THESIS

PREDICTING STREAM TEMPERATURES FOR NATIVE FISH HABITAT MANAGEMENT IN WHITE RIVER NATIONAL FOREST, COLORADO

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ABSTRACT

PREDICTING STREAM TEMPERATURES FOR NATIVE FISH HABITAT MANAGEMENT IN WHITE RIVER NATIONAL FOREST, COLORADO

Stream temperature is a critical habitat parameter for many cold-water fish, particularly the salmonids family that includes trout. Colorado River cutthroat trout (*Oncorhynchus clarkii pleuriticus*), a native fish in the Colorado River Basin, currently exists in fragmented, isolated populations as a result of degraded thermal habitat, competition with nonnative trout and other reasons. Managers of the White River National Forest in northwestern Colorado want to reintroduce this native trout to additional streams within its historic range to help protect the subspecies from extinction. To identify additional streams within the Forest that have the appropriate thermal regime for Colorado River cutthroat trout, this research has created two multiple regression models to predict summer stream temperature metrics related to lethal and sublethal thermal tolerances for the subspecies. The 7-day mean of daily maximum stream temperature for the warmest 7 days can be equated with the critical thermal maximum, which is the extreme high temperature beyond which the fish cannot survive. The mean temperature of the warmest month can be equated with the upper limit of the optimum temperature range for the species, beyond which the fish experience sublethal temperature effects. The models can be used to identify streams cool enough throughout the year to support Colorado River cutthroat trout populations. The strongest predictor variables of these metrics were the drainage area, the discharge and the residual pool volume. Most previous studies found that air temperature was the strongest predictor variable in stream temperature models, but for the mountain headwater streams in this study, variables related to stream flow volume and stream morphology had better explanatory power. The models, created from and tested against field data, were able to explain 66% and 51% of the variability in monthly mean and 7-day mean stream temperatures, respectively, and had prediction errors of less than 2°C. Results from the models suggest that many of the streams in White River National Forest still have cool enough summer thermal regimes to support Colorado River cutthroat trout populations. Management of cold-water fish that reconnects fragmented populations by reintroducing species to thermally appropriate habitat is a step toward reducing the vulnerability of the species to extirpation by future climate changes or other disturbances.

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DEDICATION

I dedicate this thesis to my father, Dale Patterson, whose love of the natural environment and belief in education inspired me to pursue a graduate degree in science. I could not have come this far without you.

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1 INTRODUCTION

Stream temperature is a critical habitat parameter for aquatic freshwater taxa, particularly cold-water fish species such as the salmonidae family that includes trout (Brookfield et al., 2009; Herb and Stefan, 2011). Temperature is a driver of many physiological processes such as growth and reproduction for these ectothermic species (Young, 2008) and, as a result, their distribution is closely linked to their thermal habitat (Brown et al., 1971; Dunham et al., 2003; Rieman et al., 2007; Isaak et al., 2012; Butryn et al., 2013; Isaak and Rieman, 2013). Stream temperatures can have indirect effects on aquatic organisms as well as direct effects because warmer water temperatures are closely correlated with lower dissolved oxygen levels (Brown et al., 1971; Beschta, 1997; Caissie, 2006) and higher suspended sediment loads (Caissie, 2006). Habitat for Colorado River cutthroat trout *Oncorhynchus clarkii pleuriticus*, a focal species for the research presented in this thesis, is limited in part by suitable thermal regimes in the streams of Colorado, Wyoming and Utah (Underwood et al., 2012). Stream temperatures that are too cold, as well as temperatures that are too warm, can have detrimental effects on individual fish growth and population survival (Mohseni et al., 1998). Water that is too cold, however, presents less of a physiological stress than water that is too warm for Colorado River cutthroat trout except for fry under a year old (Young, 2008) because their growth is limited by cold temperatures. Temperature is, of course, not the only habitat parameter that limits cold-water fish distribution (Hickman and Raleigh, 1982), but it is of special interest for management purposes, particularly with climate change models predicting warmer stream temperatures for mountain streams (Isaak et al., 2012; Jones et al., 2013; Isaak and Rieman, 2013). Under modeled global warming scenarios, cold-water fish species are projected to lose up to 36% of their current suitable thermal habitat (Mohseni et al., 2003). Native cold-water species distribution may also be reduced as a result of thermally induced changes in competition success with non-native species (De Staso and Rahel, 1994; Bear et al., 2007).

Colorado River cutthroat trout (CRCT) populations currently occupy about 11% their historic range in the Colorado River basin (Hirsch et al., 2013). The reduction in territory is the result of warming temperatures, habitat degradation from human activities, and competition with introduced, nonnative species of trout such as brook (*Salvelinus fontinalis*), brown (*Salmo trutta*) and rainbow trout (*Oncorhynchus mykiss*) (Belk et al., 2009). Reduced stream flows from water diversions for municipal and agricultural use and reduced water quality from mining, logging, agriculture and other land uses have reduced the amount of suitable habitat available to CRCT. Contact with nonnative trout has resulted in competitive exclusion of CRCT in much of its historic range (Peterson et al., 2004) and, in a few cases, hybridization with rainbow trout or other cutthroat subspecies (Belk et al., 2009). Although warming temperatures have likely resulted in shifts upstream by CRCT, migration to higher elevation reaches is not solely (or even primarily) the result of temperature warming, but also competition with nonnative species and other factors that have excluded CRCT from habitat that would otherwise still be suitable (De Staso and Rahel, 1994; Bear et al., 2007; Butryn et al., 2013).

The existing populations of genetically unique Colorado River cutthroat trout are limited to headwater streams, typically high elevation, that are protected from nonnative trout populations by either man-made or natural barriers to longitudinal stream connectivity (Young, 2008; Hirsch et al., 2013). These isolated CRCT populations are at increased risk of extirpation because they exist in small fragmented “islands” that could be eradicated by disease, lack of genetic diversity or by disturbance such as fire or debris flows (Young, 2008; Roberts et al., 2013). Climate change projections predict that CRCT suitable habitat will be further reduced as a result of warming stream temperatures and that existing CRCT populations will be at greater risk of extirpation as more extreme climate conditions decrease the recurrence interval of disturbances that threaten these populations (Roberts et al., 2013). Similar subspecies of cutthroat trout such as the greenback cutthroat trout (*Oncorhynchus clarki stomias*) on the eastern side of the continental divide in Colorado are also at risk of extinction because of fragmented populations (Cooney et al., 2005). In an effort to help protect CRCT from possible extinction as a result of their current fragmented distribution, the Forest Service CRCT Recovery Team proposes to reintroduce CRCT to additional streams within their historic range in the White River National Forest (WRNF). Models of stream pool temperature are useful tools to identify streams that have an appropriate thermal regime so that the reintroduced populations have the best chance of success.

1.1 Literature Review

During the 1960s, efforts to model water temperature began with an energy budget model that used specific physical equations for evaporation, conduction, convection, advection and net radiation fluxes to calculate and predict stream temperatures on a daily time-scale (Brown, 1969). In this early model, net radiation refers to the difference in incoming and outgoing short-wave and long-wave radiation at the stream surface. Evaporation is an energy loss to the stream system as water at the stream surface phases from liquid to vapor. Convection also occurs at the surface and refers to the transfer of heat energy between water and air molecules. Conduction is the molecule-to-molecule exchange of heat energy that transfers heat through the water column. Advection is the heat transfer between the stream water and new water of a different starting temperature entering the stream (water from precipitation, groundwater or tributaries). Brown (1969) found that solar radiation (or short-wave radiation) was the greatest energy input to the stream system, and recognized that removing riparian shade greatly increased stream temperatures.

This early model evolved into studies that focused on riparian shading effects on stream temperatures because riparian shading was recognized as one factor that reduced solar radiation energy inputs to streams (Brown et al., 1971; Brown, 1972; Beschta et al., 1987; Beschta and Taylor, 1988; Beschta, 1997; Thompson, 2005; Leach et al., 2012). Riparian shading studies were particularly prevalent in the Pacific Northwest in the context of stream temperature response to riparian shade removal by clear-cut logging (Mellina et al., 2002; Moore et al., 2005a; Moore et al., 2005b). The consensus across these studies was that streams without shading, whether naturally un-shaded or because the riparian vegetation was removed, were significantly warmer (Brown et al., 1971; Brown, 1972; Beschta et al., 1987; Beschta and Taylor, 1988; Beschta, 1997; Mellina et al., 2002; Johnson, 2004; Thompson, 2005; Moore et al., 2005a; Moore et al., 2005b; Gaffield et al., 2005), and could absorb up to 90% of the incoming solar radiation (Beschta, 1997). This effect increased maximum daily stream temperatures as much as 5° C (Moore et al., 2005b; Leach et al., 2012) compared to similar, shaded reaches. Maximum daily temperatures, particularly in summer months, showed the greatest increase as a result of loss of shading. Johnson (2004) found that loss of shading did not increase the mean daily or minimum daily temperatures, only the maximum temperatures. Maintaining a riparian buffer in clear-cut areas proved effective at preventing increases of stream temperature from logging (Brown et al., 1971; Beschta et al., 1987; Beschta, 1997), although Moore et al. (2005a) found that riparian buffer areas were not effective at cooling stream reaches that experienced un-shaded warming in upstream reaches. Stream temperatures gradually cool as clear-cut riparian corridors recover, although this can take a decade or more (Moore et al., 2005a).

In the course of examining riparian shading effects, some studies determined that not all streams or stream reaches responded to changes in riparian shading to the same degree. Several studies found that smaller streams and tributaries were more susceptible to increases in summer peak temperatures from losses in shading because of the decreased thermal capacity of smaller volumes of water (Brown et al., 1971; Constantz, 1998; Poole and Berman, 2001). Other studies found that, although stream temperature was positively related with solar radiation or local air temperature, it was negatively related with discharge (Brown, 1972; Moore et al., 2005b; Brown and Hannah, 2008) and that increasing flows in flow regulated streams might be even more vital for keeping stream temperatures cool than increasing riparian shading (Bartholow, 1991).

Other studies found that some streams or stream reaches were buffered from changes in thermal regime by groundwater inputs and hyporheic exchange that ameliorated extreme temperatures in both summer and winter (Constantz, 1998; Poole and Berman, 2001; Mellina et al., 2002; Johnson et al., 2004; Gaffield et al., 2005; Moore et al., 2005b; Wondzell, 2006; Burkholder et al., 2008; Brookfield et al., 2009; Roy et al., 2011; Wondzell, 2011). In stream reaches with riparian vegetation removal, groundwater inflow minimized increases in stream temperature (Mellina et al., 2002), or cooled the temperature of stream reaches subjected to warming in un-shaded reaches upstream (Moore et al., 2005b). Across different catchments, from alpine to Midwest plains, streams with large groundwater contributions had reduced diurnal and annual variation in stream temperature (i.e., lower daily maximum temperatures, lower summer maximum temperatures and higher winter minimum temperatures) (Constantz, 1998; Gaffield et al., 2005; Roy et al., 2011).

In addition to groundwater influence, water entering and exiting the channel through the hyporheic zone beneath the channel bottom can have an influence on habitat-scale stream temperatures. Hyporheic exchange was important for reach-scale heterogeneity in stream temperature, with cool refugia located where hyporheic water entered the channel such as at tails of riffles (Poole and Berman, 2001; Burkholder et al., 2008, Wondzell, 2011). Hyporheic residence time was greatest in unconfined reaches, and channel morphology such as step-pool spacing and pool-riffle development influenced hyporheic exchange (Poole and Berman, 2001; Wondzell, 2006). Studies on hyporheic exchange in streams agree that hyporheic upwelling zones commonly provide cool refuge habitat for aquatic species (Poole and Berman, 2001; Ebersole et al., 2003; Burkholder et al., 2008). Overall, the literature agrees that solar radiation input, and by extension, riparian shading, are the most important factors controlling stream temperatures, but that groundwater input and hyporheic exchange, and discharge or flow volume are also significant factors controlling stream temperatures (Caissie, 2006; Webb et al., 2008; Herb and Stefan, 2008; Herb and Stefan, 2011). Groundwater input, hyporheic exchange and discharge are all difficult to measure at a site because they require extensive instrumentation and substantial time in the field. Consequently, the ability to use proxy variables that correlate with these processes but can be estimated remotely from a geographic information system (GIS) layer, such as drainage area for discharge, would greatly facilitate understanding and predicting stream temperatures.

As the importance of preserving stream temperatures for aquatic organism habitat became widely recognized, managers began looking for easier ways to model stream temperatures that were not as data-collection and computationally intensive to execute as the early model by Brown (1969). With a wider understanding of the factors influencing stream temperature, models were developed that used proxy variables for net radiation, groundwater advection and discharge that were easier to measure than the complex meteorological and groundwater flow variables required by Brown (1969). Regression and stochastic models that utilized local air temperature as a proxy for solar radiation input became common. These models rely on an empirically derived relationship between air and stream temperatures to make predictions at unmonitored locations (Mohseni et al., 1998; Caissie et al., 2001). Although most of these types of models use a linear relationship between air and stream temperatures, Mohseni et al. (1998) and Mohseni and Stefan (1999) have made a case for a logistic relationship instead, especially when predicting stream temperatures based on projected future air temperatures under climate warming scenarios (Mohseni et al., 2003). The early regression and stochastic models utilized only air temperature as the predictor variable, although some also used parameters that correlated with stream flow, riparian shading and groundwater contribution (Isaak et al., 2010; Jones et al., 2013), in agreement with earlier studies that identified the influence of these factors on stream temperatures. With advances in the technology for collecting and recording meteorological data, new attempts at developing energy balance or deterministic models for stream temperature have been undertaken (Caissie, 2006; Caissie et al., 2007), although these are not as user-friendly for management purposes. Cassie et al. (2007) created a deterministic stream temperature model for a small catchment following the energy budget equations used by Brown (1969), populated by data from local meteorological stations and field-collected stream temperatures.

The most recent work in stream temperature modeling has been in developing spatial models for better predictions in unmonitored locations over large management areas such as National Forests (Isaak et al., 2010) and in modeling stream temperatures under climate warming scenarios (Hill et al., 2013; Jones et al., 2013). Temporal and spatial heterogeneity in stream temperatures has long been recognized, but the spatial distribution of stream temperatures was ignored in early models that used simple regression relationships to predict single site, or reach-scale stream temperatures for daily or weekly time scales. The new spatial models rely on GIS layers of modeled air temperature or solar radiation (Isaak et al., 2010), and have ranged in scale from a single large basin (Isaak et al., 2010) to the entire conterminous United States (Hill et al., 2013). Current spatial stream temperature models predict summer stream temperature metrics that are closely correlated with distribution of cold-water fish species rather than weekly or daily stream temperatures. These models are being utilized in conjunction with climate projections to estimate future distributions for these cold-water fish (Isaak et al., 2010; Jones et al., 2013; Hill et al., 2013; Isaak and Rieman, 2013).

Spatial structure in stream temperature modeling can be determined using Euclidean distance (the shortest distance between two points) (Gardner et al., 2003), or stream distance (distance along the stream network) with or without ranking for tributary influence (Gardner et al., 2003; Isaak et al., 2010; Hill et al., 2013; Jones et al., 2013; MacDonald et al., 2014). Spatial models of stream temperature attempt to capture and explain spatial heterogeneity on multiple spatial scales, so they commonly include meteorological, hydrological and geomorphological predictor variables (MacDonald et al., 2014) and variables readily available from a GIS layer (Isaak et al., 2010). Accounting for the spatial autocorrelation in stream temperature distribution when building a model commonly results in lower prediction errors, and better correlation coefficients (r^2 values). Jones et al. (2013) and Isaak et al. (2010) found that a model that accounted for spatial autocorrelation in the stream temperatures outperformed a non-spatial version of the model using similar predictor variables. Many spatial stream temperature models are limited by the available data, although MacDonald et al. (2014) recently had limited success circumventing that issue by creating a model that combines process-based modeling approaches with a spatial structure for mountain stream temperatures.

Spatial statistical models can be created for a variety of scales. Hill et al. (2013) created a spatial stream temperature model for the contiguous United States, although most of the studies referenced here are for much smaller spatial extents such as a National Forest or single large watershed. Across spatial and non-spatial stream temperature prediction models, air temperature is commonly the most significant predictor variable.

There is a substantial body of work covering human-caused alterations to stream thermal regimes including, but not limited to, climate-change influences. Logging (Brown, 1972; Beschta and Taylor, 1988; Mellina et al., 2002; Moore et al., 2005a; Moore et al., 2005b), flow regulation (Bartholow, 1991; Dickson et al., 2012), dam releases (Zolezzi et al., 2011), urbanization (Somers et al., 2013) and other land uses (Poole and Berman, 2001; Poole et al., 2004), as well as climate change (Mohseni et al., 1999; Rieman et al., 2007; Isaak et al., 2012; Jones et al., 2013; Isaak and Rieman, 2013), have altered stream thermal regimes. My study statistically models the natural condition of stream temperatures in watersheds with little human disturbance, so studies dealing primarily with human alteration of stream temperatures have not been mentioned in-depth in this review of the literature. Additional summaries of advances in stream temperature research, including human impacts on stream thermal regimes, can be found in Caissie (2006) and Webb et al. (2008).

My study is unique relative to other studies that have modeled stream temperature in that I am modeling temperatures to identify streams for the possible reintroduction of CRCT for fisheries management over an entire National Forest, rather than to predict the current or future distribution of the species. I am modeling stream temperature for a smaller area than regional climate models, but a larger area than many models built to identify stream temperature controls on a single stream or stream reach. The management-scale model for WRNF is based on field data collected at the reach scale, and focuses on predicting temperatures for pool habitat because pools are common thermal refugia for cold-water fish species such as CRCT (Matthews et al., 1994; Matthews and Berg, 1997; Ebersole et al., 2001; Ebersole et al., 2003). This study directly measures riparian shading and air temperature, and also indirectly includes groundwater and hyporheic exchange as possible model parameters through the proxies of valley geometry and channel substrate characteristics.

1.2 Objectives

Objective 1: Collect sufficient data to empirically derive a mathematical relationship that can be used to predict summer stream temperature metrics in pool habitat within pool-riffle channels on the WRNF.

The first objective of this project is to create a useable, empirically based stream temperature model to predict stream pool temperature in the White River National Forest (WRNF) of Colorado. This model can then be applied by the Forest Service CRCT Recovery Team to identify or eliminate streams for reintroduction of CRCT. To create a useable model that serves its intended management purpose, the dominant control variables need to be identified and quantified (Figure 1), and their relationship to the desired output of stream temperature metrics that describe pool temperature in headwater streams of WRNF determined. A model with a prediction error less than 2° C will be considered useful, based on similar models in the literature

(Isaac et al., 2010). The metrics chosen for model output must be related to CRCT thermal habitats to be of use in identifying possible reintroduction locations. In addition to creating a working model, the dataset collected, which encompasses the variability of stream conditions in the least disturbed portion of WRNF, allows for an exploration of any patterns that emerge in stream temperature (e.g., temperature increases downstream).

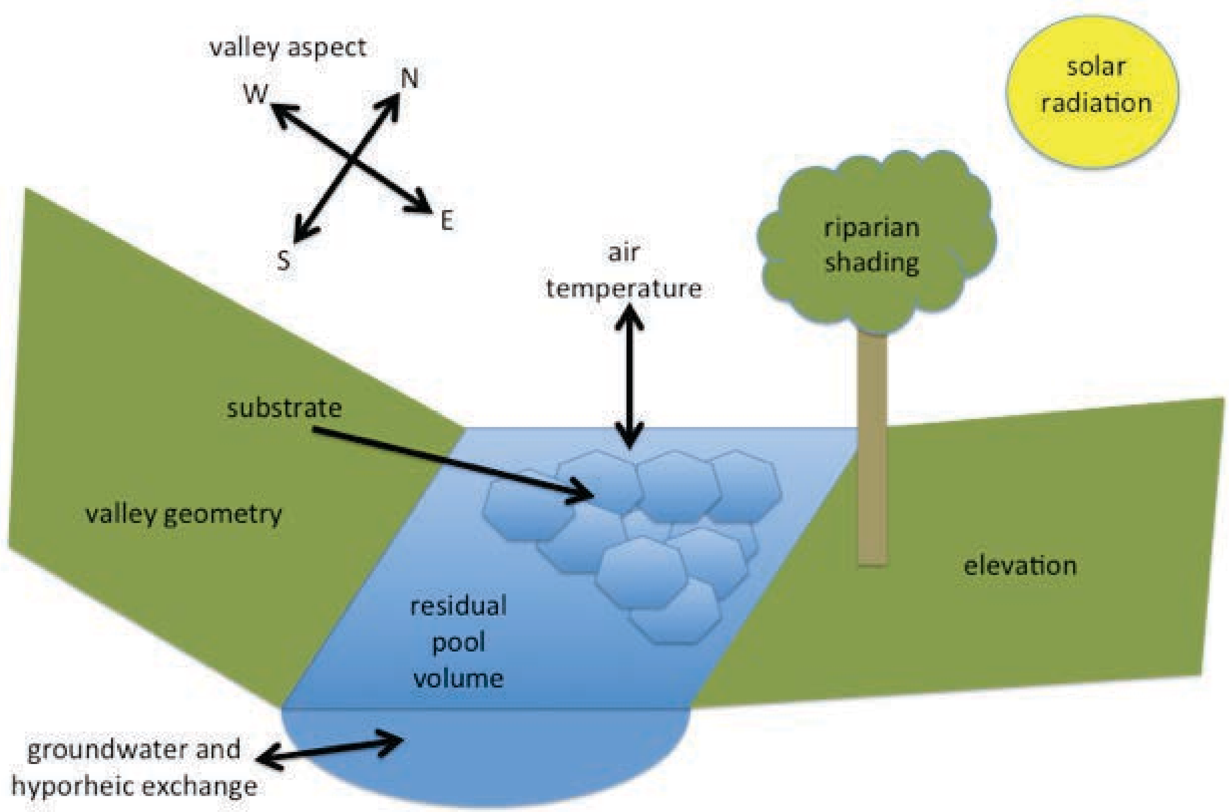

Figure 1. A conceptual cartoon of reach-scale factors influencing stream temperature in pools of pool-riffle channels. Three categories of factors are represented: above the stream (air temperature), within the stream (pool volume) and below the stream (hyporheic and groundwater exchange). The three main categories are influenced by quantifiable secondary factors. Valley aspect, elevation and riparian shading influence the air temperature. Substrate type and valley geometry influence the hyporheic and groundwater exchange. Channel geometry, drainage area and flow regime influence the water depth and residual pool volume. Solar radiation is the primary energy input to the system. Reach pool temperature is also influenced by the temperature of the water flowing into the reach from upstream.

Objective 2: Identify the dominant control variables for stream temperature.

Hypothesis 1, H_{A1}: The dominant control on stream temperature is local air temperature.

Hypothesis 2, H_{A2}: Site-specific characteristics aside from air temperature significantly influence stream temperature.

Hypothesis 1 reflects the results of previous stream temperature studies that indicate a strong correlation between mean air temperature and stream temperature (Mohseni et al., 1998; Caissie et al., 2001; Caissie, 2006; Hill et al., 2013; Jones et al., 2013; Somers et al., 2013). Hypothesis 2 reflects other studies that indicate additional factors such as groundwater input (Constantz, 1998; Mellina et al., 2002; Moore et al., 2005b; Gaffield et al., 2005; Roy et al., 2011), hyporheic exchange (Wondzell, 2006; Burkholder et al., 2008; Wondzell, 2011), or riparian shading (Brown et al., 1971; Brown, 1972; Beschta et al., 1987; Beschta and Taylor, 1988; Beschta, 1997; Mellina et al., 2002; Johnson, 2004; Moore et al., 2005a; Gaffield et al., 2005) can also have a strong control on local stream temperature. The two hypotheses are not mutually exclusive, but are intended to reflect that, although I expect local air temperature metrics to correlate most strongly with measured stream temperature at all study sites, other factors may also be significant controls on stream temperature, and may not be equally important at all sites. Site-specific characteristics that I expect to correlate strongly with stream temperature include: riparian shading and valley aspect, which influence the exposure of the stream to direct solar radiation; streambed grain size distribution and the ratio of valley width to channel width or confinement, which influence hyporheic exchange and groundwater input; and bankfull width to depth ratio, residual pool volume and drainage area, which influence temperature through thermal inertia of greater discharge and pool volume (Brown, 1969; Brown et al., 1971; Brown, 1972; Constantz, 1998).

Objective 3: Explore spatial patterns in stream temperature.

Hypothesis 3, H_{A3}: Mean pool temperature will increase downstream in the watersheds.

Hypothesis 3 is a reflection of the expected relationship between elevation and air temperature, which strongly controls stream temperature, and the idea that the farther downstream the water travels, the more it is exposed to solar radiation energy inputs, both for longer duration and because the stream cross-section will generally become wider (Beschta et al., 1987). For air temperature, increased elevation correlates strongly with decreasing air temperature (Brown et al., 2005). I expect this trend to hold for stream temperatures as well, with warmer stream temperatures corresponding with lower elevations and downstream locations in each watershed.

Objective 4: Examine the relationship between watershed "clusters" and the stream temperature control variables.

Hypothesis 4, H_{A4}: The relative strength of different control variables will change across watershed clusters.

Hypothesis 4 is a reflection of the variability that exists between watersheds in WRNF. In an assessment of aquatic and riparian resources of the Forest, watersheds were grouped into six clusters with similar characteristics in terms of lithology, stream gradient, geochemistry and elevation (Winters et al., 2011). I expect that the relative importance of the driving variables will differ between these clusters as a result of their differences in these characteristics. Motivating this hypothesis is the desire to know if certain watershed clusters are more sensitive to possible drivers of stream temperature than others. Although all of the watershed clusters are dominated by steep, snowmelt-dominated streams, the percent of each watershed having calcareous lithology or low stream gradient varies between the clusters. Streams within a cluster dominated by calcareous lithology, or with greater portion of low gradient stream length, for example, might have greater groundwater inputs. More detailed explanation of the cluster analysis and watershed assessment is included in the Methods chapter.

2 STUDY AREA AND METHODS

2.1 Study Area

White River National Forest (WRNF) is located in northwest and central Colorado, west of the Continental Divide (Figure 2). The Forest is divided into two sections that add up to a total of 9,251 km^2 (Toth et al., 1993). The southern section is elongate in the east-west direction, stretching from Dillon to Rifle. The second section lies to the northwest near the White River from which the Forest draws its name. The northern and western areas of the Forest are characterized by mesas and hills dissected by stream valleys. The southern and eastern portions of the Forest are more mountainous and include parts of the Sawatch, Elk and Gore mountain ranges (Tweto et al., 1978). These glaciated mountain ranges include several peaks greater than 4267 m (14,000 feet) and are home to most of Colorado’s major ski resorts (David et al., 2009).

