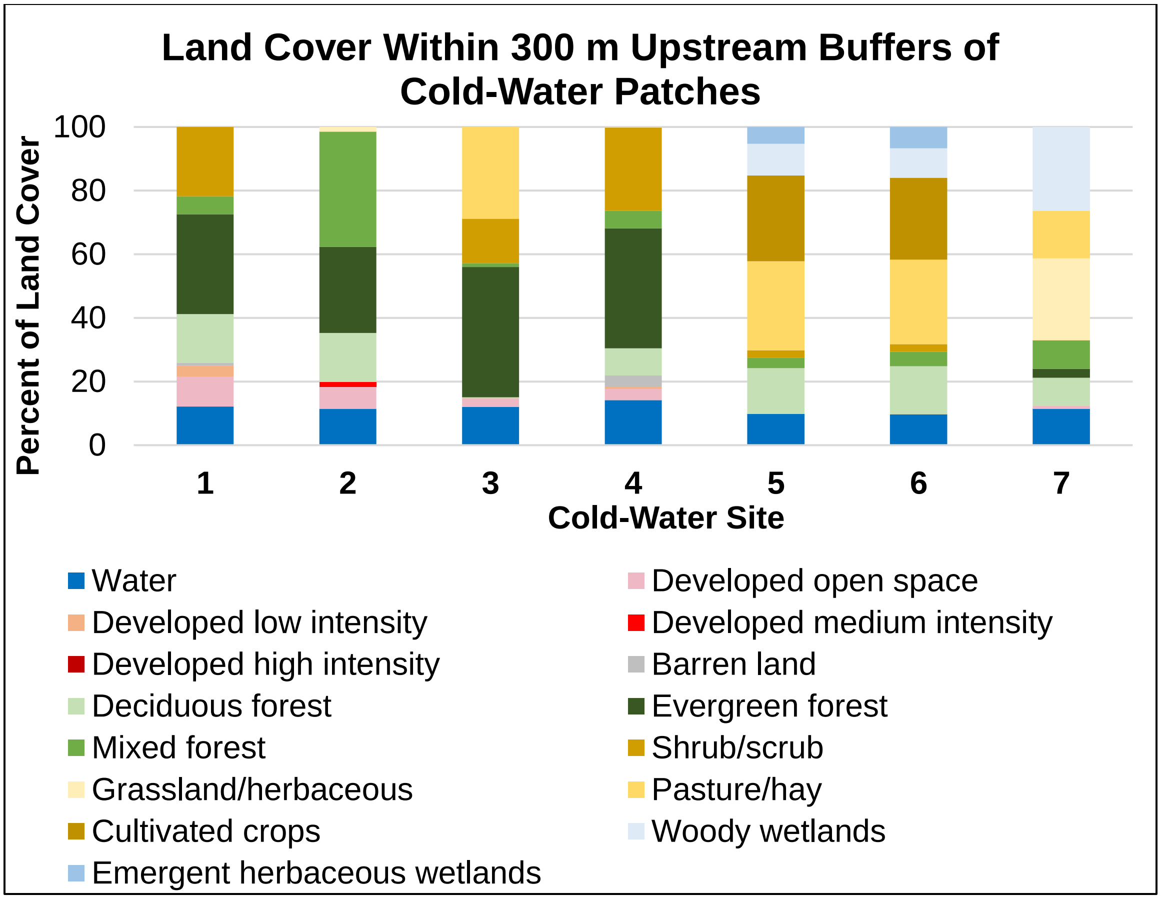

Figure 12. Land cover within 300 m upstream buffered areas for the seven cold-water patches identified.

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Appendix

Table 7. Spearman’s rank correlation coefficients for stream temperature metrics and width and flow metrics.

		MaxTw	MinTw	7DADMaxTw	7DADMinTw
MaxCMS	Correlation Coefficient	.141	.077	.180	-.195
MinCMS	Correlation Coefficient	.167	.092	-.165	-.201
7DADMaxCMS	Correlation Coefficient	.191	.120	-.180	-.242
7DADMinCMS	Correlation Coefficient	.254	.170	-.159	-.223
**. Correlation is significant at the 0.01 level (2-tailed).					
*. Correlation is significant at the 0.05 level (2-tailed).					

Table 8. Spearman’s rank correlation coefficients for stream temperature metrics and air temperature metrics.

	MinTw	MaxTw	7DADMinTw	7DADMaxTw
MinTa				
Correlation Coefficient	0.744**	0.461**	0.462*	0.437*
MaxTa				
Correlation Coefficient	0.364*	0.673**	0.394*	0.505**
7DADMinTa				
Correlation Coefficient	0.691**	0.505**	0.883**	0.789**
7DADMaxTa				
Correlation Coefficient	0.616**	0.793**	0.581**	0.737**
*. Correlation is significant at the 0.05 level (2-tailed).				
**. Correlation is significant at the 0.01 level (2-tailed).				