The watersheds within the WRNF ultimately drain into the Colorado River. Major Colorado River tributaries within the Forest include the Crystal River, Blue River, Eagle River, Fryingpan River, Roaring Fork River and the White River. The Forest includes several designated wilderness areas, including Eagles Nest, Flat Tops, Holy Cross, Hunter-Fryingpan, Maroon Bells-Snowmass, Ptarmigan Peak and Collegiate Peaks (USDA Forest Service Land and Management Plan, 2002). These wilderness areas represent the least anthropogenically influenced portions of the WRNF, because many activities such as motorized recreation allowed elsewhere in the Forest are prohibited in wilderness areas.

The geology across the White River National Forest is diverse and complex, as the WRNF covers an extensive area of disparate terrain. The eastern portion of the Forest has many

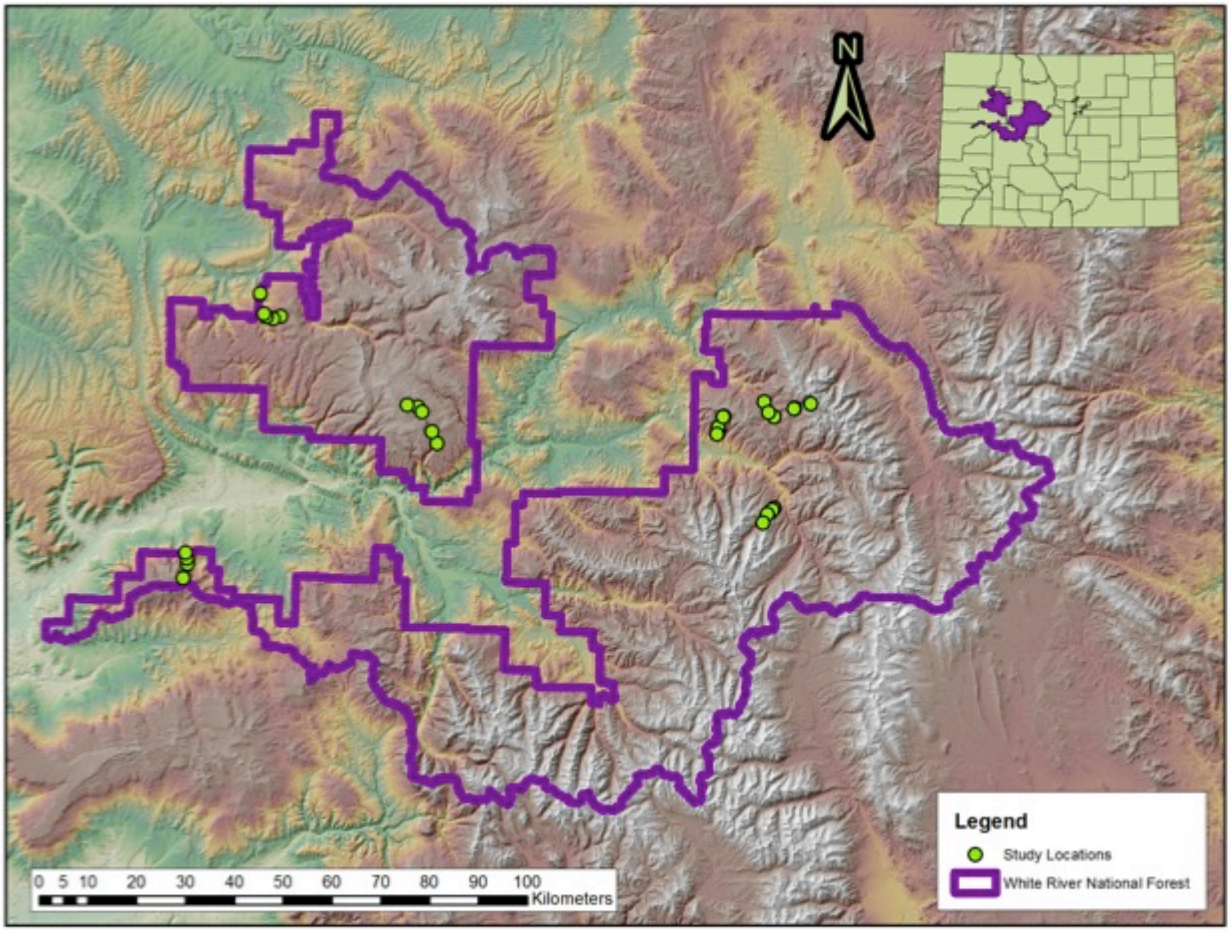

Figure 2: White River National Forest, Colorado.

crystalline Precambrian granites and gneiss that weather to coarse-grained sediment (sand and coarser). These rocks are primarily found in higher relief, mountainous areas. The western part of the Forest is primarily characterized by shale, siltstones and mudstones that weather to fine-grained sediment, including silt and clay. The Flat Tops mesa in the northwest portion of the Forest has large deposits of limestone and dolomite (Tweto et al., 1978).

Precipitation and temperature patterns across the Forest are controlled by the mountainous topography and vary with elevation (Doesken et al., 2003). The majority of the precipitation falls as snow in the higher elevations in winter months, although summer thunderstorms are also common (Doesken et al., 2003). Average annual precipitation (rain and snow) in the valleys is approximately 25 to 51 cm. On peaks and higher elevations, precipitation can be up to 130 cm of snow (USDA Forest Service Final Environmental Impact Statement, 2002). Eastern slopes tend to be drier than western-facing slopes in the eastern and southern part of the Forest. Prevailing winds from the west and the north-south orientation of most of Colorado's mountain ranges result in the majority of precipitation occurring on western-facing slopes (Doesken et al., 2003). Temperature also follows an elevation gradient in the region, with cooler temperatures generally occurring at higher elevations. Average annual temperature for the Forest ranges from 2° to 10° C, depending on elevation and topography (USDA Forest Service Final Environmental Impact Statement, 2002). In general, the western half of the WRNF is drier and warmer than the eastern half, and these differences in climate are reflected in the predominant vegetation.

Hydroclimate regime for the rivers and streams in the WRNF is primarily snowmelt, with the annual hydrograph peak occurring in May-June (USGS NWIS, 2014). U.S. Geological Survey stream gage 09085100, with records from 1967 to present on the Colorado River below Glenwood Springs, CO, reports a mean annual discharge of 94 m^3/s and a mean annual peak discharge of 429 m^3/s. The peak and mean discharge on the Colorado River have decreased since 1950 as a result of flow regulation and diversions (Pitlick et al. 1999). The study sites chosen are on portions of headwater streams in the Forest that are free from flow diversion, although flow diversions may exist downstream of the study locations.

The WRNF has a wide variety of different forest stands, with the vegetation composition varying with topography and elevation. In the Forest overall, the predominant species are quaking aspen (*Populus tremuloides*), Engelmann spruce (*Picea engelmannii*), subalpine fir

(*Abies lasiocarpa*), lodgepole pine (*Pinus contorta*), Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*). The subalpine zone, in which this study predominantly takes place, is primarily Engelmann spruce-subalpine fir forest with stands of lodgepole pine and quaking aspen interspersed (USDA Forest Service Final Environmental Impact Statement, 2002). Willow species (*Salix monticala*, *S. drummondiana*), alders (*Alnus incana*) and currants (*Ribes coloradense*, *R. wolfii*) are commonly found along stream banks and valley bottoms in wetland areas (David et al., 2009). The montane zone at lower elevations is dominated by Douglas-fir, with some ponderosa pine. In the drier, warmer, western half of the Forest, oakbrush (*Quercus gambelii*) and a variety of mountain shrubs are commonly found on the drier eastern and southern facing slopes, with forest stands of spruce, fir, pine and aspen found on wetter north and western facing slopes.

The WRNF is subject to both natural and anthropogenic disturbances. Grazing, water development, logging, mining and recreation are the primary human-caused disturbances in the Forest, but as site selection in this study has attempted to avoid locations with anthropogenic influence, the disturbances of concern are the natural disturbances. The Forest is subject to natural disturbance by fire, insect outbreak and disease. WRNF has been influenced by the recent mountain pine beetle (*Dendroctonus ponderosae*) population increases, with the majority of lodgepole pine stands experiencing outbreaks of some severity (USDA Forest Service Final Environmental Impact Statement, 2002). The Forest has not experienced any significant fires in the last decade.

An assessment of WRNF aquatic and riparian resources divided “management-scale” watersheds within the Forest into six clusters of watersheds with similar attributes (Winters et al., 2011). “Management-scale” watersheds were defined in the assessment as the 6th level hydrologic unit boundary (HUB) subwatersheds. The U.S. Geological Survey National Hydrography Dataset uses HUBs to delineate watersheds and subwatersheds. The 6th level HUBs within or intersecting the Forest boundary were divided into clusters based on statistical similarities among four ecological drivers: geochemistry, sediment production (lithology), hydroclimatic regime (elevation) and reach-scale stream gradient (Winters et al., 2011). Geochemistry refers to whether the geology of the watershed is predominantly calcareous (containing calcium carbonate $CaCO_3$) or non-calcareous rocks. Sediment production refers to whether the predominant lithology of the watershed is likely to weather to fine (silt and clay), medium (sand) or coarse-grained (gravels, cobbles and coarser) sediment. Hydroclimatic regime references the predominant form of precipitation, either snow or rain and snow. The hydroclimatic regime is closely related to the flow regime for the watershed – whether the hydrograph peak is snowmelt dominated or controlled by a combination of rain and snowmelt. Stream gradient for each watershed is broken into three categories that reflect divisions between cascade/step-pool channels (high, > 4%), transitional/plane-bed channels (medium, 2-4%) and pool-riffle channels (low, < 2%), with the designation for the watershed assessment falling into the category with the greatest percentage of stream length (Winters et al., 2011). A watershed classified as "high gradient" can still have low gradient reaches, but these do not make up the majority of stream length in the watershed. The rationale underlying the designation of ecological drivers and a description of the cluster analysis method is available in more detail in Wohl et al. (2007).

One watershed from each cluster was chosen to adequately represent the variety of watersheds that exist within WRNF (Table 1, Figure 3). Least impacted watersheds were chosen for the study in order to create a baseline temperature model under (mostly) undisturbed

Table 1: Study watersheds with their cluster characteristics and elevation ranges. Ecological driver information from Winters et al. (2011).

Management Scale Aquatic and Riparian Cluster	6th HUB Watersheds	Ecological driver based on greatest mean percentage				Elevation range of the study sites (m)
		Stream Gradient	Geochemistry	Sediment Production[1]	Hydroclimate Regime	
1	Upper Piney River 140100010801	high	non-calcareous	fine	snowfall	2550 - 3073
2	Berry Creek 140100030304	high	non-calcareous	fine	snowfall	2460 - 2899
3	Cross Creek 140100030208	high	non-calcareous	coarse	snowfall	2644 - 2845
4	Grizzly Creek 140100011602	high	calcareous	medium	snowfall	2668 - 3183
5	North Elk Creek 140500050302	high	calcareous	fine	snowfall	2151 - 2497
6	Beaver Creek 140100050701	high	calcareous	fine	rain and snow	2375 - 2941

[1] Sediment production in this context differentiates bedrock lithologies that produce predominantly cobble and coarser sediment (coarse), lithologies that produce sand-sized sediment (medium), and lithologies that produce at least some silt and clay (fine).

conditions that can then be used for comparisons with more impacted watersheds within the Forest. Several of the watersheds chosen for the study lie in wilderness areas, as these areas are the least anthropogenically influenced locations in the Forest. With the exception of North Elk Creek, which is subject to mild grazing activity, the watersheds are free from heavy anthropogenic influence and experience only low impacts from recreation such as hiking and camping. Along the primary headwater stream in each watershed, five pool-riffle reaches were chosen for monitoring stream pool temperature and local air temperature. If pool-riffle reaches were not present, the most morphologically similar reach available was chosen: typically plane-bed or lower gradient step-pool. Pool temperature was chosen because pools provide thermal

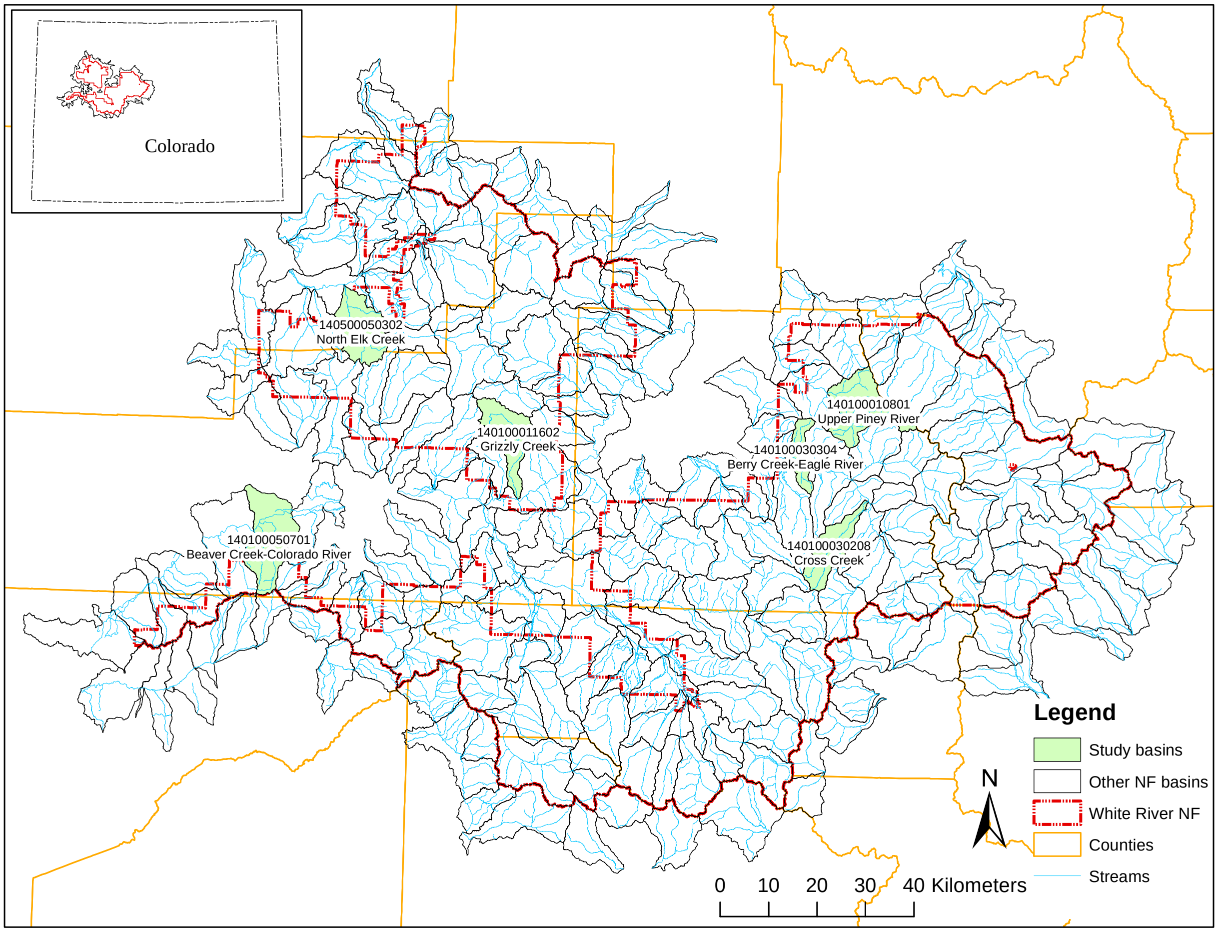

Figure 3: The six study watersheds within White River National Forest: Beaver Creek, Berry Creek, Cross Creek, Grizzly Creek, North Elk Creek and Upper Piney River.

refugia (Matthews et al., 1994; Bonneau and Scarnecchia, 1996; Matthews and Berg, 1997; Ebersole et al., 2001; Ebersole et al., 2003) and important habitat for cold-water fish species (Cooney et al., 2005; Isaak and Rieman, 2013). An attempt was made to characterize the entire watershed by dispersing the study locations along the entire length of each stream, although this was limited by the accessibility of remote parts of the watersheds, the need to avoid flow diversions, and the scarcity of low gradient reaches with pool-riffle morphology (Montgomery and Buffington, 1997). All the reaches fall between the uppermost reaches with suitable gradient for fish habitat and the lower reaches where stream diversions occur. As evidenced by the classification of all six clusters as high gradient, the majority of the channel length in all the chosen watersheds was cascade or step-pool morphology. Low gradient reaches with pool-riffle morphology were scarce.

2.2 Field Methods

Field data and measurements were collected between June 2012 and September 2013 over two summers of fieldwork. Summer 2012 was spent hiking along the main channel of the chosen watersheds, scouting locations with lower gradient reaches that fit pool-riffle morphology. In watersheds where true pool-riffle morphology was scarce, plane-bed or low gradient step-pool reaches were substituted. Once a suitable reach was found and a pool chosen, HOBO U22 Water Temp Pro and HOBO Pendant Temp/Light dataloggers were deployed to record hourly stream pool and local air temperatures, respectively (Dunham et al., 2005). The stream temperature dataloggers were housed in PVC casings to protect them from damage by mobile bed material or instream wood. The casings had holes drilled at the top and bottom and along the sides to allow water to flow through easily. The dataloggers were then tied to large cobbles with wire and sunk into the deepest, sheltered part of the chosen pools. An additional wire tether connected the datalogger casings to a tree on the bank to prevent the datalogger from being swept away should it become bed (or suspended) load in high flows. The air temperature dataloggers were housed in plastic prescription-pill bottles and attached to the north side of trees, shaded by branches, adjacent to the pools being monitored. The prescription bottle housings also had holes drilled in them to allow air to flow around the dataloggers. In addition to the five primary sites on each watershed, a few extra stream pools were also instrumented in case any dataloggers were lost as a result of high flows or human tampering.

Stream pool and local air temperature dataloggers were collected and additional field measurements were made in Summer 2013. Additional field measurements included surveys of bankfull channel cross-section, stream reach gradient, and longitudinal pool-thalweg, and characterization of bed sediment, degree of riparian shading, riparian vegetation type, and valley aspect. Cross-section, pool-thalweg and gradient surveys were conducted using a measuring tape, auto-level and stadia rod. The cross-section for each stream pool was located perpendicular to flow, through the location where the datalogger was sunk (usually the deepest part of the pool). A tape was stretched along the cross-section for horizontal distance and elevation was measured at 1 m intervals or wherever breaks in bank or channel bottom slope necessitated additional measurements. Bankfull elevation was identified using indicators in the field such as breaks in slope, changes in vegetation, tops of bars or depositional features or staining on rocks along channel margins (Wohl and Merritt, 2005). Bankfull width was calculated by finding the difference in horizontal distance between the two points identified as bankfull elevation. The pool-thalweg survey was conducted by stretching a tape along the thalweg from the riffle crest upstream of the pool to the riffle crest downstream of the pool. The elevation of the pool bottom was measured at 1 m intervals and at any breaks in slope. Bankfull width to maximum depth and bankfull width to mean depth ratios were calculated from the two surveys. The mean depth was calculated by finding the bankfull cross-section area and dividing that by bankfull width. The max depth was the deepest point measured in either the cross-section survey or the pool-thalweg survey (frequently the same depth for both surveys). Residual pool volume, or the volume of water left in the pool if the water depth is decreased to the height of the downstream riffle crest, was calculated using both the cross-section and pool-thalweg survey to estimate the mean depth, length and width of each pool (Lisle, 1987; Kaufmann et al., 1999). The gradient of the reach was determined from the riffle crest upstream of the pool to the riffle crest downstream of the pool.

Bed substrate was characterized using the Wolman (1954) pebble count in a riffle adjacent to the pool. A Wolman pebble count involves walking a transect perpendicular to flow across the channel and measuring a clast at the toe of your boot for each step. Clasts were measured along the median axis using either a centimeter ruler or a gravelometer. The centimeter ruler was only used for clasts whose size exceeded the largest opening (7 phi or 128 mm) of the gravelometer. Fifty clasts were measured for each site. Fifty clasts were considered sufficient to characterize the bed sediment for the purpose of determining whether hyporheic exchange could potentially be substantial at each site. Half phi classes were converted to millimeters and D_{50} and D_{84} (the size to which 50% or 84% of the clasts are equal or smaller, respectively) values were calculated from the grain size distribution.

Riparian shading was measured as percent overstory using a convex spherical crown densitometer (Fiala et al., 2006). The spherical crown densitometer has a grid of 24 quarter-inch squares. To measure the percent overstory density, each of these squares is mentally subdivided in four and a count is made of the number of quarter-squares reflecting canopy openings (up to 96 for a clear sky). This value is multiplied by 1.04 to give the percent of the overhead area that is not canopy. The difference between that value and 100% gives the percent of the overhead area that is canopy. Four measurements were made of the percent overstory above the pool, facing the four cardinal directions. These measurements were then averaged to obtain the final value.

Riparian vegetation type was characterized into one of six categories based on visual assessment of the dominant vegetation: coniferous, willow, grass/sedge, willow/coniferous, coniferous/grass or grass/willow. Mixed categories reflect the fact that some reaches had distinctive vegetation on opposite sides of the channel (e.g., coniferous on the right bank, willows on the left bank). Valley aspect was measured in the down-valley direction using a compass. Elevation and study location coordinates were measured with a GPS unit.

Drainage area and two-year peak discharge for each study location were estimated using USGS Stream Stats (http://water.usgs.gov/osw/streamstats/colorado.html). Stream Stats allows the user to delineate a watershed using the coordinates of each study site. The delineated watershed was used to estimate the drainage area. Two-year peak flow was estimated by Stream Stats using regression equations developed by Capesius and Stephens (2009). Two-year peak flow was chosen as a common representative of the channel forming or bankfull flow. Valley width was measured using a 10 m digital elevation model (DEM) in ArcMap. A 1 m contour map was developed from the DEM, and valley width measured perpendicular to the channel at 2 m above stream height (two contour lines above the stream on each side). With bankfull width, valley width was used to calculate the valley width to channel width ratio.

From the hourly stream pool temperature data, metrics that represent aspects of stream thermal regime important to cold-water fish thermal habitat were calculated. The stream thermal regime influences the reproduction, growth, fitness and survival of aquatic species (Todd et al., 2008), and these habitat qualities can be related to specific metrics of stream temperature (Roberts et al., 2013). These metrics will be the output from the statistical models created for management purposes. Criteria for protecting cold-water fish habitat include definitions for acute and chronic thermal tolerances. Acute thermal limits are temperatures so extreme that even short exposure (7 days or less) is lethal, and are considered the upper thermal tolerance for a species (Todd et al., 2008). These thresholds include critical thermal maximum (CTM), found in the lab by gradually increasing the temperature until the fish loses equilibrium or dies, and the upper incipient lethal temperature (UILT), found by transferring fish from a tank with one temperature (acclimation temperature) to a tank with fixed, higher temperature (Todd et al., 2008). The UILT is the higher temperature at which 50% of the fish population expires (Todd et al., 2008). The 7-day mean of daily maximum temperatures for the warmest 7-day period (7-day mean) is the metric that best represents these acute thermal criteria (Roberts et al., 2013). Underwood et al. (2012) found that the CTM for CRCT acclimated to 15°C was 26.9°C. Johnstone and Rahel (2003) and Wagner et al. (2001) found slightly lower CTM (at lower acclimatization temperature) for Bonneville cutthroat trout (*Oncorhynchus clarkii utah*), a cutthroat subspecies closely related to CRCT (Loxterman and Keeley, 2012). Schrank et al. (2003) found that under diurnal fluctuations in field conditions, cutthroat trout species could survive temperatures up to 28°C. Using these same studies, Roberts et al. (2013) arrived at 26°C as the CTM threshold for CRCT for their study. The predicted 7-day mean can be used to eliminate streams within WRNF that exceed this thermal criterion from being considered as potential locations for CRCT reintroduction.

Chronic thermal limits refer to sub-lethal exposure to warm temperatures that result in reduced fitness, growth or reproduction of cold-water fish species (Todd et al., 2008). A temperature metric well suited to represent chronic thermal tolerances is mean monthly temperature of the warmest month, typically July or August (Roberts et al., 2013). Bear et al. (2007) found that westslope cutthroat trout (*Oncorhynchus clarkii lewisi*), another cutthroat trout subspecies, had optimal growth between 9.5°C and 18°C, so 18°C would be a reasonable threshold for chronic thermal criterion, above which the CRCT would be exposed to sublethal thermal effects. The predicted mean monthly temperature of the warmest month will be used to provide additional information for a stream's habitat suitability aside from whether the stream has warm temperatures extreme enough to extirpate a potential CRCT population. At almost all the study sites, the warmest 7-days fell within the warmest month for the two field seasons.

I calculated mean monthly temperature for the warmest month and the 7-day average of the daily maximum temperature for the warmest 7 days from two summers of field-collected local air temperature data for possible use as driving variables in the model. Additional air metrics from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) (Oregon State University, http://prism.oregonstate.edu, accessed 4/10/2014) were also used as potential predictor variables in the model, to better represent the air temperature information currently available to the Forest Service, and to determine whether the air temperature data available from PRISM could predict stream temperature with enough accuracy to be of use in a model for management applications. PRISM calculates 30-year normal temperature metrics for 30-arcsec grids using a climate-elevation regression for each grid cell, with weighting assigned to the nearest meteorological station based on physiographic similarity (Daly et al., 2008). I used the July maximum, July mean, annual maximum and annual mean 30-year normal temperature metrics for the period 1981 to 2010 as possible explanatory variables in the models, because these metrics most closely resembled the metrics of interest for this study from the available PRISM data.

2.3 Statistical Methods and Data Analysis

Once all the field data were collected, I organized the data and calculated metrics from the field measurements in Microsoft Excel. I organized these metrics into potential predictor variables for the models, and ran common statistical tests to verify that the distribution of each variable satisfied the necessary assumptions for multiple regression models. All statistical analysis for this project was run in R version 2.15.1 and ArcGIS versions 10 and 10.1. The assumptions that must be met for multiple linear regression models are normality of distribution of the independent and dependent variables, a linear or quadratic relationship between the independent (predictor) and dependent variables, and (after running the model) homoscedasticity of errors (i.e., the variance in the errors is equally distributed across the predicted values).

I used histograms and quantile-quantile (QQ) plots, along with the Shapiro-Wilk test of normality, to evaluate whether my potential model variables fit normality. For normally distributed data, the histogram plot should display a symmetrical bell-shaped curve with equal-size "tails." The QQ-plot, which displays the actual quantiles plotted against the theoretical quantiles if the data were normally distributed, should fall in a straight line with neither "tail" of the data falling off the line. For the Shapiro-Wilk test of normality, p-values greater than $\alpha = 0.05$ significance level used in this study indicate the alternative hypothesis of non-normality should be rejected and the data accepted as normal. For those variables that were non-normal, I used a natural log transformation and then re-examined the plots and tests. A natural log transformation solved the normality issue for nearly all my variables. For the three variables that were still non-normal, I applied a square root transformation.

I created scatter plots and examined a plot of the residual versus predicted values from simple linear regressions run between my dependent variable – the stream temperature metrics –

and each potential predictor variable, to verify that a linear relationship existed between the independent and dependent variables being considered for the multiple regression models. With the wide variability in study site location characteristics, some variables had stronger linear relationships than others. The residual plots show linearity when they are equally distributed along the line of zero residual (they do not show a curved shape). The residual plots from these simple linear regression models and the scatter plots are not perfectly linear, but are close enough for model construction (Ott and Longnecker, 2010).

Residual versus predicted value plots of simple linear regressions run between the dependent stream temperature metrics and each possible variable were also examined to verify homoscedasticity of variance for the model residuals. Homoscedasticity is met when the residuals have an even distribution of variance across the range of predicted values. The residuals plots should not show a megaphone shape, or bow-tie shape. Although some of the original variables had heteroscedasticity in the variance pre-transformation, the transformation commonly aided in stabilizing the variance as well as making the data distribution more normal. A few variables that could not be transformed to adequately meet the assumptions of multiple linear regression were discarded from consideration as parameters in the models. Plots and test results for determining whether the variables met the model assumptions are available in Appendix A. The complete list of variables, including transformations applied where necessary, is in Table 2.

To develop the models, I started with some exploratory data analysis to narrow the potential variables for the multiple regression models. To examine the variance and correlation that existed between potential model variables, I performed a principal component analysis

Table 2: Complete list of directly measured variables considered for inclusion in the stream temperature models, including transformations, acronyms and units. This table does not include temperature predictor metrics derived from regional models.

Variable Acronym	Variable
logD50	Natural log of the D_{50} sediment size in mm
logD84	Natural log of the D_{84} sediment size in mm
logSlope	Natural log of the reach slope
W_Dmax	Ratio of bankfull width to maximum channel depth
logW_Dmean	Natural log of the ratio of bankfull width to mean channel depth
BF_Width	Bankfull width in meters
logPoolVol	Natural log of the residual pool volume in m^3
SQRTOver	Square root of the percent overstory density
Elevation	Elevation in meters
SQRTAspect	Square root of the valley aspect in degrees
logVCW	Natural log of the ratio of valley width to channel width
SQRTDA	Square root of the drainage area in km^2
QPK2_cms	2-year peak discharge in cubic meters per second
Air_Month	Mean monthly air temperature for the warmest month in °C
logAir7	7-Day mean of the maximum daily air temperature for the warmest 7 days in °C

(PCA). PCA is a data transformation that produces multiple new, uncorrelated variables (principal components) that represent the variability in the data. The first principal component contains the largest percentage of the data variance, with each successive component containing the next largest percentage until all the variance in the data is accounted for. PCA biplots (e.g., Figure 4) can be used to reduce the number of potential variables in a multivariate analysis because they display the potential variables as vectors that demonstrate how much a particular variable explains the variance in each principal component direction. Variables that plot with the same direction and magnitude are equally able to explain the variance in that direction and only one of such a pair should be included in building the model. I discarded three variables from consideration that plotted similarly with variables I included in the model. The variables excluded were rejected over the variables they plotted with because they either explained less of the variability in that principal component direction or they did not satisfy the assumptions of multiple linear regression models as well as the variable retained. PCA plots are also useful in looking at whether different study locations have similar values for different components (variables). Study locations that plot close together indicate that they have similar values for the variables that explain the most variance in the plot's principal component directions. I used these plots to help identify whether the watersheds chosen from the cluster analysis were distinct from one another in their variable values.

After narrowing potential model variables, I ran a best subsets linear models analysis. Best subsets in the "leaps" package in R does an exhaustive comparison of all possible models built using forward or backward stepwise, or sequential replacement model building methods. The output is a plot displaying the ten best models as evaluated by Schwartz's information criterion (BIC), which is a metric for comparing model performance among different models, with the best model having the lowest BIC value (e.g., Figure 5). The plot displays the BIC along the y-axis, and an intercept and the possible model variables along the x-axis. The best model appears at the top in the darkest gray and has a mark corresponding to the variables chosen to parameterize that particular model. Best subsets does not actually run each of the models, but is a useful tool for determining which variables to include in a multiple regression model.

Best subsets analysis was run on different pools of potential model variables. The complete model variable pool included some variables that are highly correlated, such as discharge and drainage area. High correlation in model predictor variables in multiple linear regression is referred to as collinearity or multicollinearity and can have some consequences for conclusions drawn from the model. Multicollinearity does not affect the predictions or reliability of a model, but it can affect conclusions drawn about the relationship between each predictor variable and the dependent variable being modeled (Ott and Longnecker, 2010). When two (or more) predictor variables are collinear, it becomes difficult to determine which of these correlated variables is most correlated with the dependent variable, or explains the variation in the dependent variable. Removing one or more of the correlated predictor variables can alter the relative strength or predictive power of the other predictor variables in the model, so conclusions about relative strength of predictor variables in explaining the variability in the dependent variable should be treated with caution. In addition to the complete pool of model variables, best subsets was run on a pool of variables without multicollinearity, and on a pool that included the PRISM stream temperature metrics.

I ran the best multiple linear regression models as determined by the best subsets analysis, first including all the data, and afterward, using a ten-fold cross-validation to investigate the utility of the model at predicting stream temperature metrics. Ten-fold cross-validation divides the dataset into ten random subsets. Nine of the subsets are used to train the model to determine the intercept and coefficients of the parameters. The model then predicts the dependent variable for the remaining subset. This process is repeated ten times so that during each model run, the sites being predicted are different. Metrics of model performance can be calculated and averaged over the ten times the model was run for evaluation of the prediction error and comparison with other models. I calculated the r^2 value and the root mean square error (RMSE) of prediction to compare model performance. From these data, I chose the best model to predict each stream temperature metric (H2O_Month and H2O_7Day). I divided the data into a training dataset (2/3) and a validation dataset (1/3) using a random number generator process and then determined the parameter coefficients for each model using the training dataset. The models were then used to predict the stream temperature metrics for the validation datasets and metrics of model performance were calculated.

The relative importance of the parameters chosen for each model were calculated, to determine which variable is the most important control or driving variable in explaining the dependent or predicted variable; in this case, the stream temperature metrics. Metrics to gauge relative importance include "lmg" and "pratt." Lmg is a metric that divides the contribution to the r^2 among the predictor variables, normalized to 100%. The pratt metric is the product of the variable coefficient and the r^2 value. Relative importance of the model parameters was calculated for both the models that included correlated variables and the models that excluded correlated variables in order to make determinations about the relative explanatory strength of different predictor variables with confidence.

To address alterative hypothesis H_{A3}, a scatterplot was created with linear trend lines between the H2O_Month and elevation for each watershed. The Pearson correlation coefficient (r^2) was calculated to determine the strength of the elevation-stream temperature trend. For two watersheds, an outlier study location was removed and the linear trend line and r^2 value were calculated for the remaining study sites without any outlier effect. The outliers were determined visually from the plot and using subjective knowledge of the study locations and their distinct differences from the rest of the sites in the respective watershed.

Significant differences in the means of each variable between watersheds were determined using boxplots, and ANOVA and Kruskall-Wallis comparisons of means tests. ANOVA was used for variables with equality of variance between the watersheds and normality of the residuals. For watersheds that did not meet these assumptions of the ANOVA test, the Kruskall-Wallis non-parametric test of means was substituted. For variables with significant differences in means (significant p-values from the ANOVA and Kruskall-Wallis tests), Tukey HSD pairwise comparison tests were run to determine which watersheds had significantly different means. The results are displayed on the boxplots of each variable.

3 RESULTS AND DISCUSSION

Results from the model-building process begin with parameter selection and culminate in several models created for different management purposes. I will present the results of the model-building process and final models first, and address results that relate to specific hypotheses afterward. The results and discussion sections have been combined so that I can discuss the model results as I present them.

3.1 Objective 1

Objective 1: Collect sufficient data to empirically derive a mathematical relationship that can be used to predict stream temperature in pool habitat within pool-riffle channels on the WRNF.

The original, untransformed dataset of variables calculated from the measured field and ArcGIS data is available in Appendix B. Appendix C provides a summary of the original variables with mean, standard deviation and range calculated for each variable, and for each watershed. I originally had 38 study sites instrumented, but a few of the dataloggers were not recovered as a result of high flows and human tampering. Only 31 of the total original sites had complete data and could be used for model building.

3.1.1 Parameter and Model Selection

Exploratory data analysis using principal components resulted in three variables being removed from the list of potential variables considered for the model-building portion of the analysis. The D_{84} and D_{50} vectors plotted directly on top of each other in the PCA biplot of PC1 versus PC2 (Figure 4). D_{50} had a slightly larger magnitude, indicating that it explained slightly more of the variability in the principal components, and it better fit the assumptions of normality and homoscedasticity of variance, so D_{50} was retained for inclusion in the model building and D_{84} was discarded. The vectors for slope and percent overstory density also overlapped each other (Figure 4). Although overstory density appears to explain more of the variability in the

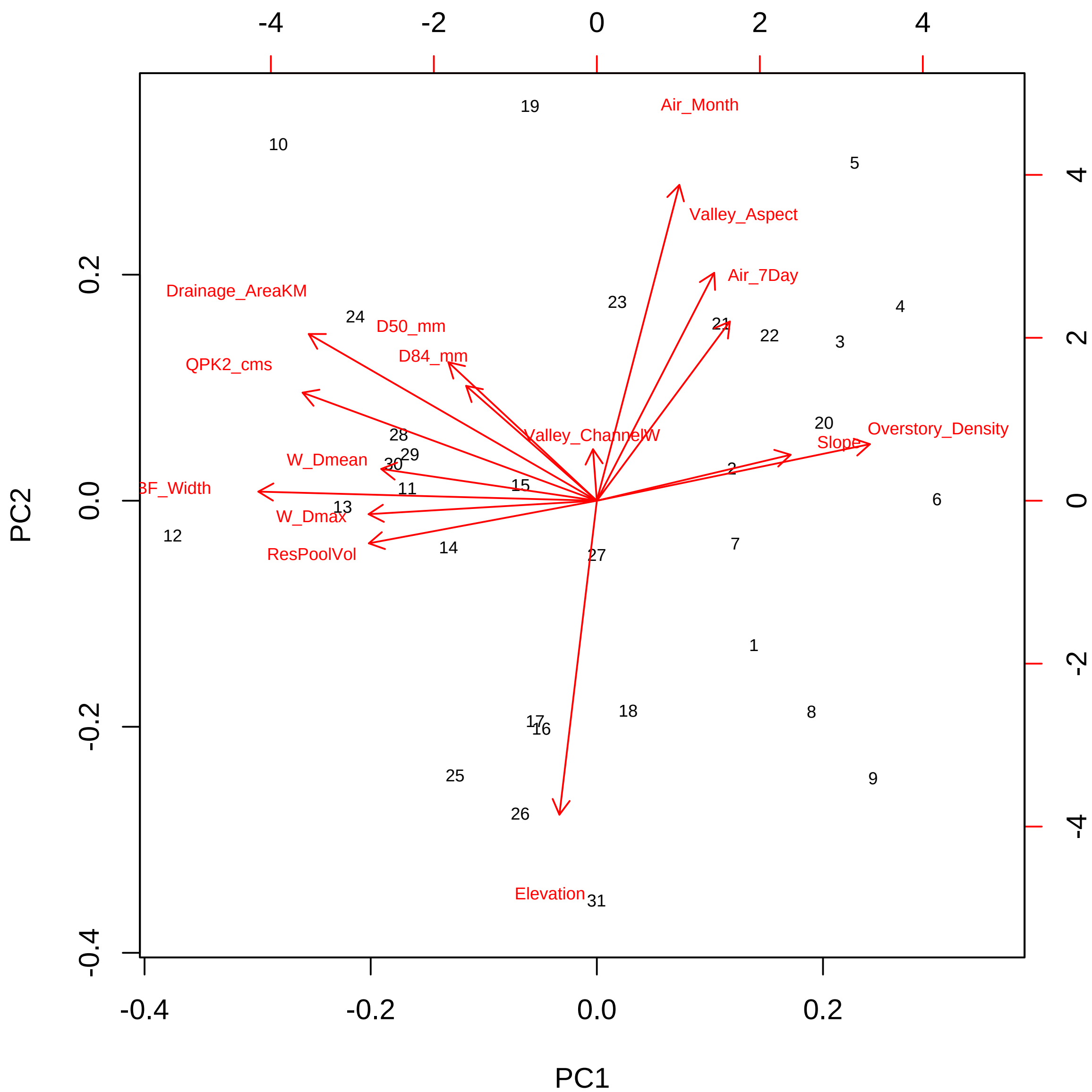

Figure 4: Principal components analysis biplot showing principal component 1 (PC1) against principal component 2 (PC2).

first principal component, it was discarded rather than slope because it did not satisfy the model assumptions as well as slope. The last variable eliminated from consideration was valley aspect, which was excluded because it could not be transformed to sufficiently satisfy the multiple linear regression model assumptions (Appendix A), and its explanatory power is roughly similar to that of the air temperature metrics.

After the number of potential model variables was reduced, the best subsets analysis selected parameters for each of the two models: one to predict mean monthly stream pool temperature for the warmest month (H2O_Month), and one to predict the 7-day mean of the daily maximum temperatures for the warmest 7 days (H2O_7Day). I conducted multiple runs of the best subsets procedure to compare model parameters selected from a pool of variables that included all the remaining potential explanatory variables, a reduced pool that excluded highly correlated variables, and a pool that included the PRISM air temperature metrics as potential variables. Figures 5 and 6 show the best subsets plots for predicting H2O_Month and H2O_7Day selected from the complete pool of potential variables. The best model is the one with the lowest BIC value, and appears at the top of the plot, in the darkest color. The best H2O_Month model, Model 1.1, included elevation, 2-year peak discharge, residual pool volume (log-transformed), drainage area (square-root transformed), and the 7-day air temperature metric (log transformed) as explanatory variables (Figure 5, Table 3). The best H2O_7Day model, Model 2.1, did not include any air metrics, but did include the drainage area, residual pool volume and the 2-year peak discharge, which are all variables related to flow volume (Figure 6, Table 3). All of the potential models chosen by best subsets included an intercept. The best H2O_Month model had better model performance than the best H2O_7Day model as evaluated by any of the model performance metrics (Table 3).

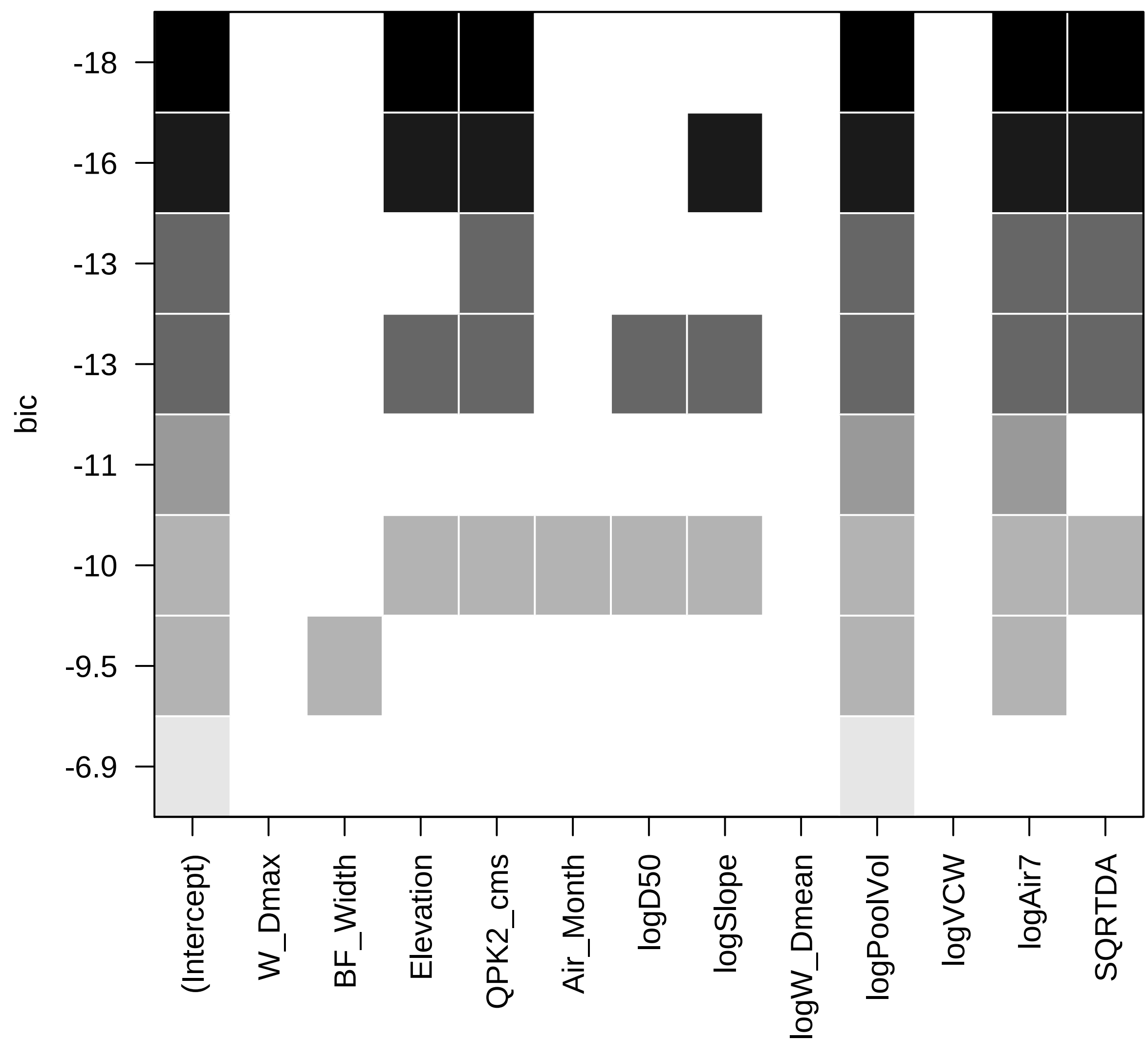

Figure 5: Best subsets plot displaying the top ten models for predicting the H2O_Month stream temperature selected from the complete pool of potential model variables. The potential model variables are listed across the x-axis. The y-axis is the Schwartz's information criterion (BIC) used to compare the models. The best model has the lowest BIC and is listed at the top, with the black boxes corresponding to the model parameters chosen. The best model in this chart corresponds to model 1.1 in Tables 3, 4 and 5.

I ran a second set of best subsets analyses with a pool of variables that excluded one of each of a set of predictor variables that show high collinearity (the relationship between the two explanatory variables is highly correlated). As discussed in the statistical methods section, multicollinearity does not affect the predictive power or the reliability of a model, but it may not

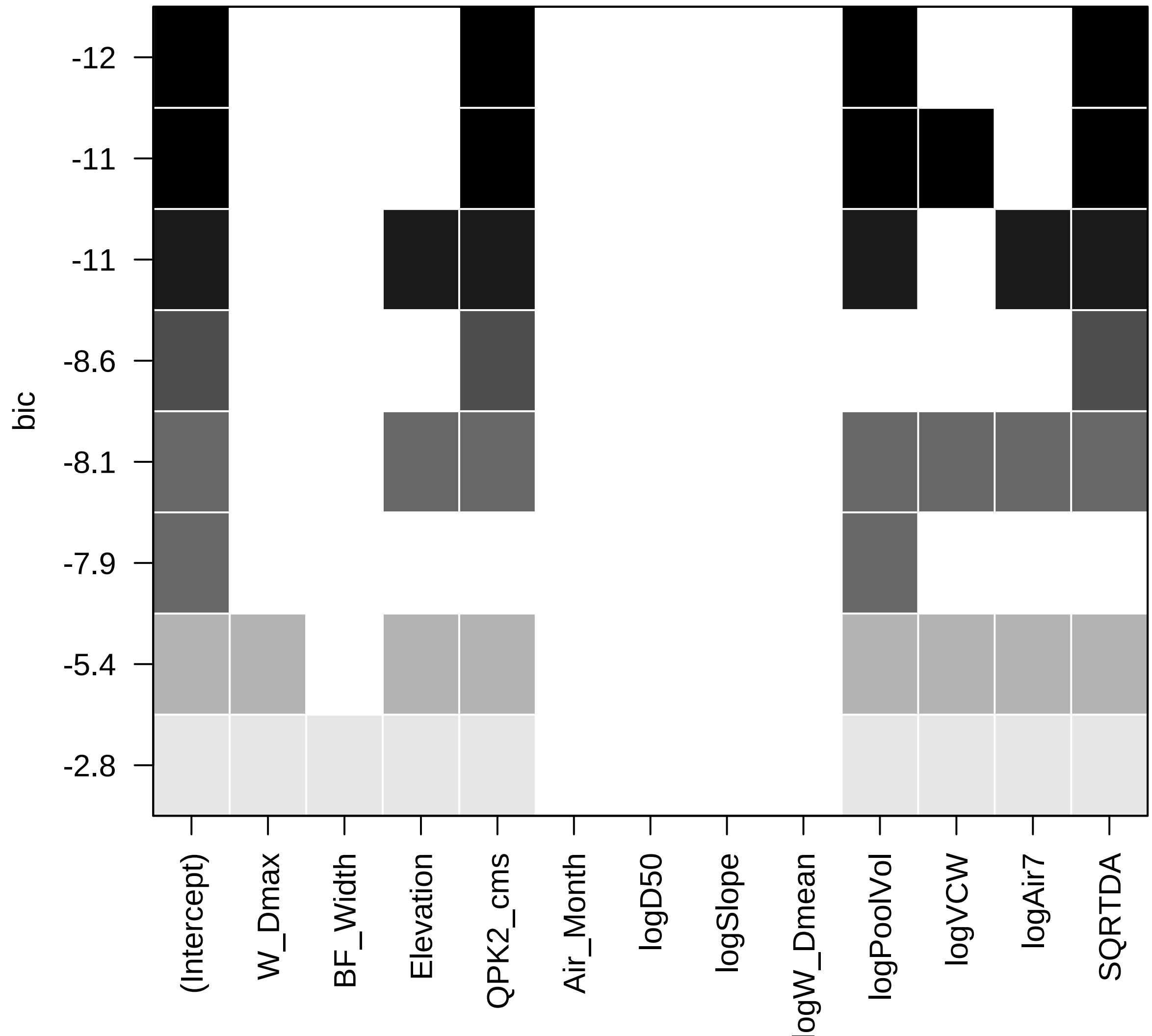

Figure 6: Best subsets plot displaying the ten best models for predicting the H2O_7Day stream temperature selected from the complete pool of potential explanatory variables. The best model at the top of this plot corresponds with model 2.1 in Tables 3, 4 and 5.

result in valid conclusions about the relative predictive power of the variables themselves (i.e., the impact each individual variable has on the dependent variable), or whether any variables are redundant. I included both the models that have some highly correlated variables and the models without highly correlated variables. The models including highly correlated variables are superior at predicting stream temperatures to the models without them, but a model without

Table 3: Parameters, coefficients and model performance metrics calculated for the top models from each best subsets result, as well as models with only air metric predictor variables. Models in bold are the best models for predicting H2O_Month and H2O_7Day.

Response Variable	Model	Parameter	Coefficient Estimate	Std. Error	P-value	Adjusted R^2	RMSE Orig (°C)	RMSE Pred (°C)	BIC
Mean Monthly Stream Pool Temperature (°C)	**Model 1.1**	Intercept	-25.007	8.20	0.0054*	**0.657**	**1.27**	**1.56**	**-18**
		Elevation	0.00397	0.0014	0.0105*				
		QPK2_cms	-1.038	0.25	0.000292*				
		logPoolVol	0.758	0.24	0.00371*				
		logAir7	6.119	1.64	0.000977*				
		SQRTDA	1.673	0.39	0.000212*				
	Model N1.1	Intercept	-21.830	9.48	0.0296*	0.535	1.51	1.88	-11
		Elevation	0.00492	0.0016	0.0057*				
		QPK2_cms	-1.03554	0.29	0.0013*				
		logAir7	3.965	1.74	0.0311*				
		SQRTDA	2.091	0.42	4.0e-05*				
	Model 1.4	Intercept	-6.806	6.41	0.297	0.457	1.69	1.87	-11
		logPoolVol	0.985	0.19	1.7e-05*				
		logAir7	5.005	1.83	0.0108*				
	Model 1.6	Intercept	-5.543	6.58	0.407	0.454	1.67	1.90	-8.3
		logPoolVol	0.787	0.29	0.0112*				
		logAir7	4.396	1.96	0.033*				
		SQRTDA	0.176	0.19	0.373				
	Model 1.7	Intercept	8.516	3.49	0.0212*	-0.0102	2.35	2.50	6.1
		Air_Month	0.191	0.23	0.4105				
7-Day Stream Pool Temperature (°C)	**Model 2.1**	Intercept	10.694	1.45	6.32e-08*	**0.512**	**2.29**	**2.51**	**-12**
		QPK2_cms	-1.029	0.36	0.00779*				
		logPoolVol	0.869	0.34	0.0180*				
		SQRTDA	1.668	0.50	0.00242*				
	Model N2.1	Intercept	-4.398	7.055	0.538	0.471	2.38	2.74	-9.3
		Elevation	0.0044	0.0023	0.0615				
		QPK2_cms	-1.35	0.43	0.0043*				
		SQRTDA	2.69	0.63	0.0002*				
	Model 2.3	Intercept	14.5	0.57	<2e-16*	0.357	2.72	2.92	-7.9
		logPoolVol	1.153	0.27	0.000232*				
	Model 2.4	Intercept	13.165	5.13	0.0156*	-0.0263	3.44	3.69	6.6
		Air_Month	0.161	0.34	0.635				
	Model 2.5	Intercept	19.044	11.58	0.111	-0.0313	3.45	3.79	
		logAir7	-0.996	3.35	0.768				

Table 3: Continued

Response Variable	Model	Parameter	Coefficient Estimate	Std. Error	P-value	Adjusted r^2	RMSE Orig (°C)	RMSE Pred (°C)	BIC
Mean Monthly Stream Pool Temperature (°C)	Model P1.2	Intercept	8.035	1.04	2.58e-08*	0.470	1.64	1.83	-9.2
		QPK2_cms	-0.629	0.26	0.0208*				
		logPoolVol	0.536	0.25	0.0389*				
		SQRTDA	1.083	0.36	0.00528*				
	Model P1.5	Intercept	4.858	4.26	0.264	0.327	1.88	2.13	-4.1
		PRISM_07max	1.215	0.30	0.000387*				
		PRISM_07mean	-1.431	0.4	0.00127*				
	Model P1.6	Intercept	3.220	5.03	0.527	0.0529	2.27	2.50	
		PRISM_07max	0.350	0.21	0.113				
	Model P1.7	Intercept	13.571	4.54	0.00561*	-0.0264	2.37	2.51	
		PRISM_07mean	-0.141	0.30	0.636				
7-Day Stream Pool Temperature (°C)	Model P2.2	Intercept	5.935	5.24	0.268	0.534	2.20	2.54	-11
		PRISM_07max	1.395	0.44	0.00376*				
		PRISM_07mean	-1.341	0.59	0.0323*				
		logPoolVol	0.677	0.29	0.0272*				
		logVCW	-1.607	0.77	0.0472*				
	Model P2.3	Intercept	3.787	5.90	0.526	0.391	2.61	2.95	-7.2
		PRISM_07max	1.918	0.42	8.38e-05*				
		PRISM_07mean	-2.162	0.55	0.000536*				
	Model P2.4	Intercept	1.313	7.17	0.856	0.0911	3.24	3.58	
		PRISM_07max	0.611	0.31	0.0547				
	Model P2.5	Intercept	17.542	6.62	0.0129*	-0.0314	3.45	3.69	
		PRISM_07mean	-0.127	0.43	0.771				

multicollinearity is useful to investigate the relative importance of predictor variables. Two-year peak discharge and drainage area were highly correlated, as were bankfull discharge, W/Dmean and W/Dmax, as well as elevation and Air_Month (Appendix D). One of each of these correlated variables was retained for potential inclusion in the model and the rest eliminated. The best models for predicting H2O_Month and H2O_7Day from the set of variables that are not highly correlated are shown in best subsets Figures 7 and 8. The best model in each case did not include any of the variables that had high correlation with a variable that was excluded. Without collinear variables, the best model to predict H2O_Month included residual pool volume and the Air_7Day metric. To predict H2O_7Day, the model included just the residual pool volume, and no other variable.