	21	22	23	24	41	42	43	52	71	81	82	90	95	Canopy %	Impervious surface %	Width (m)
21	1	.459*	0.296	0.250	-0.407	.610**	0.081	0.213	-0.019	0.059	-.616**	-0.188	-0.319	0.003	0.246	-0.206
22		1	.657**	0.245	-0.271	-0.004	-.466*	0.101	-0.218	0.250	-0.375	-0.027	-0.151	-0.369	.532*	-0.213
23			1	0.319	-0.181	0.157	-0.183	-0.143	-0.263	0.031	-0.214	-0.182	-0.103	-0.124	.508*	0.087
24				1	0.061	.448*	0.019	-0.183	-0.176	-0.326	-0.135	0.240	-0.064	0.192	0.328	0.239
41					1	0.135	0.018	-0.106	-0.193	-.425*	-0.002	-0.010	0.325	.431*	-0.145	.574**
42						1	.552*	-0.129	-0.221	-0.365	-0.423	-0.293	-0.261	.487*	0.065	0.279
43							1	0.062	0.043	-0.362	-0.084	-0.280	0.081	.576**	-0.160	0.212
52								1	-0.390	-0.292	-0.088	0.101	-0.052	0.296	-0.010	-0.212
71									1	0.221	-0.033	-0.022	-0.191	-0.346	0.053	0.081
81										1	-0.305	-0.264	-0.075	-.678**	0.259	-0.344
82											1	0.220	0.223	-0.057	-.530*	-0.128
90												1	-0.165	0.149	-0.033	-0.198
95													1	-0.004	-0.302	0.195
Canopy %														1	-0.040	0.205
Impervious surface %															1	0.276
Width (m)																1

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 9. Pearson correlation coefficients between land cover, percent of impervious surfaces, canopy cover percent, and width (m) for 300 m upstream buffered areas for all stream temperature monitoring sites (n=22). Land cover classes align with the 2011 NLCD legend (Homer et al. 2015) where 21=developed open space, 22= developed low intensity, 23= developed medium intensity, 24= developed high intensity, 41= deciduous forest, 42= evergreen forest, 43= mixed forest, 52= shrub/scrub, 71= grassland/herbaceous, 81= pasture/hay, 82= cultivated crops, 90= woody wetlands, 95= emergent herbaceous wetlands.

	21	22	23	24	41	42	43	52	71	81	82	90	95	Canopy %	Impervious surface %	Width (m)
21	1	.568*	0.226	0.234	-0.275	0.271	-0.019	0.101	-0.008	-0.124	-.516*	-0.016	-0.144	0.030	.481*	-0.023
22		1	0.388	0.085	-.489*	-0.119	-0.405	0.143	-0.318	0.220	-0.374	0.274	0.203	-.488*	.677**	-0.398
23			1	0.294	-0.361	0.108	-0.046	-0.022	-0.144	0.105	-0.230	-0.089	-0.228	-0.181	.587**	0.033
24				1	-0.089	.476*	0.240	-0.019	-0.203	-0.339	-0.181	0.166	-0.152	0.244	0.343	0.239
41					1	-0.078	0.330	-0.102	-0.052	-.687**	.463*	0.084	0.107	.535*	-.465*	0.380
42						1	.624**	0.090	0.065	-0.421	-0.387	-	-.456*	.544**	0.102	0.346
43							1	-0.098	-0.016	-.588**	-0.126	-0.213	-0.246	.721**	-0.240	0.116
52								1	-0.422	-0.114	-0.247	0.026	0.384	-0.064	-0.035	-0.111
71									1	0.351	-0.377	-0.188	-.560**	-0.004	0.026	0.375
81										1	-0.263	-0.008	0.017	-.755**	0.326	-0.310
82											1	0.015	0.116	0.069	-.534*	-0.202
90												1	0.386	-0.082	-0.030	-0.219
95													1	-0.265	0.016	-0.059
Canopy %														1	-0.347	0.248
Impervious surface %															1	0.127
Width (m)																1

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 10. Pearson correlation coefficients between land cover, percent of impervious surfaces, canopy cover percent, and width (m) for 1 km upstream buffered areas for all stream temperature monitoring sites (n=22). Land cover classes align with the 2011 NLCD legend (Homer et al. 2015) where 21=developed open space, 22= developed low intensity, 23= developed medium intensity, 24= developed high intensity, 41= deciduous forest, 42= evergreen forest, 43= mixed forest, 52= shrub/scrub, 71= grassland/herbaceous, 81= pasture/hay, 82= cultivated crops, 90= woody wetlands, 95= emergent herbaceous wetlands.