I also ran best subsets with four different metrics from the PRISM model included as potential explanatory variables to compare whether air temperature metrics from regional models were as effective as locally collected air temperature metrics for explaining stream temperature. For predicting H2O_Month, with PRISM air metrics included as possible parameters, the best subsets indicated that the best model did not include any of the PRISM metrics. When best subsets was run with only the four possible PRISM metrics included, the best models for both H2O_Month and H2O_7Day included the temperature metrics for July mean and July maximum temperature (Figure 9), although, according to the BIC, these PRISM metrics had better explanatory power for H2O_7Day (BIC= -7.2) than for H2O_Month (BIC= -4.1).

All of the best models, predicting both H2O_Month and H2O_7Day, with and without correlated predictor variables, included the natural log of residual pool volume as a predictor. This variable is one of the more difficult variables to accurately measure and requires intensive fieldwork to collect and calculate. To create a less-intensive, user-friendly version of the models,

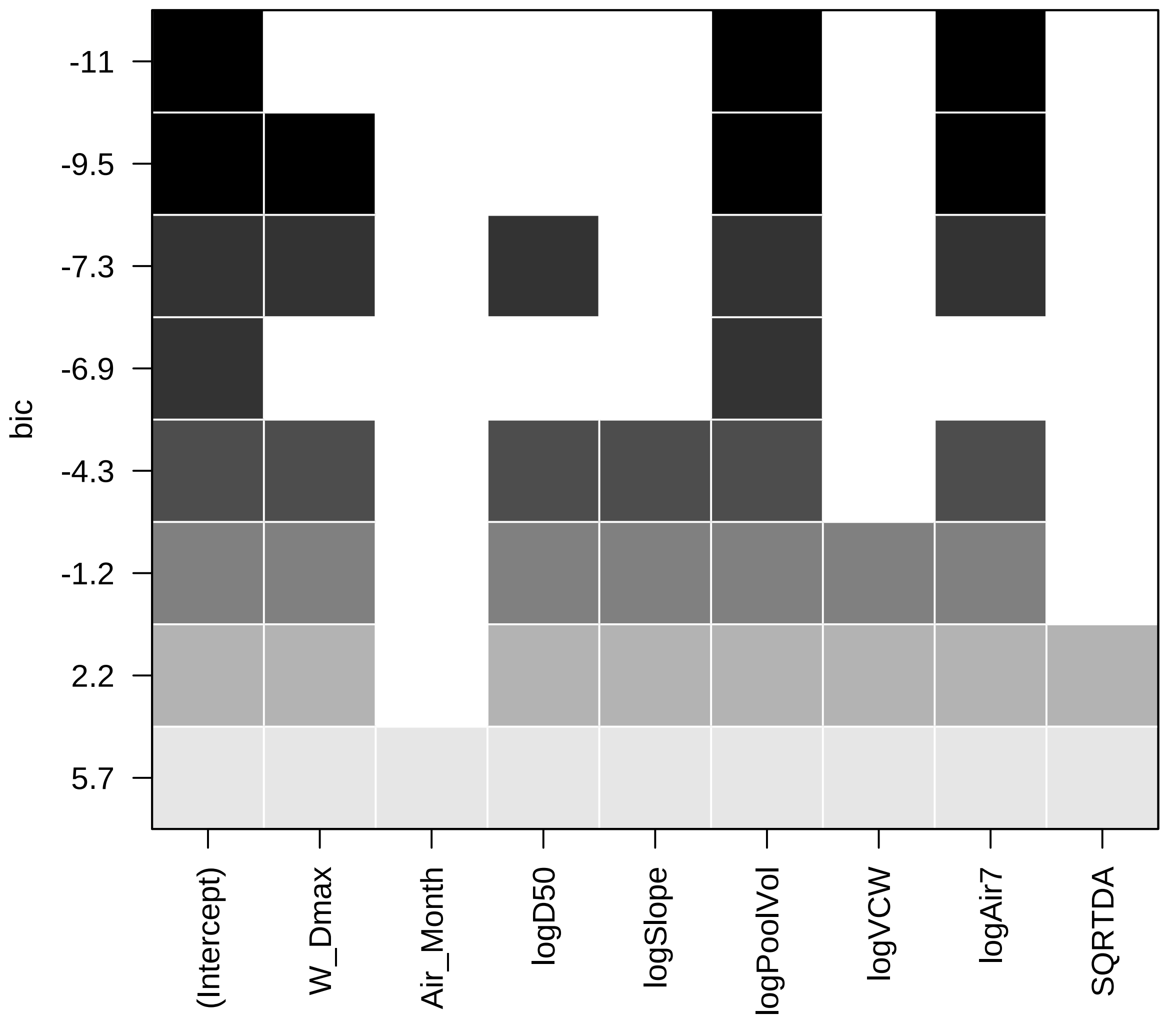

Figure 7: Best subsets plot showing the top ten models for predicting H2O_Month from a pool of potential variables that were not highly correlated with each other. The best model in this plot corresponds with model 1.4 in Tables 3 and 5.

I attempted to substitute the maximum residual pool depth in meters for the log of the residual pool volume because these two variables are well-correlated (Figure 10, models N1.1 and N2.1) and maximum residual pool depth is easier to measure in the field. The best subsets results with maximum residual pool depth in place of residual pool volume indicated that other variables (e.g., SQRTDA, Elevation) were better predictors than maximum residual pool depth in the absence of residual pool volume (Figure 11). The best models without residual pool volume had poorer

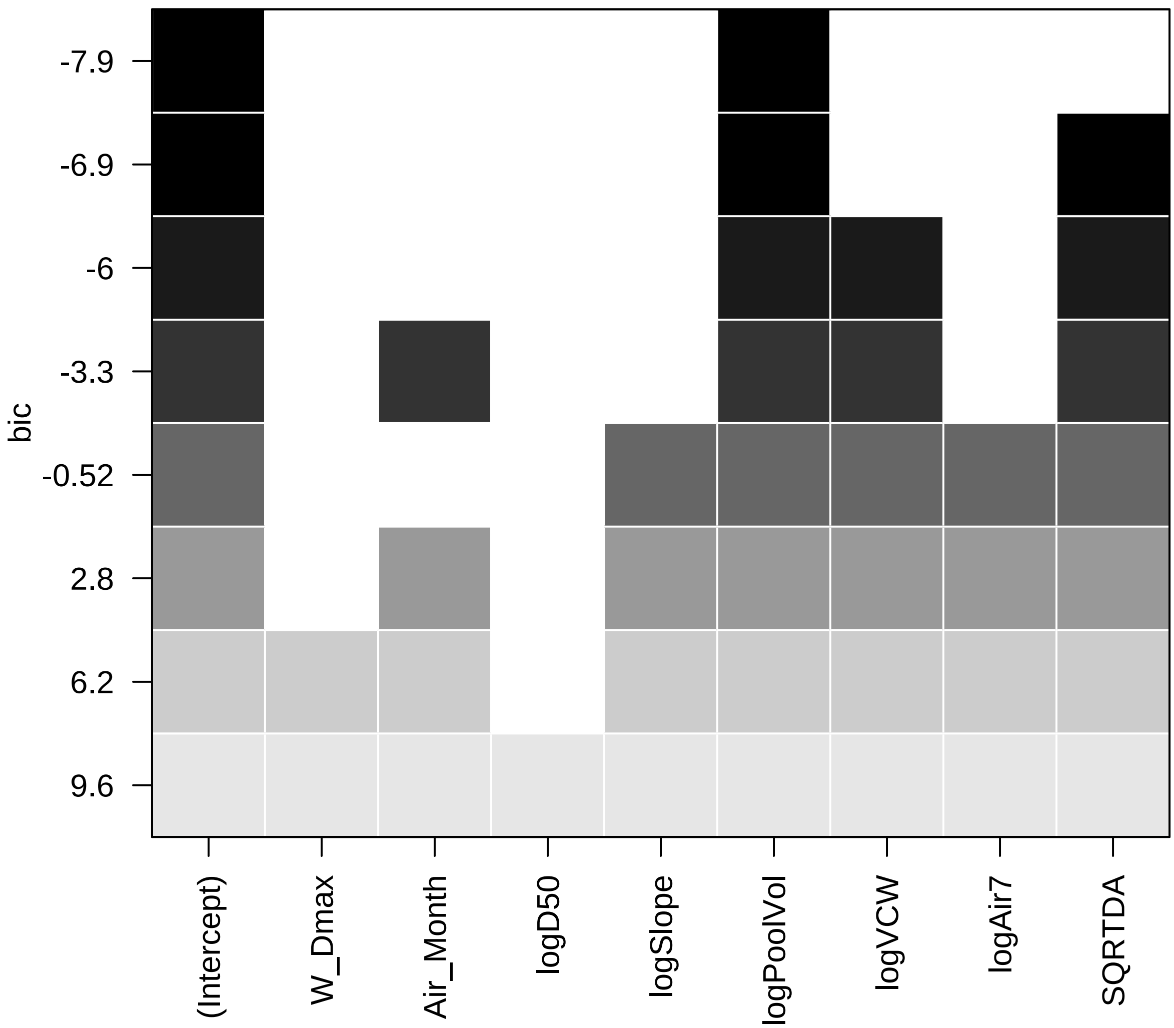

Figure 8: Best subsets plot showing the top ten models for predicting H2O_7Day from a pool of potential variables that were not highly correlated with each other. The best model in this plot corresponds to model 2.3 in Tables 3 and 5.

performance compared to the models with residual pool volume, but the model to predict H2O_Month still had a root mean square error of prediction less than 2° C (Table 3). The model to predict H2O_7Day utilized one less variable, and had a root mean square error of prediction greater than 2° C (Table 3).

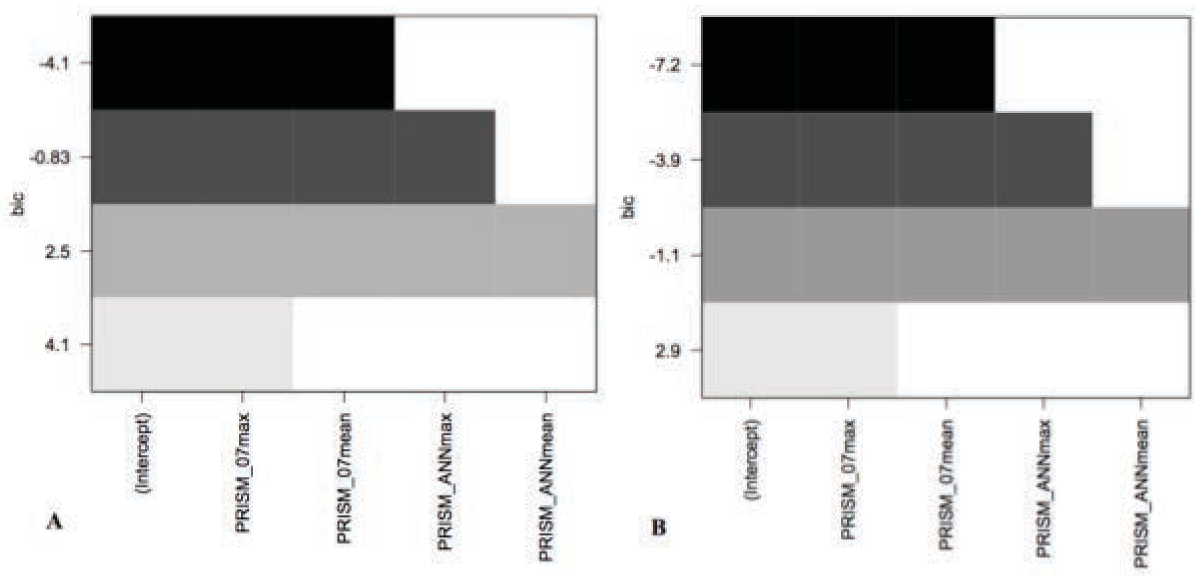

Figure 9: Best subsets plots for A) H2O_Month and B) H2O_7Day when only PRISM air temperature variables were offered as potential predictor variables. The best model in A) corresponds to model P1.5 and the best model in B) corresponds to model P2.3 in Table 3.

3.1.2 Model Validation

Table 3 summarizes the parameters, their coefficients and standard errors, whether the model parameters are significant, and several metrics of model performance for all the models chosen by the best subsets from the various parameter pools, as well as additional models that use air temperature metrics alone as predictor variables. These models were developed using the entire dataset initially in order to determine the best predictor variables. Included in the table as well, is the RMSE of prediction, which is a prediction error averaged over the ten model runs from the 10-fold cross validation procedure. This RMSE value is naturally worse than that of the original model using all the study sites because it is predicting the temperature at locations not included in the model-training phase. The ten-fold cross validation RMSE is only an indication of potential model performance for streams outside of the data collection area, and does not reflect the actual model performance for White River National Forest overall.

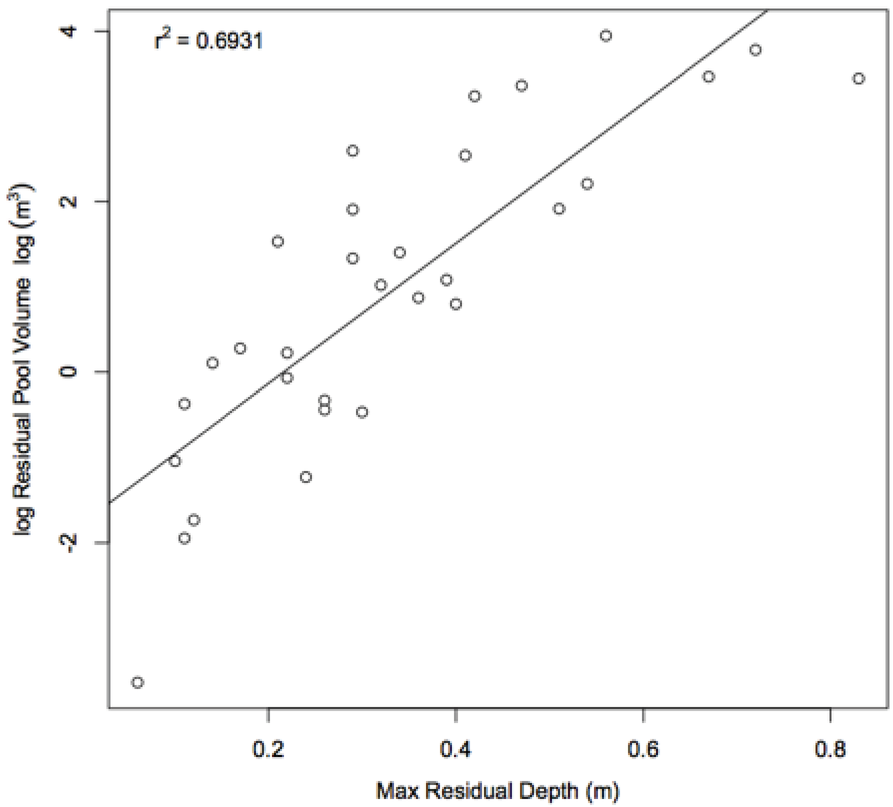

Figure 10: Scatterplot with linear trendline and r^2 value showing the correlation between the log of the residual pool volume and the maximum residual pool depth. This high correlation indicates that the easier-to-measure maximum residual depth might be an adequate substitute for the more difficult-to-obtain metric of residual pool volume as a model predictor variable.

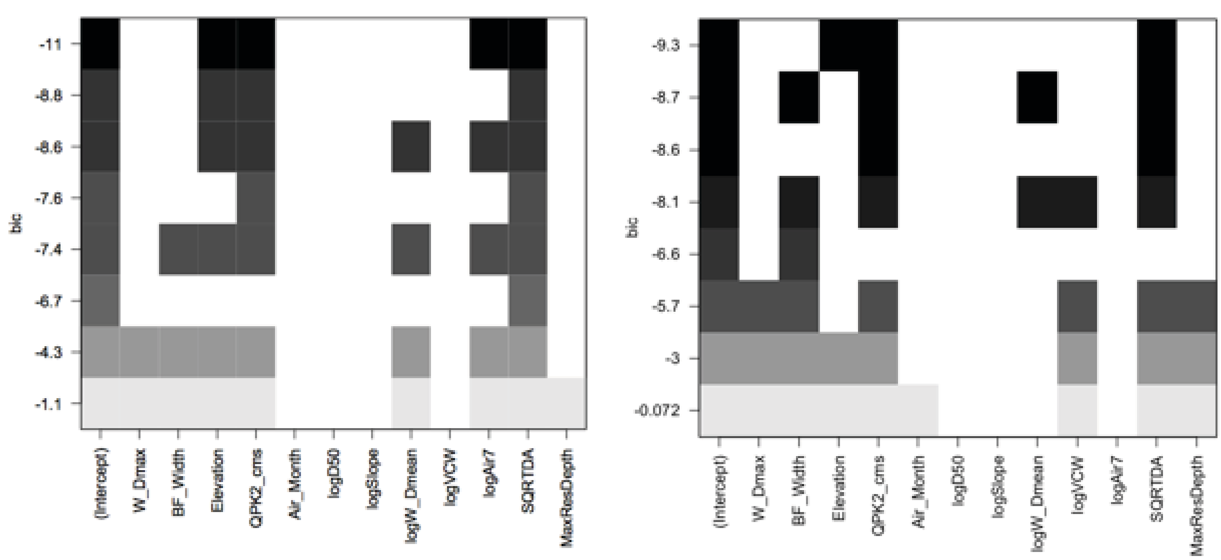

Figure 11: Best subsets plot showing the best "user-friendly" versions of the models. The best models in this plot correspond to models A) N1.1 and B) N2.1 in Table 3.

Although many other studies have utilized air temperature in simple regression to predict stream temperatures, the models 1.7, 2.4 and 2.5 using only air temperature metrics as the predictor in this study had the poorest performance according to all the model performance metrics (Table 3). These models had the worst r^2 values, indicating they do not capture much of the variability in the stream temperature metrics. They also had the worst RMSE for the original models and for the 10-fold cross validation procedure, which indicates that they had poor prediction among all the study sites in the original model, and even poorer prediction of sites not included in the model training. My results for these relations likely differ so much from the studies that found good correlation between air and stream temperature because of the local, site-specific spatial and temporal scale of the dependent and independent temperature metrics I measured and calculated. Most of the previous models that found strong correlation between air and stream temperatures were predicting temperatures on a daily or weekly time scale, and so the diurnal variation in both air and stream temperatures were well-correlated. For the single summer stream temperature metrics I am predicting, diurnal and seasonal variation in stream and air temperatures that are well correlated for daily or weekly time scales may be obscured because the summer long data is being averaged or simplified to a single metric. Conversely, the small, site-specific spatial scale of my study sites includes variability that is obscured in regional models that average temperatures over larger stream sections. In addition, given that my study sites are all mountain headwater streams, mostly well-shaded, the local air temperature is likely a less influential factor in controlling stream temperature than factors such as groundwater contribution and pool volume. Previous studies in mountain regions have mostly focused on the effects of removing riparian shading and neglected the influences on mountain stream temperatures when the riparian corridor is intact.

The PRISM models also had fairly poor performance compared with the models that included stream and valley geomorphic characteristics. It is interesting to note, however, that the models for both H2O_Month and H2O_7Day that used two PRISM air metrics performed better than the models that included only one locally measured air temperature metric. The local air temperature metrics added more explanatory power to the models and were chosen over the PRISM air metrics when the best subsets analysis had both types of air metrics to choose from and geomorphic variables were included.

The best model for H2O_Month and H2O_7Day was model 1.1 and 2.1, respectively. I ran the same models (i.e., the same parameters from best subsets) as training runs and test or validation runs by dividing the dataset into thirds and using two thirds for training and the last third for validation. The datasets were divided randomly, using a random number generator process. The RMSE and r^2 values for the training and test sets are listed in Table 4. Prediction power of the model as measured by the RMSE of prediction for the validation dataset is reduced compared to the RMSE of the training dataset. The model of H2O_Month had better performance at predicting and better adjusted r^2 value than the model of H2O_7Day, both for the training data and for the validation set.

Model 1.1 for predicting H2O_Month had some similar predictor variables as multiple linear regression models developed by Isaak et al. (2010) and Jones et al. (2013). Jones et al. (2013) included latitude, longitude, slope, local air temperature, elevation and a lake effect term in their model, and reported an r^2 value of 0.56 and a RMSE of prediction of 1.88 °C for predicting August mean temperatures in their validation dataset in the Flathead River basin of Montana (14,430 km^2). Isaak et al. (2010) included elevation, solar radiation, mean air temperature and mean discharge in their model, and reported an r^2 value of 0.679 and a RMSE of

Table 4: Parameters, coefficients and performance metrics for the training and validation datasets for the best models for predicting H2O_Month and H2O_7Day stream temperatures.

			Training Data		Validation Data	
Model	Parameter	Coefficient (Std. Error)	Adjusted r^2	RMSE Pred. (°C)	Adjusted r^2	RMSE Pred. (°C)
Model 1.1	Elevation QPK2_cms logPoolVol logAir7 SQRTDA	0.00407 (0.0017) -0.908 (0.29) 0.597 (0.36) 6.369 (1.9) 1.548 (0.43)	0.562	1.25	0.397	1.41
Model 2.1	QPK2_cms logPoolVol SQRTDA	-0.96 (0.5) 0.938 (0.50) 1.623 (0.64)	0.505	2.53	-0.028	1.73

prediction of 1.53 °C for predicting summer mean stream temperatures for their pooled data in the Boise River basin of Idaho (6900 km^2). These results are similar to the RMSE of prediction of 1.41 °C for predicting mean temperature for the warmest month in the validation dataset in this study. The r^2 value of 0.397 for model 1.1 is lower than the r^2 values achieved by Jones et al. (2013) in their validation dataset, although the r^2 from the pooled (0.657, Table 3), and training (0.562, Table 4) datasets for model 1.1 are more in line with the pooled r^2 for the model from Isaak et al. (2010) and the training dataset r^2 value of 0.49 from Jones et al. (2013). Model 1.1 to predict H2O_Month includes 5 predictor variables, which is likely too many predictor variables given there were 31 observations used to develop the multiple linear regression model. General consensus in the literature recommends a ratio of no more than 1 predictor variable for every 10 observations. Inclusion of additional variables improves model performance, but may result in overfitting of the model to the random error or noise in the 31 observations rather than the overall trends or relationships in the data. Model 1.1 includes two very highly correlated variables, square root of the drainage area and 2-year peak discharge, because the Capesius and

Stephens (2009) equations that estimate 2-year peak flow are based on drainage area. Excluding the 2-year peak flow reduces the number of predictor variables, but it also decreases the model performance for predicting stream temperature (Model 1.4, Table 3). Model 2.1 has an appropriate ratio of predictor variables to observations.

Isaak et al. (2010) also created a second multiple linear regression model to predict the 7-day average of maximum daily stream temperatures for the warmest 7 days. In their model, they utilized elevation, solar radiation, 7-day average of the maximum daily air temperatures for the warmest 7 days, and mean discharge for the basin. The only overlapping variable between the model they developed and model 2.1 in this study was the discharge. Isaak et al. (2010) report an r^2 of 0.543 and a RMSE of prediction of 2.75 °C for their pooled dataset. I had a similar r^2 of 0.512 and a RMSE of prediction of 2.29 °C for the pooled dataset (Table 3). When model 2.1 was run on the validation dataset, the adjusted r^2 value dropped to -0.028, indicating it explains almost none of the variability in H2O_7Day temperatures across the WRNF, although the RMSE of prediction was also reduced to 1.73 °C. The drop in RMSE of prediction indicates that although the model is poor at capturing the variability in stream temperature across the validation study sites, its ability to make point predictions in H2O_7Day temperature actually improved. My model results are comparable to results from similar studies that included a variety of geomorphic, meteorological and flow variables in their multiple regression models for predicting stream temperatures.

3.1.3 Model Limitations

The final models for H2O_Month and H2O_7Day have several limitations that make them unsuitable for application outside of certain conditions. First of all, the data that populated the parameters from which the models were built were collected over two summer field seasons, with the temperature data only covering a single complete set of the summer months. The temperature data for both streams and local air are reflective of the particular conditions in summer 2012 and 2013. Temperature data collected over a longer time period would provide a better idea of average conditions for the streams included, rather than solely the temperatures under the particular temperature and precipitation or flow conditions of 2012 and 2013. In addition, because the data collected for this project are only for pool habitats in headwater streams, in this particular region of the Rocky Mountains of Colorado, the model is not applicable outside of headwater streams within WRNF. The models are designed to provide estimates of two specific stream temperature metrics and should not be considered as models of the overall thermal regime of these stream environments, but rather, as a tool to be used as a very rough pass at eliminating unsuitable streams for CRCT reintroduction. Finally, both of the best prediction stream temperature models include residual pool volume as a predictor variable. This limits their ease-of-use for locations that were not included as study sites in this research because measuring residual pool volume requires extensive field visits with survey equipment. Field visits to every potential reintroduction reach are both time and cost prohibitive. Models N1.1 and N2.1 that have less accuracy in prediction than the “best” models, but that only require predictor variables such as drainage area that are readily available from a GIS layer, might be more useful for management purposes than the “best” models presented here. In addition, a model that accounts for spatial autocorrelation in stream temperature across the Forest could potentially provide more accurate predictions and wider applicability within the Forest and nearby environs. A spatial model, however, was outside the scope of this study.

3.2 Objective 2

Objective 2: Identify the dominant control variables for stream temperature.

Results from the model building best subsets analysis and some additional analysis were used to identify the dominant control variables for explaining stream pool temperature out of all the possible metrics I measured and calculated.

Hypothesis 1, H_{A1}: The dominant control on stream temperature is local air temperature.

The results from the best subsets model-building analysis indicate that, for these models, local air temperature is not the dominant explanatory variable for pool stream temperature. Although the 7-day local air metric was included in the multiple linear regression model to predict H2O_Month, no air temperature metrics were included in the model for predicting H2O_7Day (Table 4, Figures 5 and 6). All the models that included air temperature metrics alone had much poorer fit and poorer prediction than the models that included geomorphic variables (Table 3).

The relative importance of the air temperature metrics in the models that included these metrics indicate that they are of low importance in explaining the variability in stream pool temperature relative to the other variables included (models 1.1, 1.4 and 1.6, Table 5). This is true both for the models with collinearity (model 1.1, N1.1, 2.1, N2.1) and the ones that excluded highly correlated variables (models 1.4 and 1.6), whose relative importance results are a bit more reliable. The low relative importance of the temperature variables in each of these models further supports the idea that air temperature is not the dominant control variable for stream pool temperature in my study. Alternative hypothesis H_{A1} is not supported by my data.

Table 5: Relative importance of the explanatory variables in each of the models calculated using the lmg and pratt metrics. Bold variables are the dominant explanatory variables for the particular model. Models in italics indicate models without highly correlated predictor variables.

		Method	
Model	Variables	lmg	pratt
Model 1.1	Elevation	0.0516	-0.0874
	QPK2_cms	0.2053	-0.9464
	logPoolVol	0.3056	0.4932
	logAir7	0.1059	0.0614
	SQRTDA	**0.3317**	**1.4791**
Model N1.1	Elevation	0.0855	-0.1297
	QPK2_cms	0.2969	-1.1292
	logAir7	0.0505	0.0476
	SQRTDA	**0.5672**	**2.2112**
Model 1.4	**logPoolVol**	**0.855**	**0.9273**
	logAir7	0.145	0.0727
Model 1.6	**logPoolVol**	**0.503**	**0.72**
	logAir7	0.116	0.062
	SQRTDA	0.382	0.218
Model 2.1	QPK2_cms	0.224	-0.79
	logPoolVol	0.365	0.508
	SQRTDA	**0.411**	**1.282**
Model N2.1	Elevation	0.0663	-0.11
	QPK2_cms	0.3155	-1.11
	SQRTDA	**0.6181**	**2.22**

Hypothesis 2, H_{A2}: Site-specific characteristics aside from air temperature significantly influence the stream temperature.

Across the models, residual pool volume and drainage area were the most important explanatory variables (Table 5). Model 1.1 and model N1.1 have drainage area as the most important explanatory variable, accounting for the most variability in stream temperature, but these models include predictor variables with high correlation (namely drainage area and 2-year peak discharge), so this result includes some uncertainty. The models that did not have collinear variables both indicate that residual pool volume is the strongest predictor variable, and can be interpreted with more confidence than the results for model 1.1. Residual pool volume is a reflection of the stream geomorphic planform. Drainage area is highly correlated with flow volume and both drainage area and residual pool volume indicate that cooler temperatures in these streams are correlated with larger volumes of water (whether measured as discharge or pool volume). This result is likely a reflection of the study sites where the data were collected. Stream pool volume is significant, likely because of the thermal inertia of larger volumes of water, but also because pools are where the data collection occurred. In addition, all the study sites are located on headwater streams and therefore have limited stream length over which to absorb solar radiation. Smaller bankfull widths closer to the stream origin also result in greater shading over the channel, because there is not as much open water between the banks to be exposed to solar radiation. Solar radiation (and local air temperature) effects on stream temperature increase downstream, and it may be that these headwater study site locations are not far enough downstream to include a significant effect from solar radiation and local air temperature. Alternative hypothesis H_{A2}, that other variables aside from air temperature will be important explanatory variables, is supported by both the model selection and the relative importance metrics. In fact, residual pool volume, drainage area and discharge were more important than local air temperature in these models.

My results for strongest driving variables for predicting stream temperature are in contrast with many other studies that have found that local air temperature is strongly correlated with stream temperature (Mohseni et al., 1998; Mohseni and Stefan, 1999). The differing importance of the air temperature predictors between this study and others is likely the result of the mountain headwater location and the temperature metrics calculated in this study compared to earlier studies. These results do agree with Bartholow (1991), who found that flow volume was a stronger influence on stream temperature than riparian shading in a stream with substantial flow regulation. Although the stream reaches included in this study are free from flow regulation, the result that greater flow volume correlates with cooler stream temperatures is true for these streams, as well as the flow-regulated streams in Bartholow (1991).

3.3 Objective 3

Objective 3: Explore spatial patterns in stream temperature.

Hypothesis 3, H_{A3}: Mean pool temperature will increase downstream in the watersheds.

Strong trends in increasing downstream temperature are present along Beaver Creek, Berry Creek and Piney Creek (Figure 12). Cross Creek does not have a strong downstream trend, although this is likely a result of the sites being so close together in elevation and stream distance. Grizzly Creek shows a trend of decreasing stream temperature downstream in the watershed rather than increasing stream temperature, although this trend has a low correlation coefficient (0.217) and is the result of a single anomalous or outlier site (Figure 12). The anomalous site has the highest elevation, but also the highest stream temperature as a result of having the lowest flow volume and lacking shading. This site is located in a wide, flat meadow with no tall, shading vegetation on a section of the creek above a large drop-off into the canyon below. The lack of shading exposes this site to large amounts of solar radiation and the much lower flow

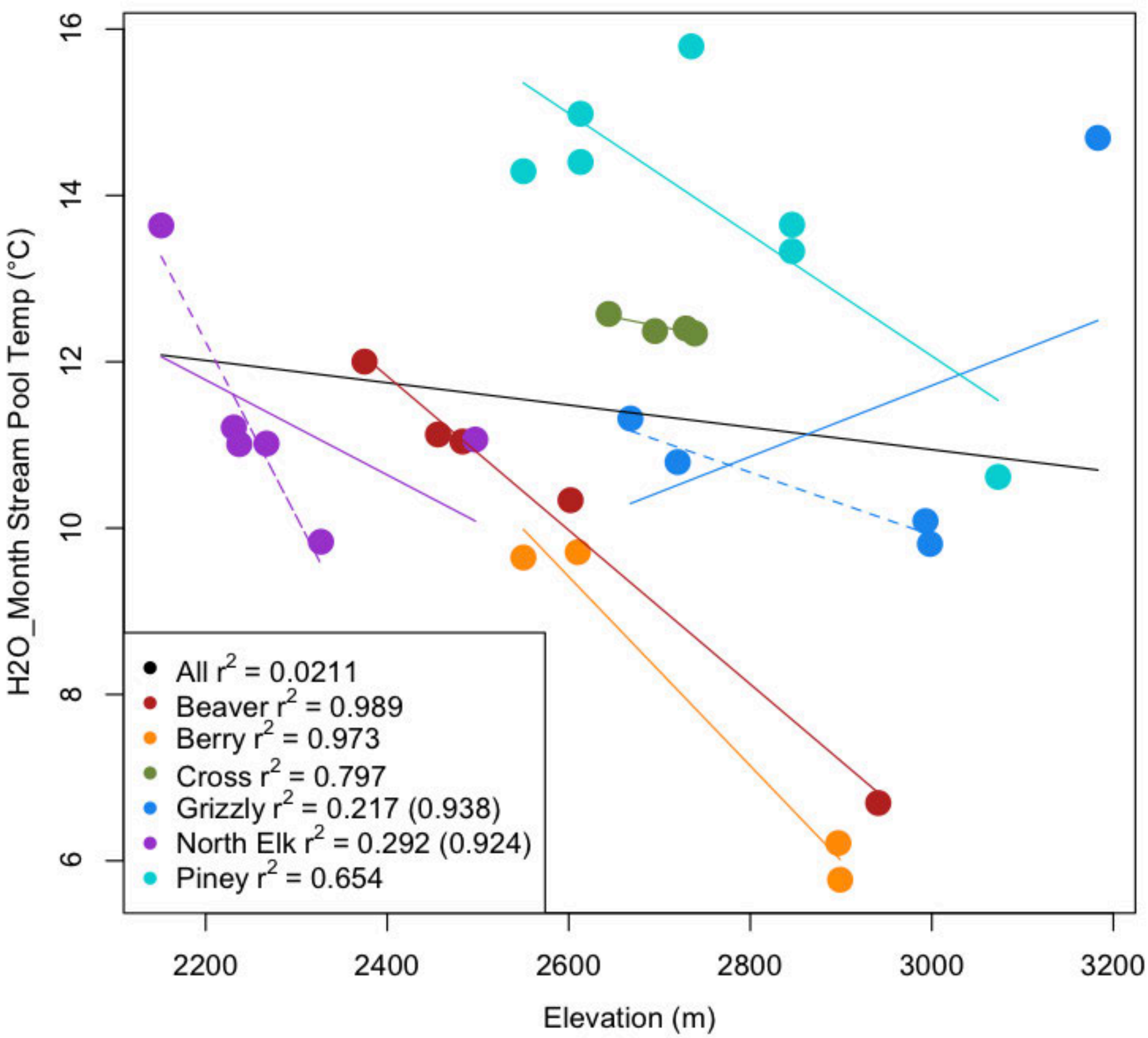

Figure 12. Mean monthly stream pool temperature for the warmest monthly, plotted against the elevation of the study sites. Values of r^2 in the legend correspond to the solid trend lines for all the data, and for each watershed. Values of r^2 in parentheses for Grizzly Creek and North Elk Creek correspond to the dashed trend lines for these watersheds and are the correlation coefficients for the watershed with the outlier study sites removed.

volume warms quickly, likely accounting for the high stream temperatures at this site. If this outlier is removed, Grizzly Creek has an increasing stream temperature trend downstream with a high r^2 value (see dashed line and r^2 value in parentheses, Figure 12).

North Elk Creek also has an anomalous site, which has reduced the strength of the downstream temperature trend shown in Figure 12. Like Grizzly Creek, this outlier is also the highest elevation site for this drainage, although the high temperature recorded for this site likely results from its location above a confluence with a tributary, whereas the rest of the study sites are below this confluence. The tributary that joins the main channel downstream is likely carrying cooler water that “resets” the stream to cooler temperature. If this outlier is removed, the downstream trend in warming stream temperature is much stronger, and the r^2 value for the relationship is much greater (Figure 12). The anomalous or outlier sites were identified subjectively based on their plotting position and subjective field knowledge of the study locations.

Figure 12 is a useful tool for identifying watersheds that may have greater susceptibility of the stream temperatures to climate warming. A steeper trendline in Figure 12 indicates a stronger relationship between elevation and stream temperature, with North Elk, Beaver and Berry Creek watersheds having the steepest or strongest trends. Because elevation is known to have a strong relationship with local air temperature, there is an indication that the relationship between stream and air temperatures is stronger in these watersheds as well, and hence, they may be susceptible to warming if air temperatures increase in the mountain regions of Colorado. Grizzly Creek and Cross Creek have the weakest relationship between elevation and stream temperature. For Cross Creek, the weak relationship may not be a result of a truly poor relationship with the elevation, but rather a lack of data that covers sufficient range in elevation to distinguish a trend. For Grizzly Creek, the weak relationship is most probably a result of the calcareous geology in the watershed that buffers the stream from increased temperature from the local air by mixing with abundant groundwater sources along the channel. Overall, hypothesis

H_{A3} is partially supported by the drainages included in this study, although it appears that there are local effects that can alter the hypothesized downstream increase in mean pool temperature, such as tributaries and shading effects.

3.4 Objective 4

Objective 4: Examine the relationship between watershed “clusters” and the stream temperature control variables.

Hypothesis 4, H_{A4}: The relative strength of different control variables will change across watershed clusters.

To determine whether the values of the various variables were significantly different across the six watershed clusters examined in this study, the principal components analysis biplot and a series of boxplots were utilized. Additional ANOVA and Kruskall-Wallis comparison of means tests were performed and Tukey HSD pairwise comparisons used to label the boxplots with drainages that were (dis)similar in mean variable values. In the PCA biplot, where the study sites plot in the diagram is related to their values for the explanatory variables (Figure 13). Study sites that plot closer together have more similar values for these variables than study sites that plot farther apart. If there is a difference in the variable values between the watershed clusters, the study sites belonging to each watershed cluster should plot close together, but be distinct from the other watershed plotting positions. Figure 13 displays the watershed study sites plotted in the PCA biplot, with circles distinguishing each watershed from the others. Upper Piney River and Grizzly Creek appear to have many similar values for the variables collected, as indicated by their overlapping plotting positions in the diagram. Upper Piney River appears to

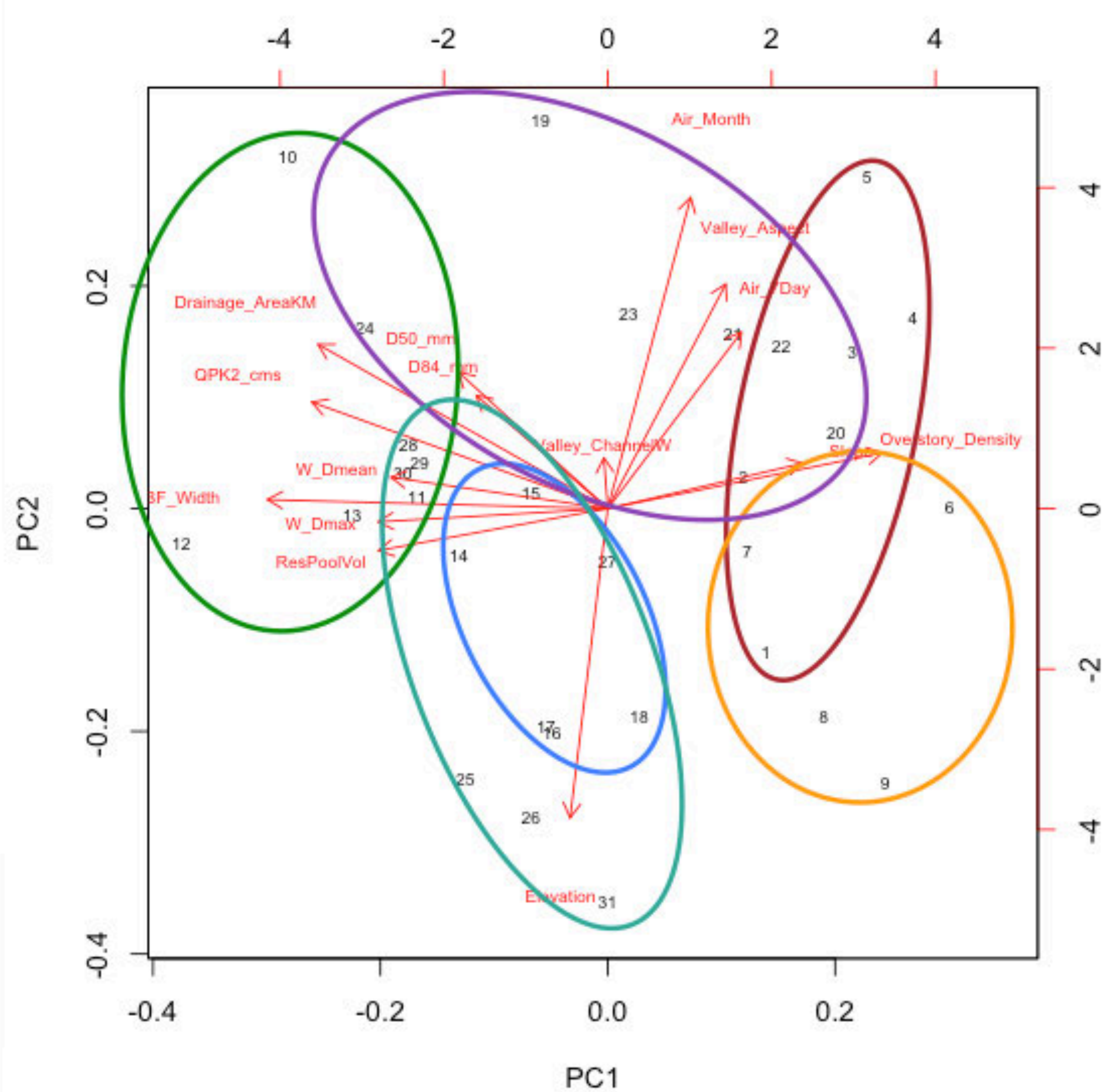

Figure 13: PCA biplot showing clustering in the values for the unique variables among the watersheds. Beaver Creek is study sites 1-5, circled in red. Berry Creek is sites 6-9, circled in orange. Cross Creek is sites 10-13, circled in green. Grizzly Creek is sites 14-18, circled in blue. North Elk Creek is sites 19-24, circled in purple. Upper Piney River is sites 25-31, circled in teal.

have greater variability in the values than Grizzly Creek, however (i.e., the study sites do not plot as tightly together as the sites for Grizzly Creek). Study watersheds that plot opposite each other along the axis of a single, or several, watershed variables have values for that variable that are distinct from each other. For example, Cross Creek, one of the largest creeks, plots opposite from Beaver Creek and Berry Creek, two of the smallest watersheds, along the rough axis direction for drainage area and two-year peak discharge (Figure 13). Likewise, North Elk Creek, the lowest elevation watershed, plots opposite from Grizzly Creek and Upper Piney River, two of the higher elevation creeks in the study (Figure 13). Based solely on this plot, there appear to be differences in the variables collected for each watershed. Some of these differences are potentially related to the cluster analysis drivers (sediment size and elevation), and some are not (such as drainage area).

Results from the boxplots and comparison of means tests provide clearer information on which watersheds are different from the others. First, I want to point out variables that are not significantly different across the watersheds according to the ANOVA and Kruskall-Wallis tests. Although Cross Creek appears to have the largest residual pool volume, and Berry and Beaver Creeks appear to have the smallest, the differences in residual pool volume are not significantly different between the watersheds (Table 6, Figure 14). This reflects the fact that, although small creeks such as Beaver Creek and Berry Creek do not have large pools (and without the aid of beavers or log jams are unlikely to have large pools given their low flow volume), the larger creeks can have pools of all sizes depending on the type of pool (channel-spanning, bend-pool or other). The lack of difference in residual pool volume across the watersheds suggests that there is no difference in sensitivity to changes in pool morphology across the watershed clusters. This could be important for management decisions relating to stream temperature given that the strongest predictor for stream pool temperature was residual pool volume.

Another set of variables that were not significantly different across watersheds are the variables pertaining to the channel bed substrate size: D_{50} and D_{84} (Table 6). Like residual pool volume, Cross Creek appears to have the largest sediment size (Figure 15), but the mean

Table 6: ANOVA and Kruskall-Wallis tests for significant difference in watershed variable means. Significant P-values (*) indicate that not all the means of the variable are equal between the six watersheds.

Variable	P-value	Test
D50	0.071	Kruskall-Wallis
D84	0.255	Kruskall-Wallis
Slope	0.014*	Kruskall-Wallis
W/Dmax	0.018*	ANOVA
W/Dmean	0.298	Kruskall-Wallis
BF Width	0.00037*	Kruskall-Wallis
Res. Pool Vol.	0.16	ANOVA
Overstory Density	0.0013*	ANOVA
Elevation	8.3e-05*	ANOVA
Valley Aspect	0.00033*	ANOVA
V/C Width	0.094	ANOVA
Drainage Area	0.0013*	Kruskall-Wallis
Discharge	0.00048*	Kruskall-Wallis
Air_Month	0.00031*	ANOVA
Air_7Day	0.14	ANOVA

sediment size was not different between this and the other watersheds. This result was somewhat surprising because lithology that weathers to different sediment sizes was one of the driving variables that distinguished watersheds in the cluster analysis (Winters et al., 2011). Cross Creek is in the cluster that contains predominantly lithologies that weather to coarse sediment (Table 1), but it is surprising that a more significant difference was not seen between the watersheds. This lack of difference could be a result of the sampling method, which has on occasion been considered biased toward larger clasts, the location of the sampling in the stream (riffles rather than pools), or a reflection of the time of year the sampling was conducted, when higher flows had mobilized finer sediments downstream.

Variables that were significantly different between the watersheds include percent overstory density and bankfull width (Figure 16), drainage area and discharge (Figure 17), and

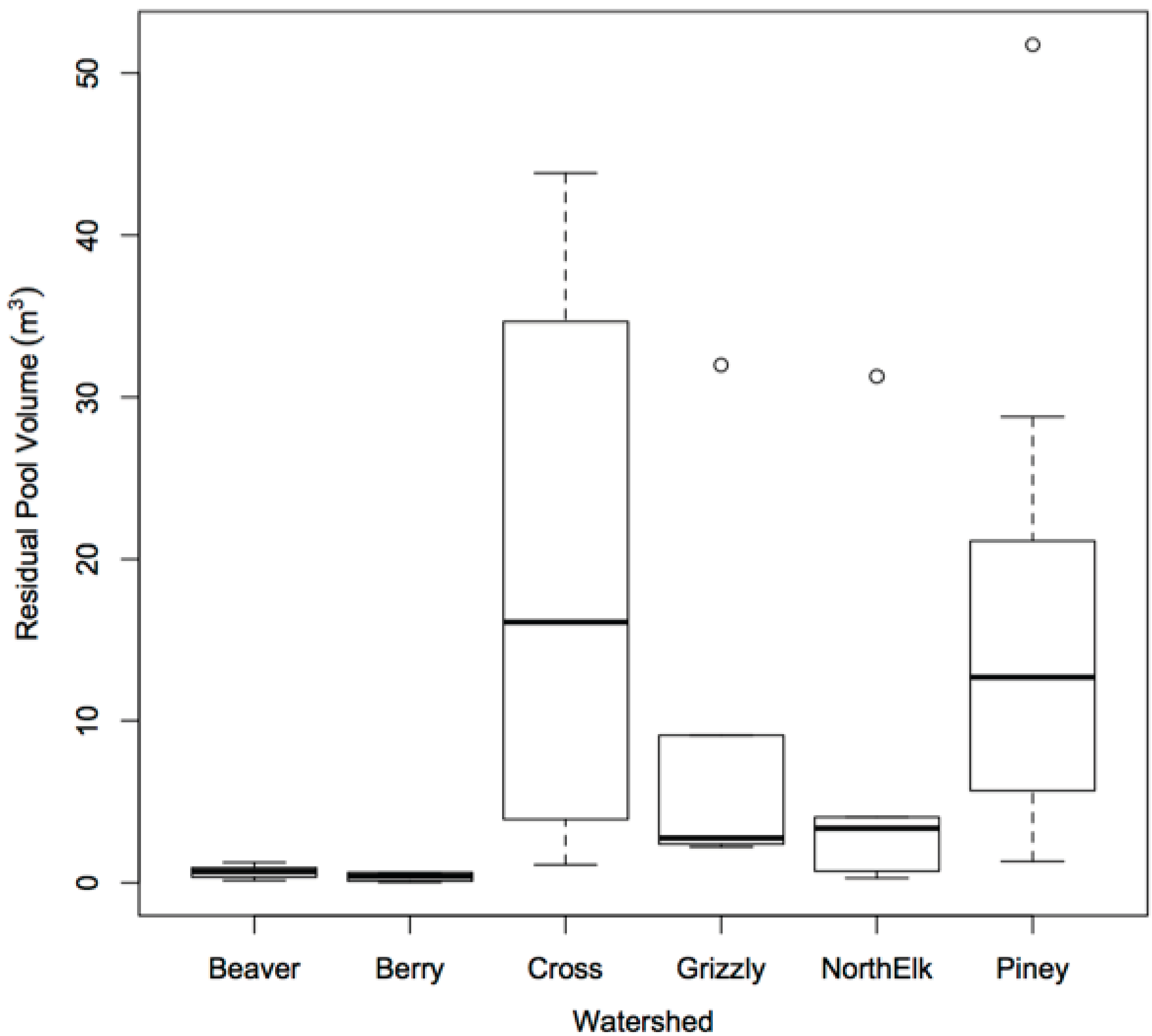

Figure 14: Boxplots of residual pool volume across the six study watersheds. The thick bar in the middle of each boxplot is the median value. The box represents the middle 50% of the data and the whiskers extend to the maximum and minimum value. Circles outside of the box-and-whiskers represent outliers. There is no significant difference in mean values for residual pool volume across the watersheds.

elevation (Figure 18). I grouped the variables this way because percent overstory density is related to bankfull width: the wider the stream is, the less that vegetation on the banks is able to shade the center of the channel. The boxplots for percent overstory density and bankfull width support this assessment because the narrowest channels have the greatest shading (Figure 16).

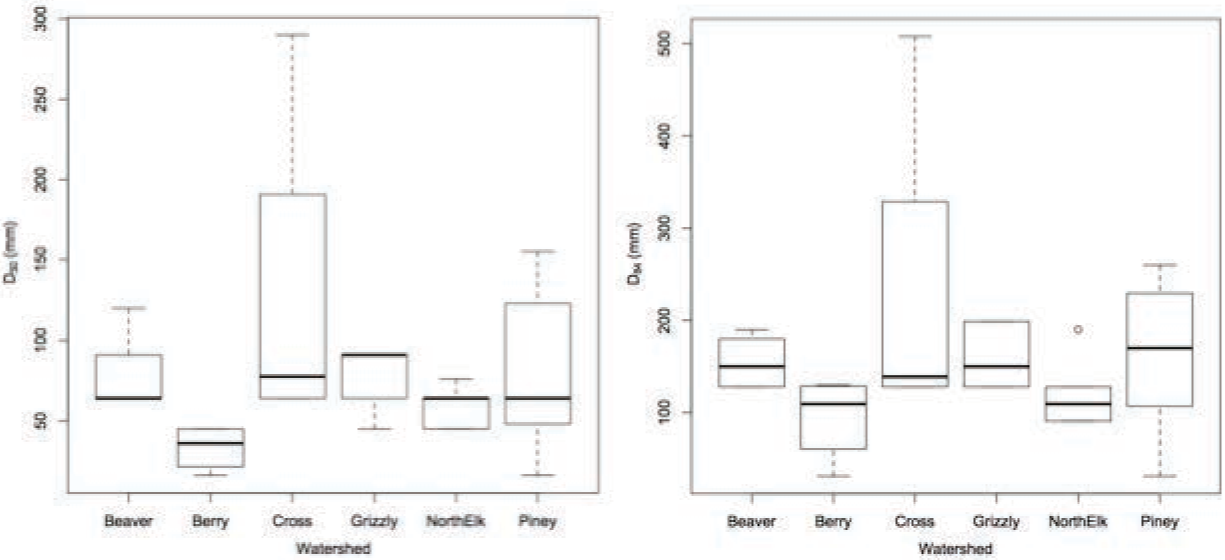

Figure 15: Boxplots of D_{50} and D_{84} bed sediment size. There was no significant difference in mean bed sediment size characteristics across the watersheds.

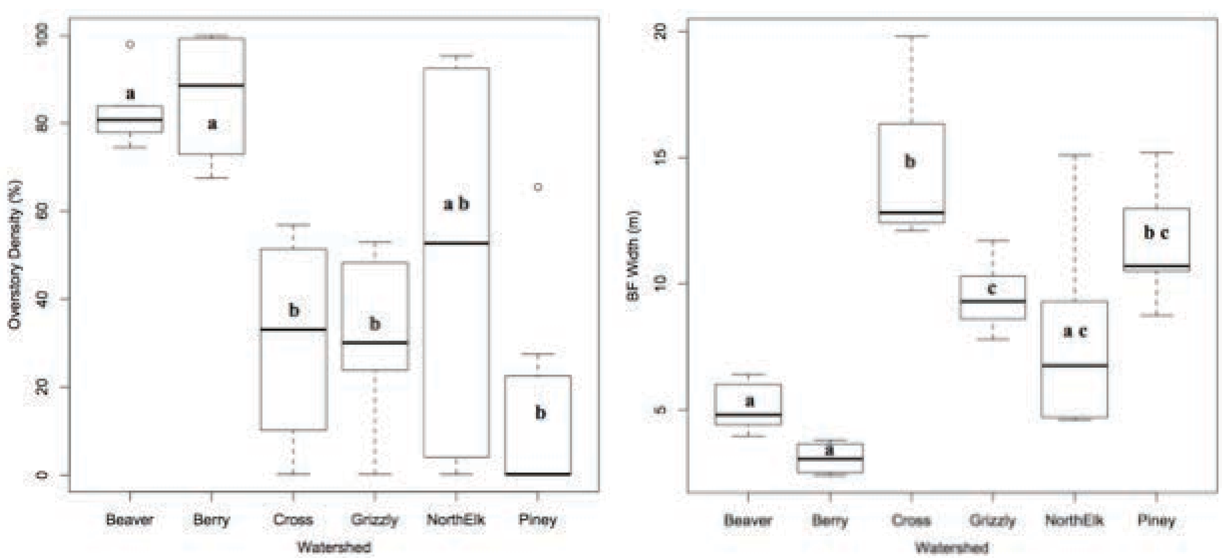

Figure 16: Boxplots of percent overstory density and bankfull width. The narrower streams have the greater percent overstory density. Boxes with the same lower case letter are statistically similar.

The smallest streams, Beaver Creek and Berry Creek, had significantly narrower cross-sections and significantly more overstory density than the largest streams. North Elk Creek, falling between the smallest and largest creeks in both width and shading, was not significantly different from either the smallest or largest creeks. If solar radiation input and local air temperature become more important parameters under future climate warming, wider streams with less shading could potentially be at greater risk for increased stream temperatures, although this conclusion seems to contrast with the findings from Figure 12 that show Berry Creek, Beaver Creek and North Elk Creek having the strongest relationship with elevation (and hence, air temperature) even though they have the greatest shading and narrowest bankfull widths. The contrast in these interpretations leads me to believe that pool volume or flow volume are more important than solar radiation and shading in modulating the air temperature/stream temperature relationship for these mountain streams (i.e., lower flow volume streams seem to have a stronger relationship with elevation and air temperature, regardless of shading). For the headwater streams in this study, local air temperature and shading were not significant explanatory variables for stream temperature, further supporting this interpretation. For streams farther from the headwaters in WRNF, the increase in local air temperature from climate change could potentially be more of a concern.

Drainage area and discharge follow similar boxplot patterns, with Beaver Creek and Berry Creek having significantly smaller drainage areas and discharges and Cross Creek having significantly larger drainage area and discharge (Figure 17). Grizzly Creek, North Elk Creek and Upper Piney River fall somewhere between these extremes. Grizzly Creek is an interesting case, as it has a comparatively small drainage area relative to its discharge. This could be an indication that Grizzly Creek has substantial flow contribution from groundwater sources, which is a reasonable conclusion as Grizzly Creek is the only creek flowing through a predominantly calcium-carbonate-rich lithology. Because drainage area and discharge were both significant

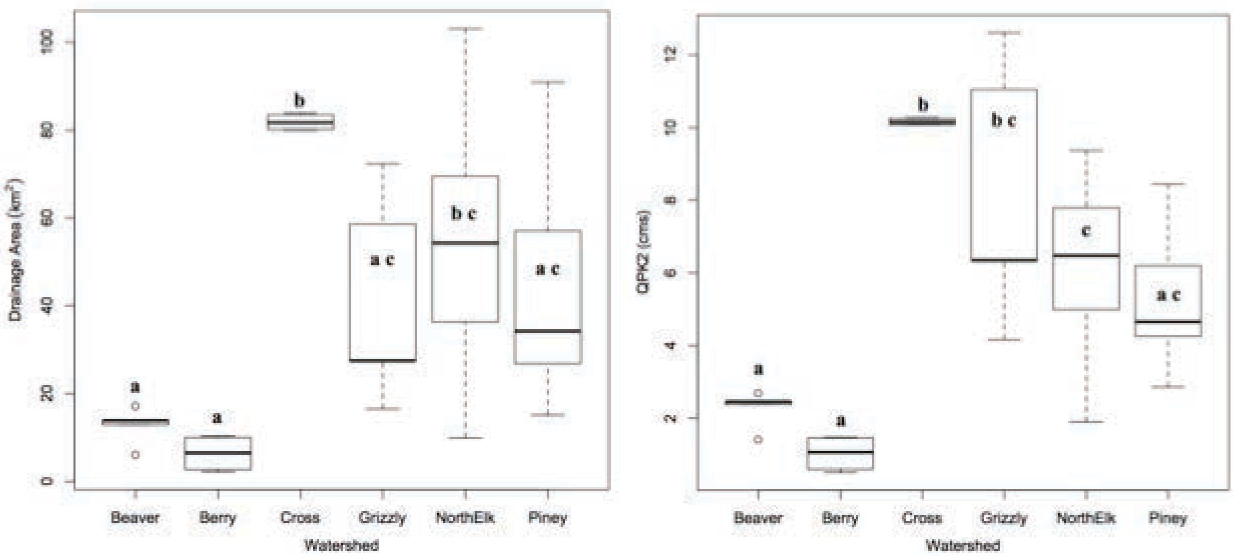

Figure 17: Boxplots of drainage area and discharge. Larger drainage areas correspond to greater discharge, although Grizzly Creek has a comparatively large discharge for the size of its drainage area.

variables in the stream temperature prediction models, with higher flows and larger drainages corresponding to cooler temperatures, those watersheds with low flow volume may be more susceptible to increases in stream temperature in future. This agrees with the conclusions derived from Figures 12 and 16. Watersheds or watershed clusters with high percentage of calcareous lithology may be somewhat buffered from changes in overland flow accumulation from reduced precipitation if they receive significant portions of their flow from groundwater sources (although reduced precipitation will also slow groundwater recharge).

North Elk Creek is the only drainage with significantly different elevation from most of the other watersheds, except Beaver Creek (Figure 18). This result is interesting, because Beaver Creek is the only watershed that falls into a cluster defined by a mixed rain and snow hydroclimatic regime, and North Elk Creek is in a cluster defined by a snow hydroclimatic regime. All the streams in my study have higher elevations as a consequence of being headwater streams in a mountainous region. The watersheds are likely to have a wider range of elevations within each cluster than are represented in my study sites because I have only included a single watershed from each cluster. North Elk Creek is likely lower in elevation than many of the other watersheds that make up the cluster to which it belongs. Boxplots of additional variables are available in Appendix F.

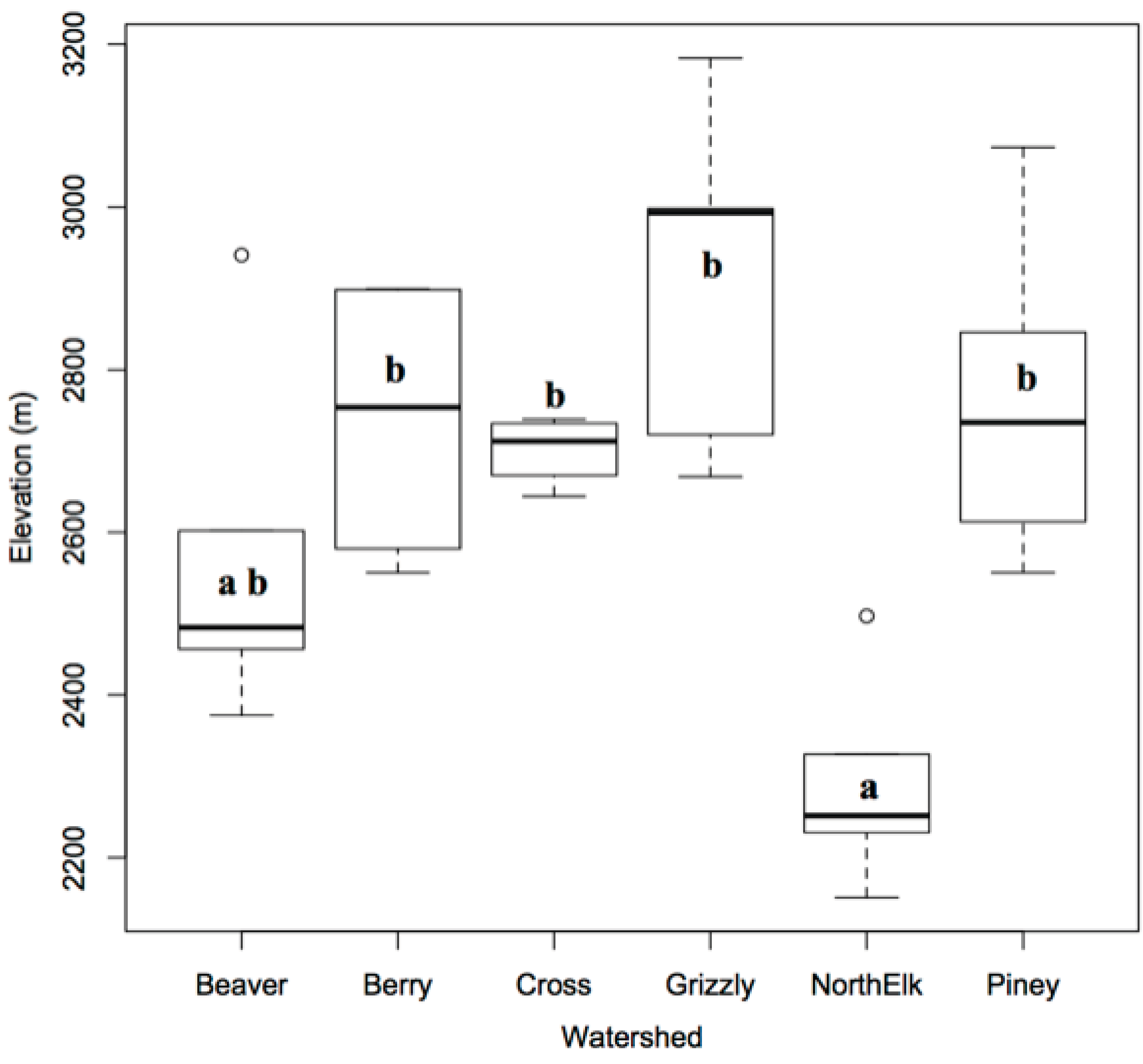

Figure 18: Boxplots of elevation across the six watersheds. North Elk Creek is the only watershed with significantly different elevation from all the other watersheds except Beaver Creek.

4 CONCLUSIONS

From the previous work in stream temperature modeling, I expected local air temperature to be the strongest predictor variable in the stream temperature models for WRNF. In contrast to those earlier studies, the strongest predictor variables in the models I developed were related to water or flow volume: residual pool volume, drainage area and discharge. Residual pool volume, discharge and drainage area were important predictor variables for both stream temperature metrics, although elevation and the 7-day mean air temperature metric were also significant predictor variables in the model for mean stream temperature of the warmest month. Because flow volume characteristics are influential, with cooler temperatures associated with larger flow volume, streams that receive a substantial portion of their flow from groundwater sources rather than overland flow accumulation could be buffered from stream temperature increases if mountain precipitation is reduced, as is expected in a warming climate (Mote et al., 2005). Downstream trends in increasing stream temperature can be seen in mountain headwater streams, although the trend may be interrupted or altered by tributary influence and changes in riparian shading between reaches.

For mountain headwater streams, air temperature may not be as significant as geomorphic and stream flow variables for predicting stream temperatures because of the reduced length of stream exposed to solar radiation. Particularly in natural or reference condition headwater streams, where riparian vegetation has not been disturbed and provides shading for these narrow mountain channels, the flow volume and channel morphology play a greater role in controlling the stream temperature. To maintain the cool temperatures that provide refuges for thermally threatened taxa, management policies that protect the riparian corridor and maintain complex pool-forming stream morphologies should be a priority.

For cold-water fish, climate warming poses a threat to their already diminished habitat. For subspecies like CRCT, whose current range is fragmented not only by thermal conditions but also by competition with nonnative species and other anthropogenic factors, models can help identify places where habitat connectivity can be restored in least anthropogenically influenced streams if competition with nonnative species can be eliminated. If climate change increases temperatures to the point that these fishes are limited to headwater streams, not just by competition and human impacts, but also by thermal limitations, the fragmented populations will be at greater risk of extirpation. There is an opportunity now to help reduce fragmentation by identifying locations farther downstream in watersheds that still have the appropriate summer thermal regime, and that allow connectivity between headwater stream populations. All the sites included in my study are well within the thermal tolerance limits for CRCT, even with an increase of 2° C in stream temperatures, and reintroducing the native fish to these locations could potentially help make the fragmented and threatened populations more robust and better able to weather future climate changes and disturbances. The conclusions from this study could potentially apply to management opportunities for other, native cold-water fish such as other cutthroat trout subspecies or other salmonids that face competition and human influences, as well as climate pressures.

4.1 Future Work

Many studies have found that, for predicting stream temperatures across a basin, rather than at a single site, spatial models are better able to capture the variability in stream temperature, as well as make more accurate point predictions for stream temperature. The reduction in error in these models comes from accounting for the spatial autocorrelation that exists in stream networks and stream temperature data. Beneficial future work would include the development of a spatial model for predicting the same summer stream metrics used in this study across the WRNF. I recommend further data collection in at least one additional drainage for each of the watershed clusters within the forest to better capture the sensitivity of specific watershed clusters to changes in variables driving stream temperature. An effort to include more drainages with calcareous lithology in the data collection would allow for a comparison of a model created for drainages with greater groundwater influence (calcareous lithology) with a model created for predominantly overland flow drainages (non-calcareous lithology) to investigate the relative importance of the possible driving variables between watersheds with those distinct lithologies and whether one is more susceptible than the other to future climate changes. A longer-term dataset, that spans at least five years, would also aid in developing a stronger multiple linear regression model for more average conditions than could be represented with the limited data collected for this thesis. A dataset that is both spatially and temporally larger will likely improve predictive models because of the increase in information.

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6 APPENDICES

6.1 Appendix A: Model assumption diagnostic plots and test results

Table 7: Shapiro-Wilk tests of normality for original and transformed variables. Significant p-values* at α = 0.05 indicate the variable is non-normal.

Variable	P-value
D50_mm	4.7e-06*
D84_mm	1.9e-05*
Slope	2.1e-07*
W_Dmax	0.24
W_Dmean	0.003*
BF_Width	0.28
ResPoolVol	9.7e-07*
Overstory_Density	0.0028*
Elevation	0.89
Valley_Aspect	0.0036*
Valley_ChannelW	0.031*
Drainage_AreaKM	0.0064*
QPK2_cms	0.087
Air_Month	0.32
Air_7Day	0.011*
logD50	0.043
logD84	0.0059*
logSlope	0.21
logW_Dmean	0.20
logPoolVol	0.62
logOver	1.3e-06*
logAspect	0.00022*
logVCW	0.67
logDA	0.040*
logAir7	0.067
SQRTOver	0.00063*
SQRTAspect	0.0019*
SQRTDA	0.082

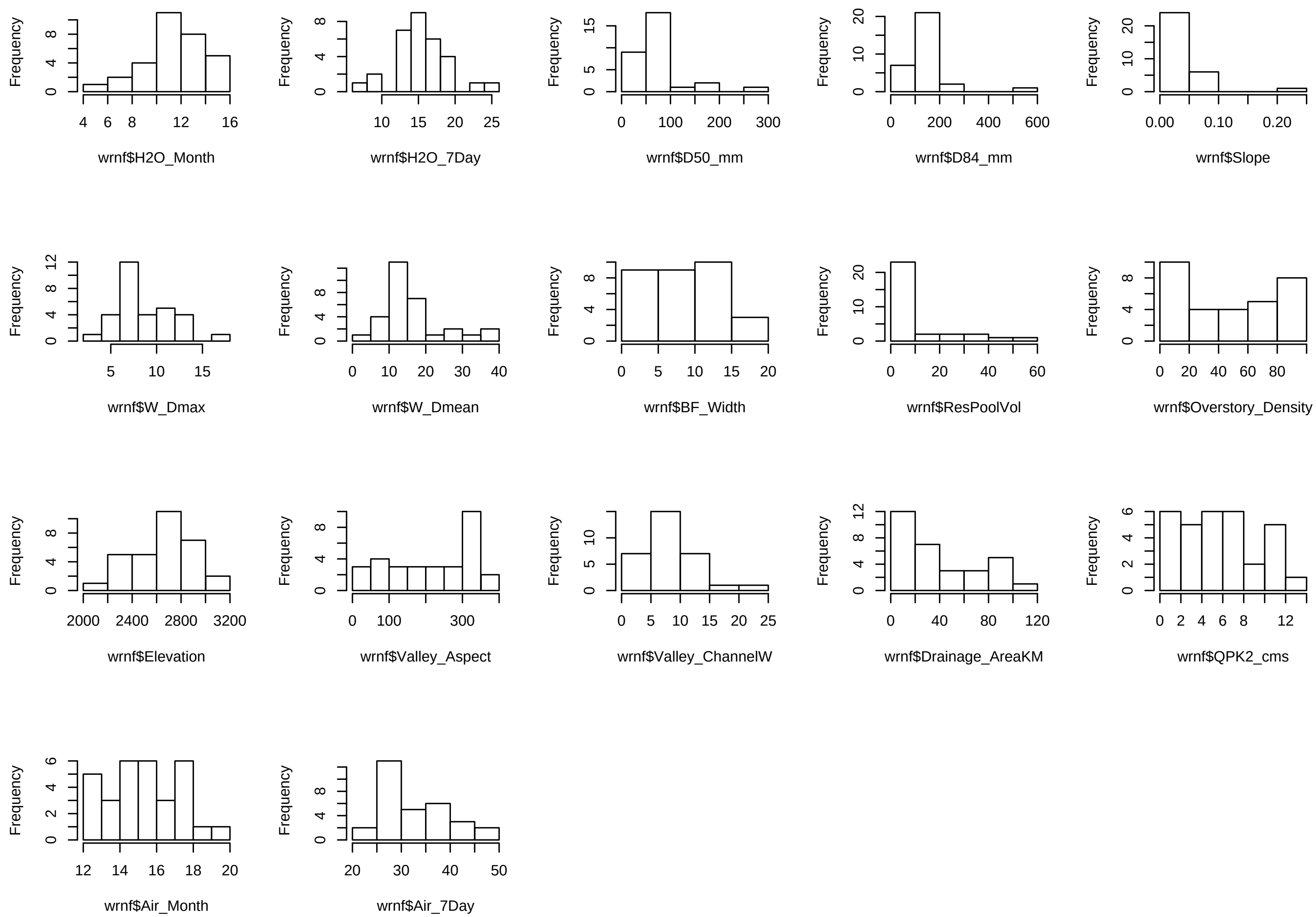

Figure 19: Histograms of the original, untransformed variables to check normality.

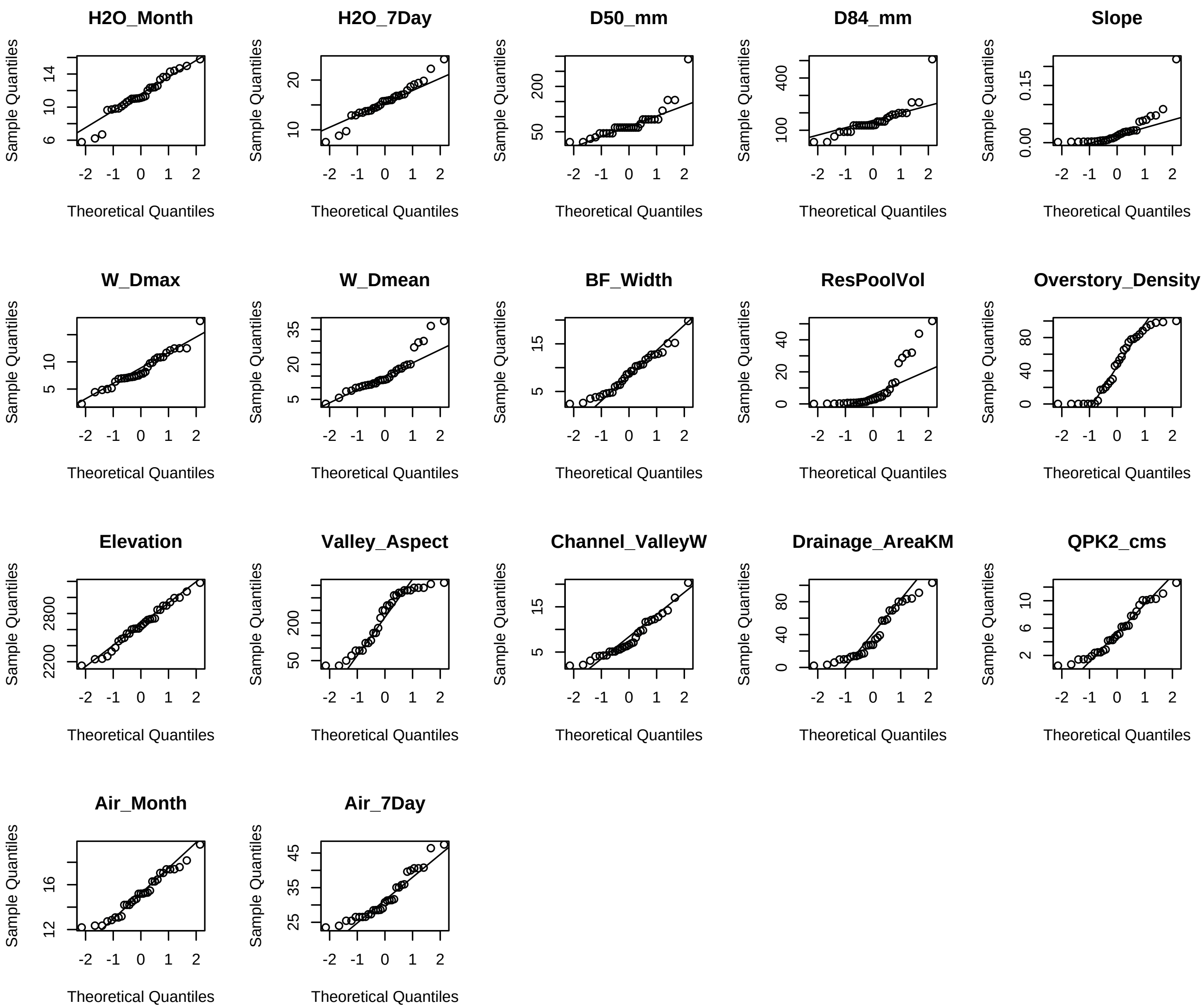

Figure 20: QQ plots of the original, untransformed variables to check normality.

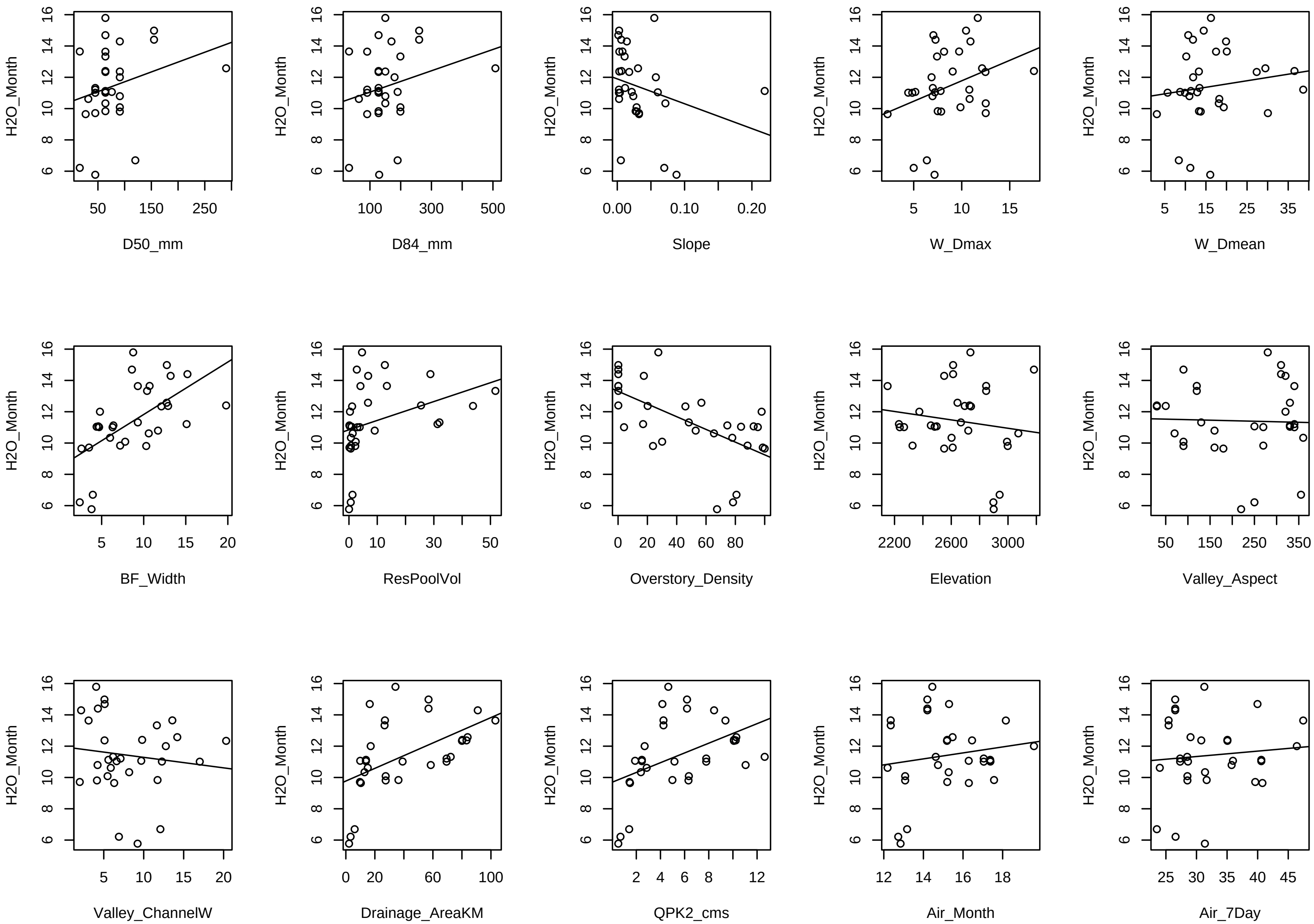

Figure 21: Scatterplots between the original variables and H2O_Month to check linearity.

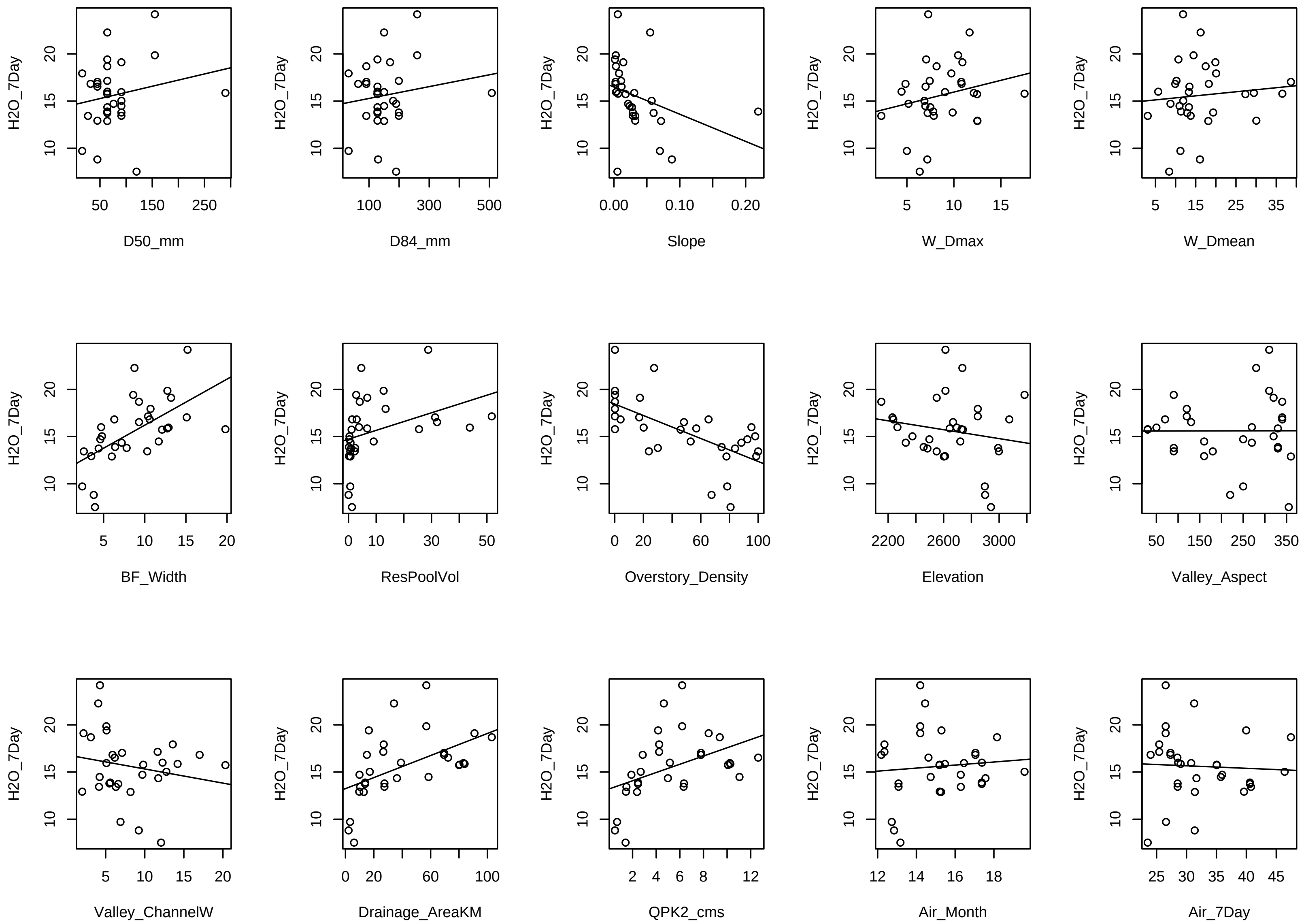

Figure 22: Scatterplots between the original variables and H2O_7Day to check linearity.

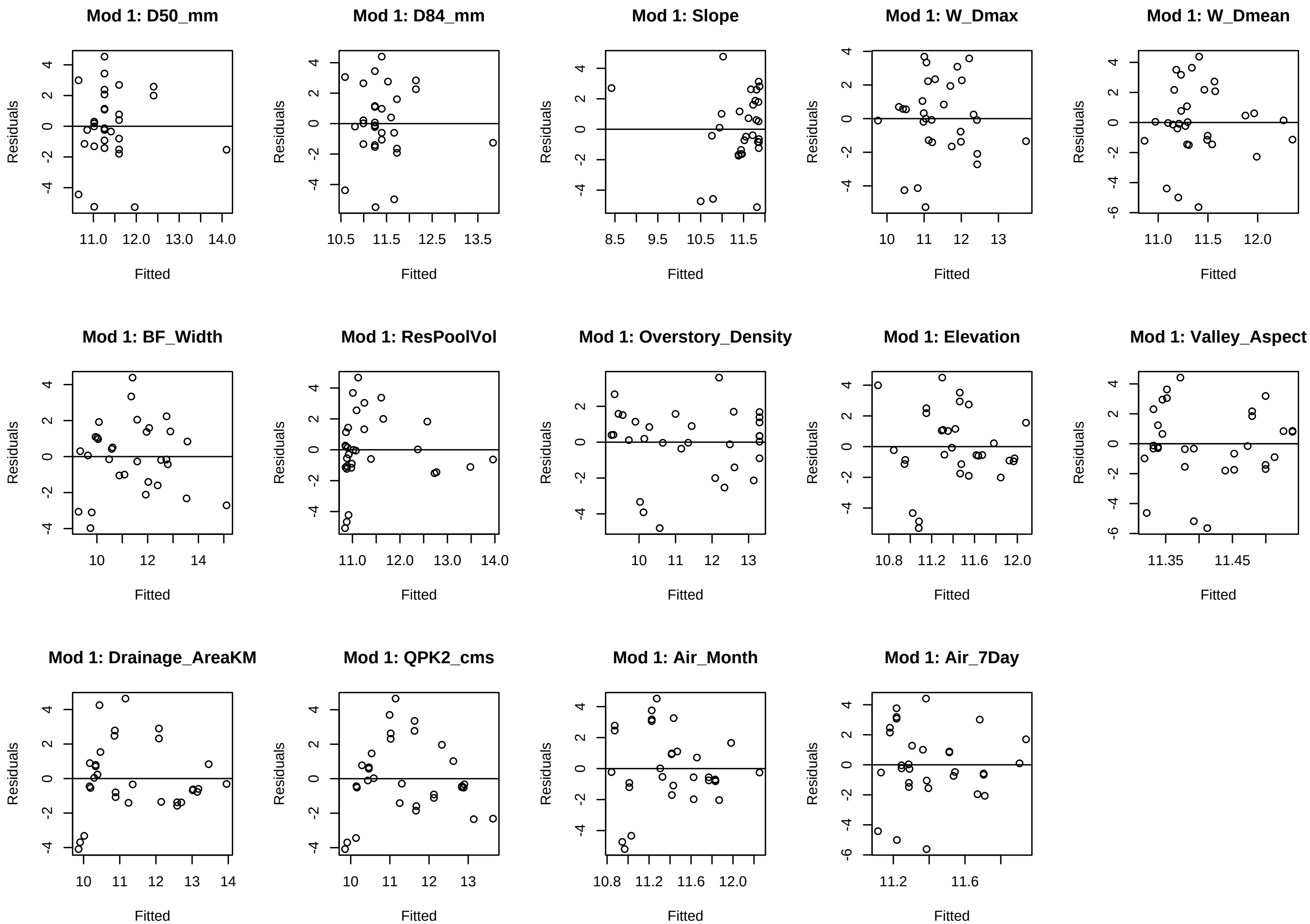

Figure 23: Residual versus predicted values for simple linear regressions between the original variables and H2O_Month to check homoscedasticity of variance.

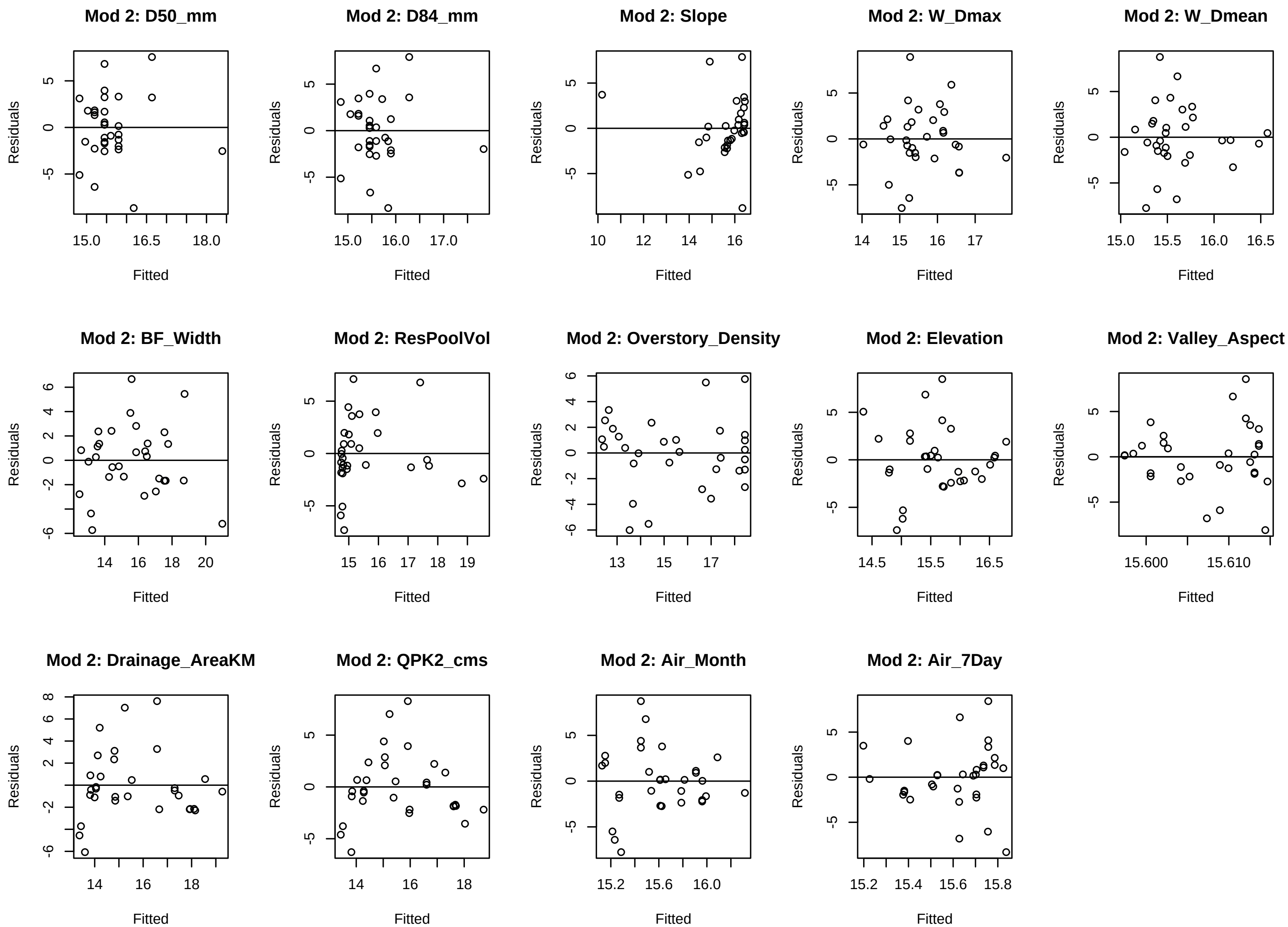

Figure 24: Residual versus predicted values for simple linear regressions between the original variables and H2O_7Day to check homoscedasticity of variance.

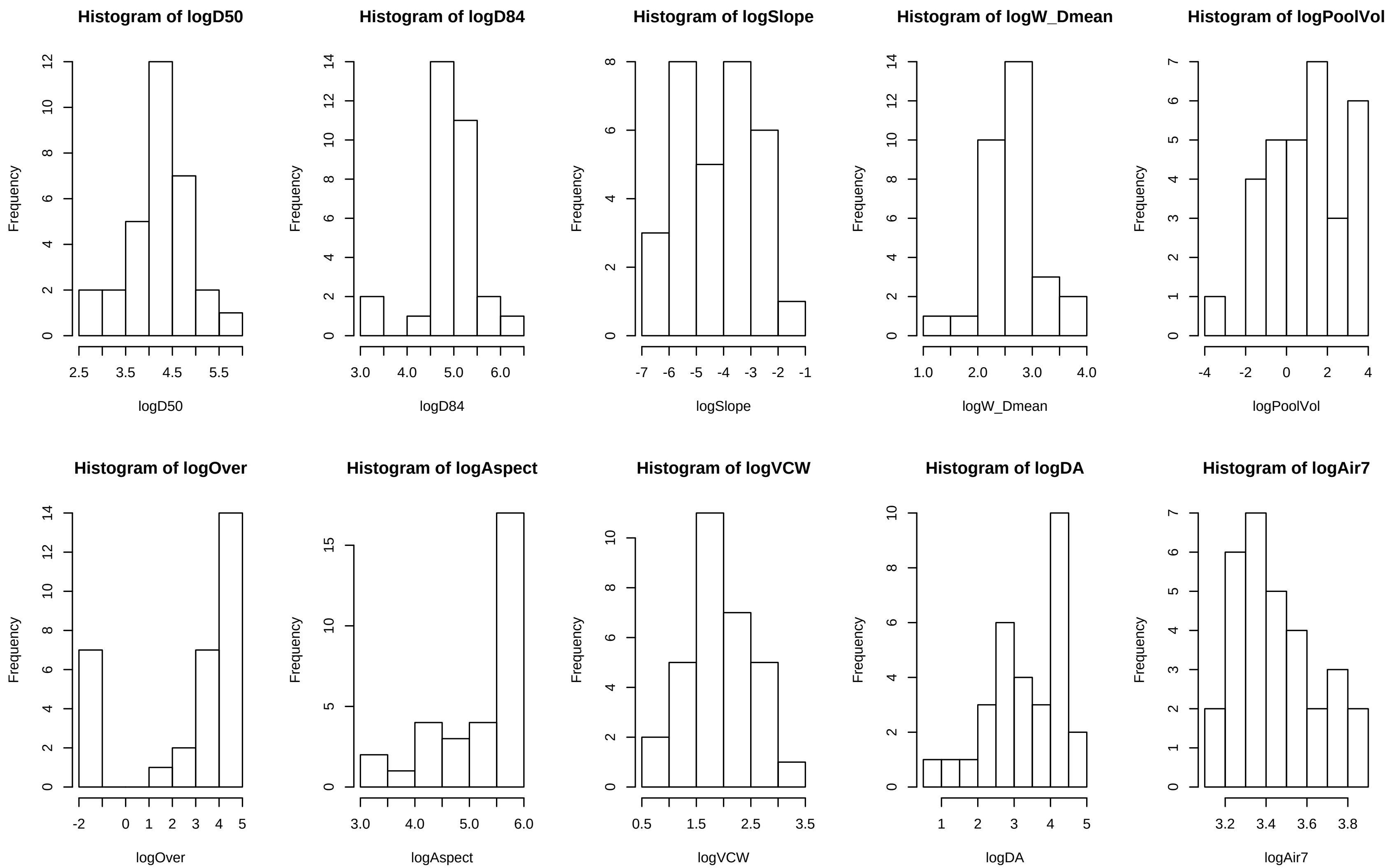

Figure 25: Histograms of the log transformed variables to check for normality after the transformation.

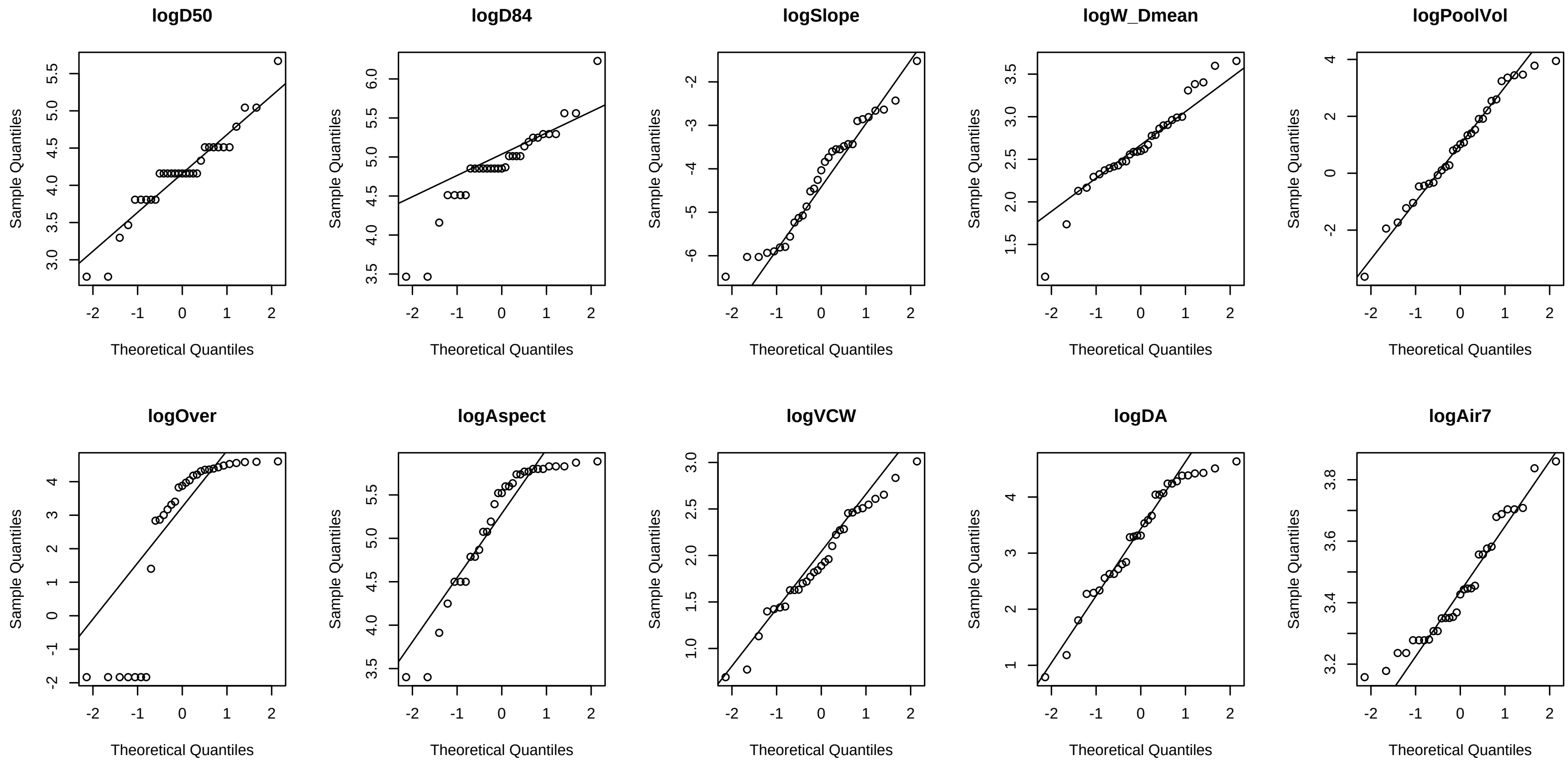

Figure 26: QQ plots of the log transformed variables to check for normality after the transformation.

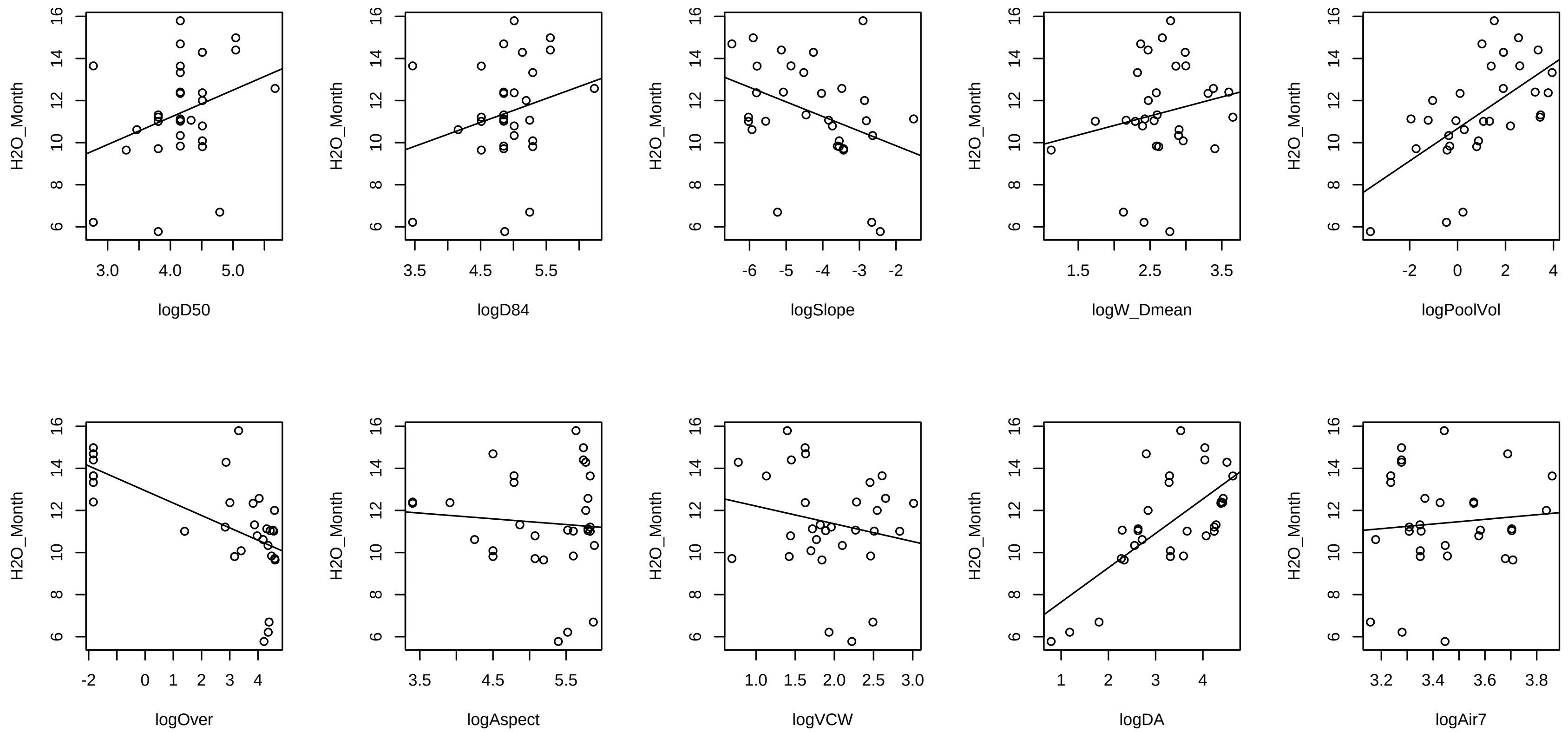

Figure 27: Scatterplots between the log transformed variables and H2O_Month to check for linearity.

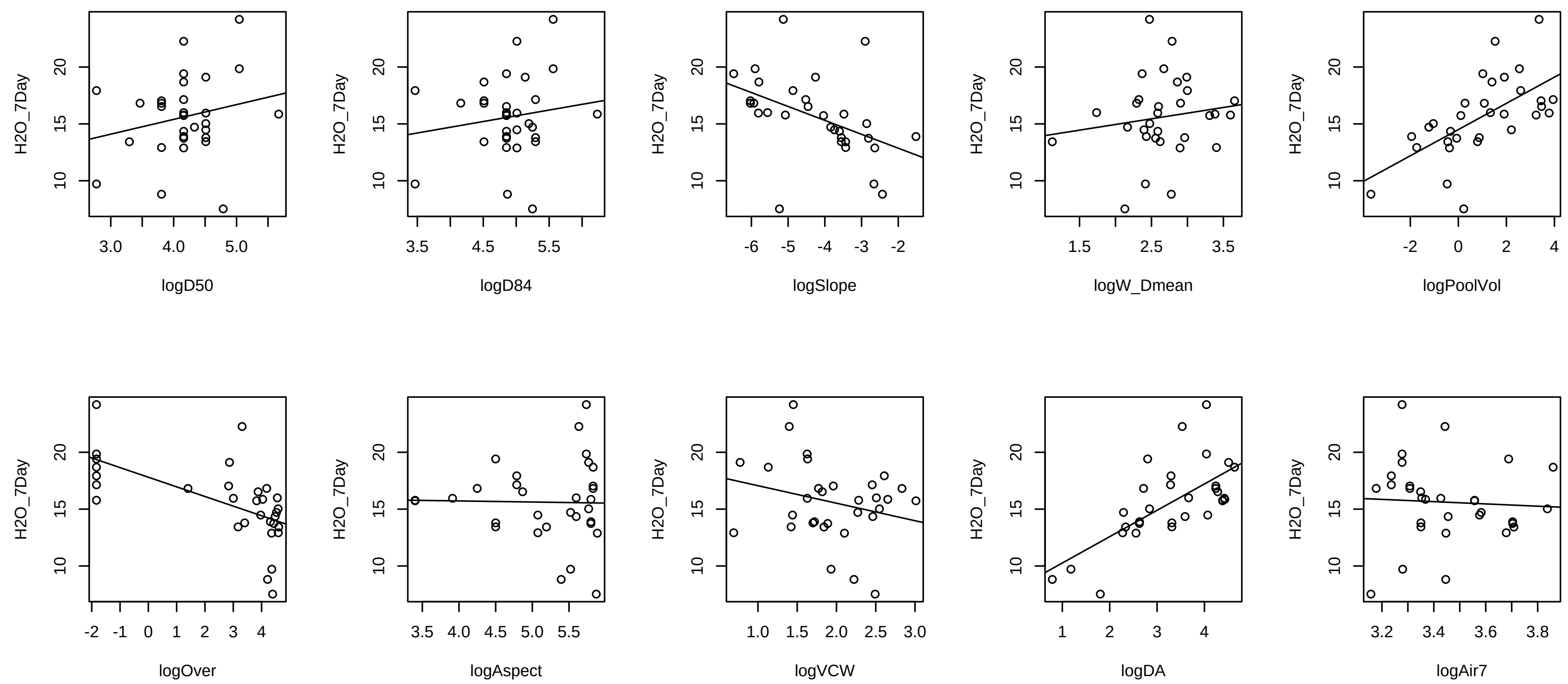

Figure 28: Scatterplots between the log transformed variables and H2O_7Day to check for linearity.

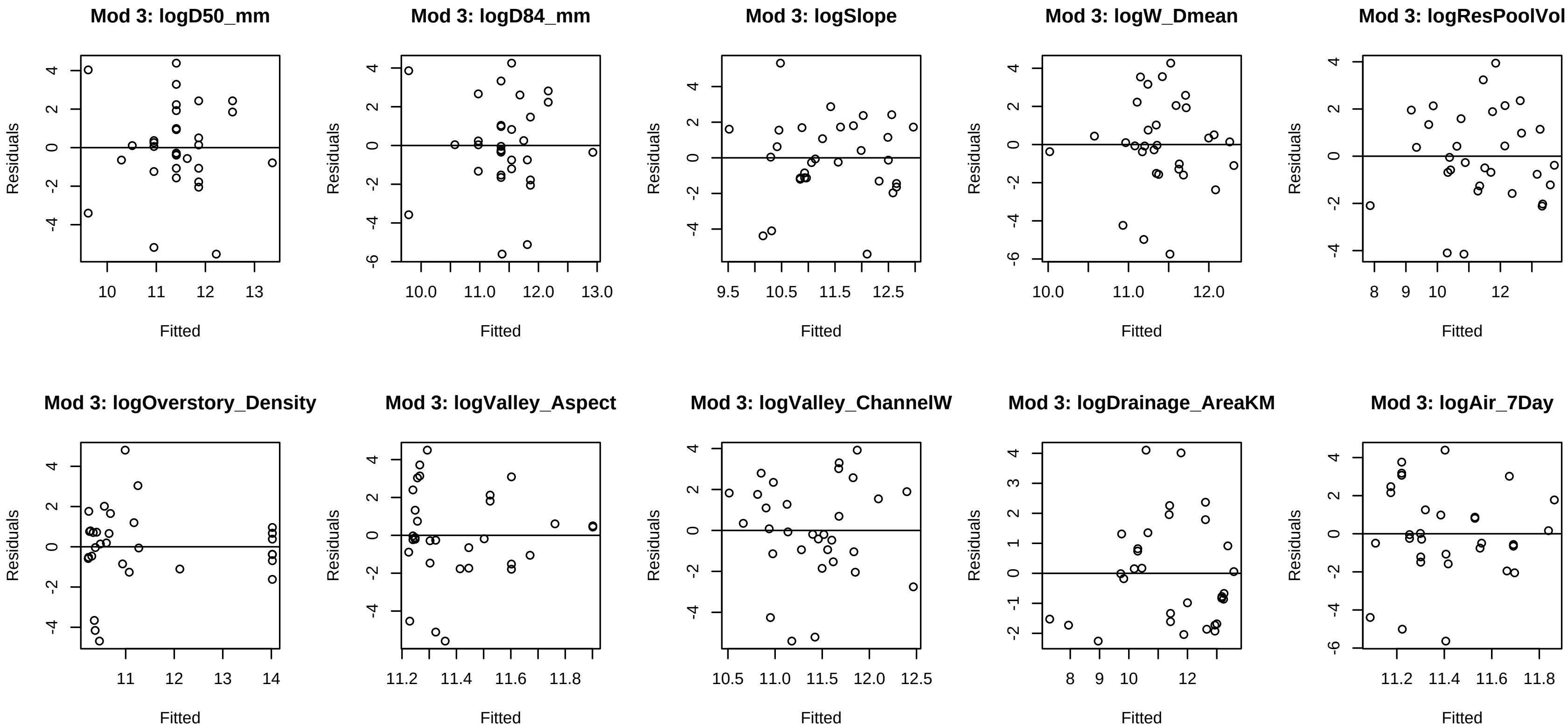

Figure 29: Residual versus predicted values for simple linear regressions between the log transformed variables and H2O_Month to check for homoscedasticity of variance.

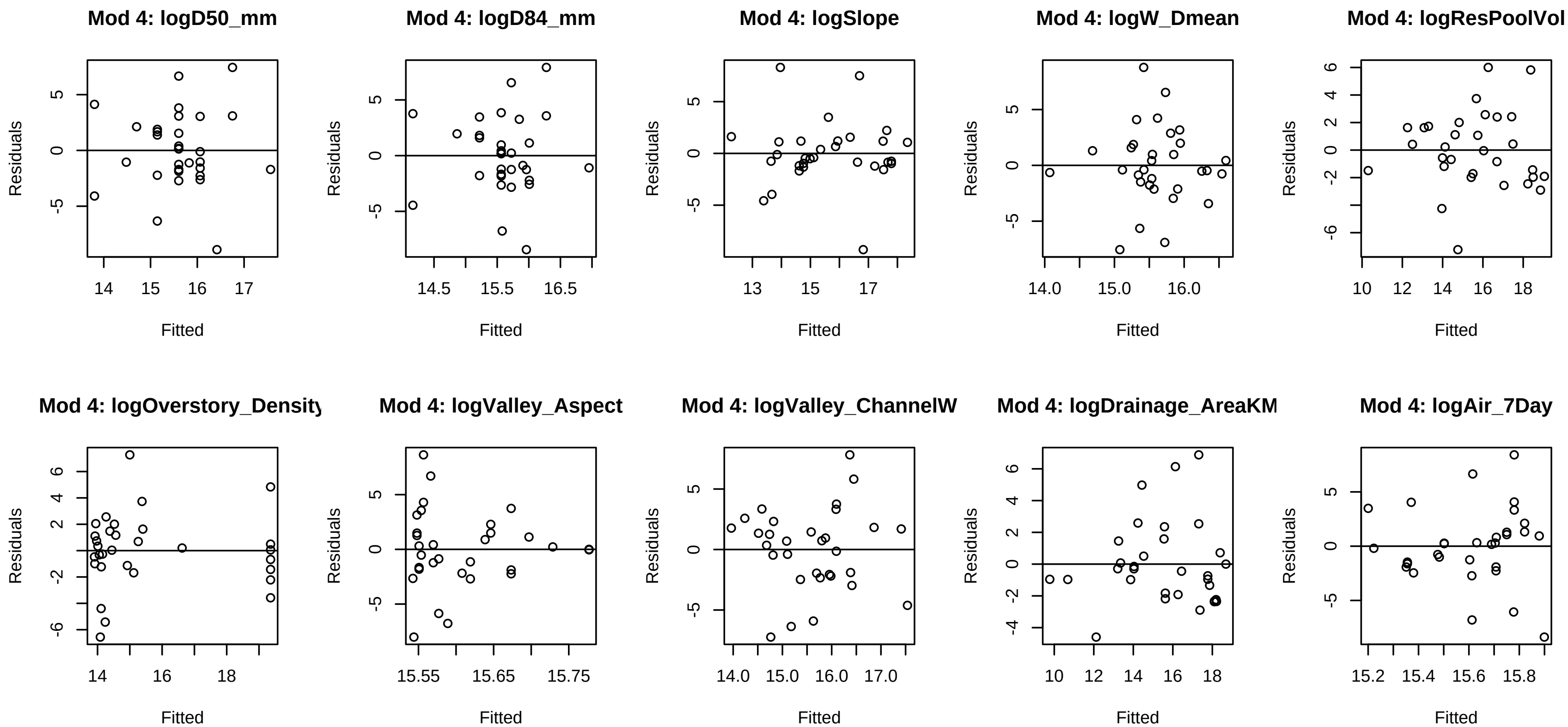

Figure 30: Residual versus predicted values for simple linear regressions between the log transformed variables and H2O_7Day to check for homoscedasticity of variance.

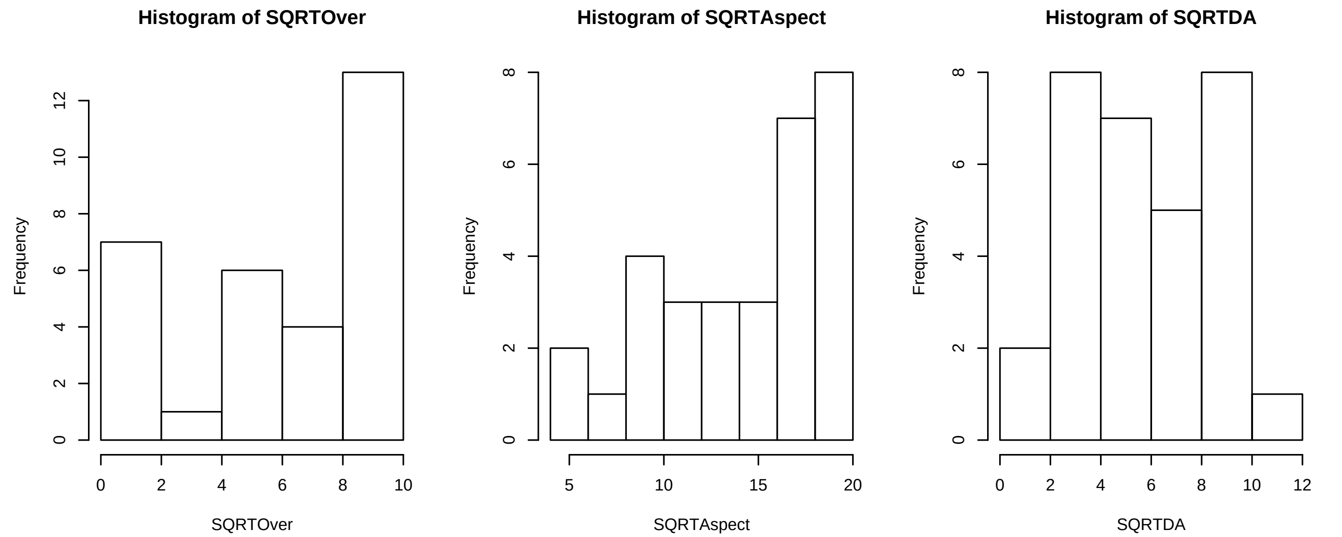

Figure 31: Histograms of the square root transformed variables to check for normality after the transformation.

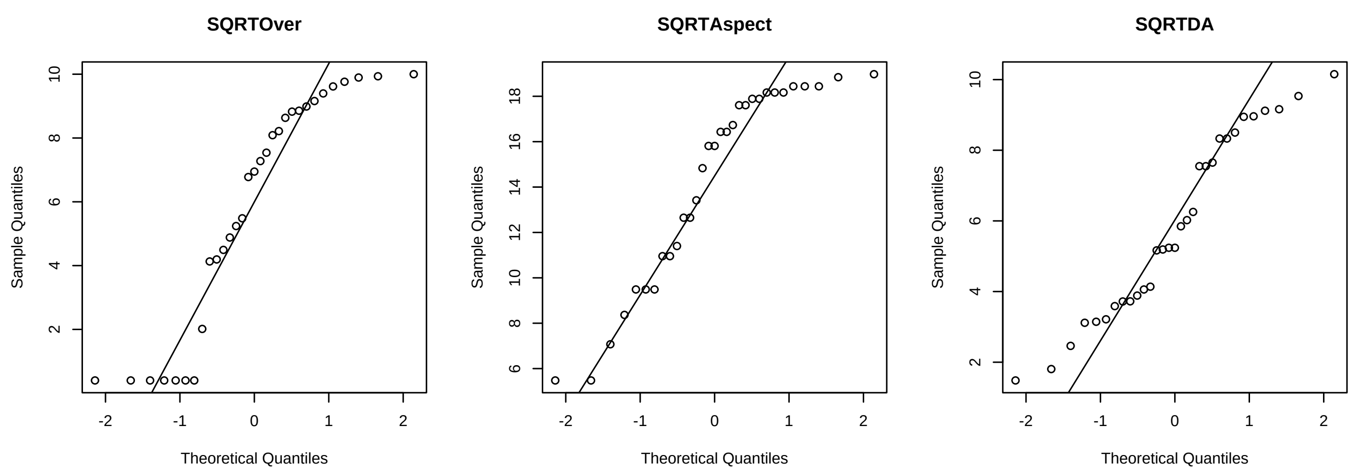

Figure 32: QQ plots of the square root transformed variables to check for normality after the transformation.

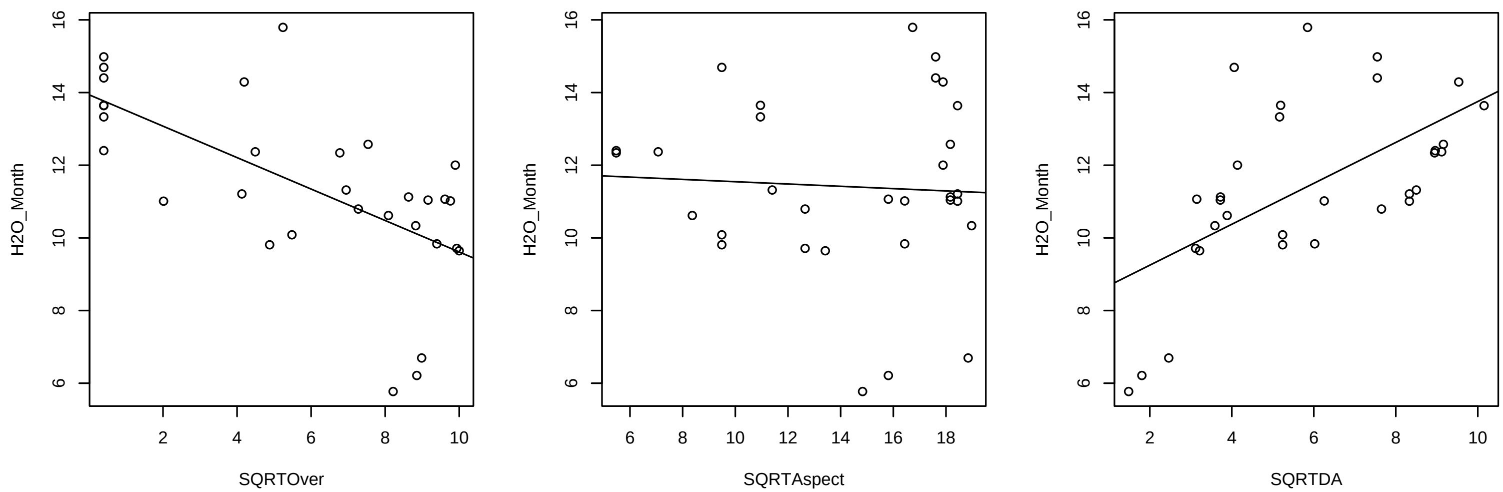

Figure 33: Scatterplots between the square root transformed variables and H2O_Month to check linearity.

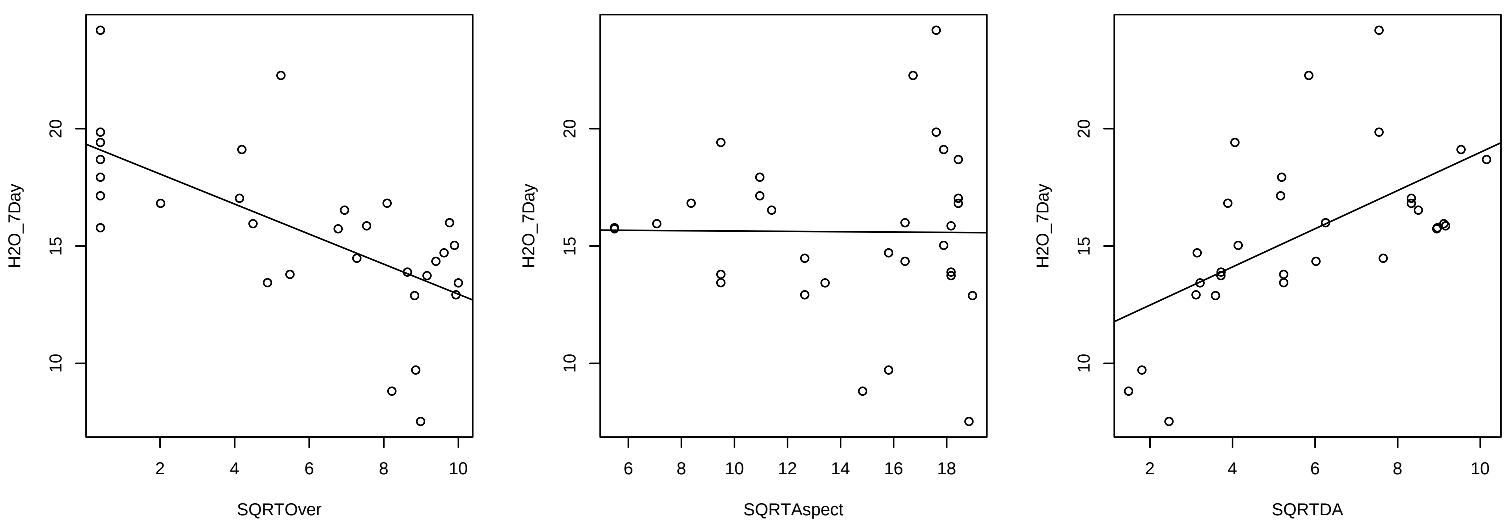

Figure 34: Scatterplots between the square root transformed variables and H2O_7Day to check linearity.

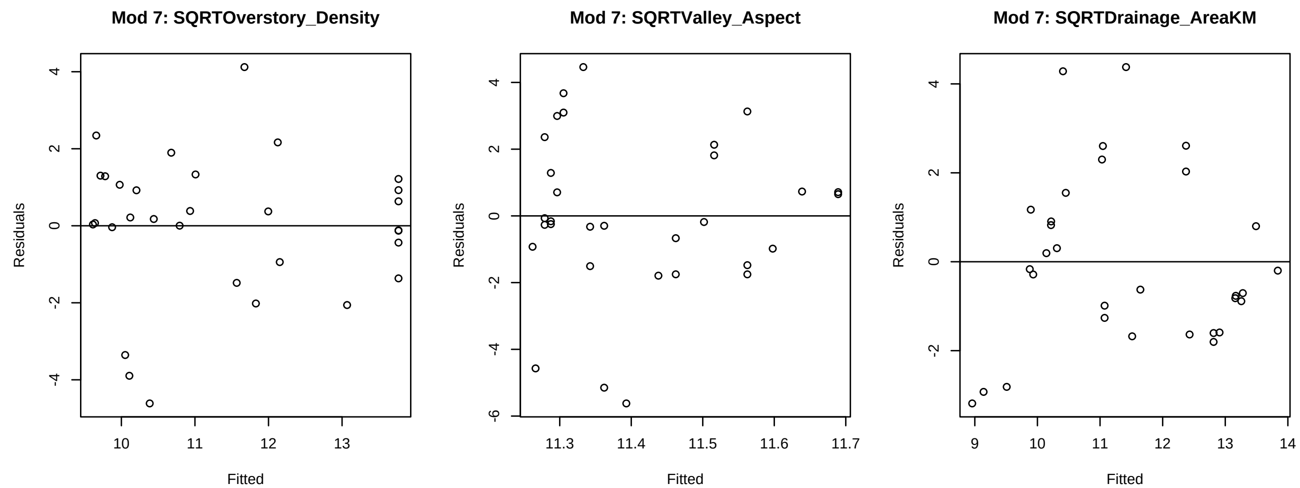

Figure 35: Residual versus predicted values for simple linear regressions between the square root transformed variables and H2O_Month to check for homoscedasticity of variance.

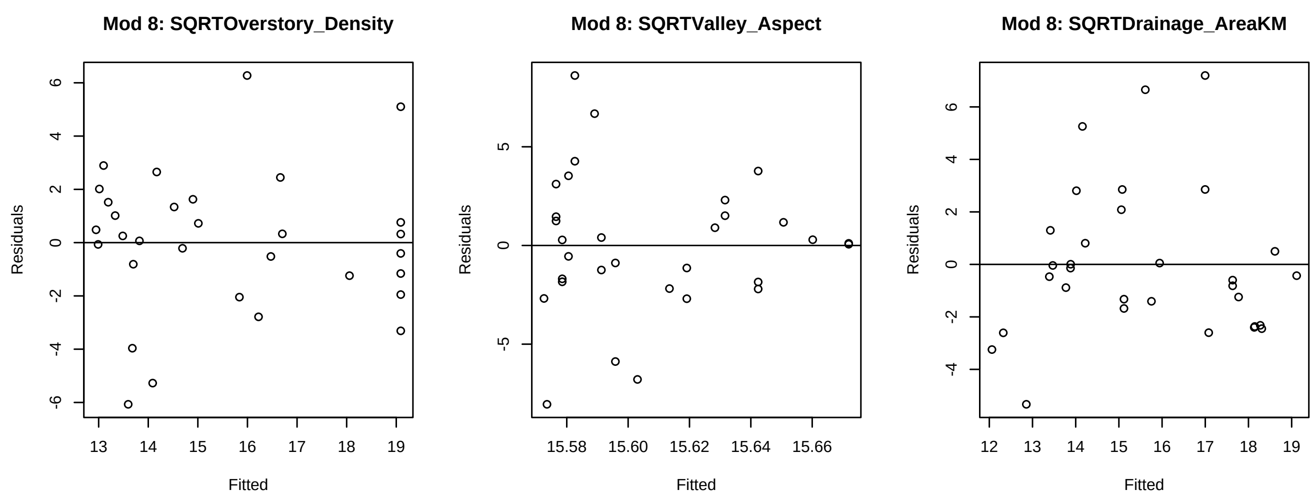

Figure 36: Residual versus predicted values for simple linear regressions between the square root transformed variables and H2O_7Day to check for homoscedasticity of variance.

6.2 Appendix B: Original dataset of field and GIS data

Site No.	Site Name	UTM_X	UTM_Y	Mean Monthly Stream Pool Temp (°C)	7-Day Stream Pool Temp (°C)	D_{50} (mm)	D_{84} (mm)	Slope
1	Beaver Creek 1	255850	4363446	6.70	7.53	120	190	0.00532
2	Beaver Creek 2	256717	4366619	10.34	12.89	64	150	0.0715
4	Beaver Creek 4	256616	4367511	11.04	13.74	64	128	0.0602
5	Beaver Creek 4.5	256591	4367557	11.13	13.89	64	128	0.219
6	Beaver Creek 5	256300	4368699	12.00	15.03	91	180	0.0573
7	Berry Creek 1	365375	4393796	9.65	13.43	27	91	0.0323
8	Berry Creek 2	365342	4394374	9.71	12.92	45	128	0.0323
10	Berry Creek 4	366480	4396708	5.77	8.82	45	130	0.088
11	Berry Creek 5	366281	4396567	6.21	9.72	16	32	0.0698
12	Cross Creek 1	376796	4377918	12.58	15.86	290	508	0.0308
13	Cross Creek 2	375852	4376911	12.34	15.73	64	128	0.0177
14	Cross Creek 2.5	375990	4376942	12.40	15.78	64	128	0.00625
15	Cross Creek 3	376317	4377515	12.37	15.95	91	150	0.003
18	Grizzly Creek 1	307697	4391112	11.32	16.53	45	128	0.0116
19	Grizzly Creek 2	306777	4393467	10.79	14.48	91	150	0.0238
22	Grizzly Creek 4	304692	4397552	9.81	13.44	91	199	0.0287
23	Grizzly Creek 4.5	304700	4397541	10.09	13.79	91	199	0.0287
24	Grizzly Creek 5	301716	4398928	14.69	19.41	64	128	0.00153
25	North Elk Creek 1	271544	4421699	13.64	18.69	64	91	0.00304
27	North Elk Creek 2	275749	4417163	11.07	14.71	76	190	0.0215
28	North Elk Creek 3	274166	4416632	9.84	14.35	64	128	0.0273
29	North Elk Creek 4	272868	4417026	11.02	15.99	64	128	0.00385
30	North Elk Creek 5	272296	4417654	11.01	16.82	45	91	0.00241
31	North Elk Creek 5.5	272322	4417664	11.21	17.03	45	91	0.00241
32	Upper Piney River 1	380987	4398268	13.33	17.14	64	199	0.0109
33	Upper Piney River 1.5	380840	4398192	13.65	17.93	16	32	0.00769
34	Upper Piney River 2	376698	4396481	15.79	22.27	64	150	0.055
35	Upper Piney River 3	374707	4399556	14.29	19.11	91	170	0.0142
36	Upper Piney River 4	375590	4397454	14.98	19.85	155	260	0.00274
37	Upper Piney River 4.5	375590	4397454	14.40	24.19	155	260	0.00591
38	Upper Piney River 5	384251	4399261	10.62	16.82	32	64	0.00265

Site Name	W/Dmax	W/Dmean	BF Width (m)	Residual Pool Volume (m^3)	Overstory Density (%)	Riparian Veg. Type	Elevation (m)	Valley Aspect (°)	V/C Width
Beaver Creek 1	6.37	8.41	3.95	1.251	80.76	coniferous	2941	355	12.1
Beaver Creek 2	12.50	18.13	6	0.691	77.9	coniferous	2602	0	8.2
Beaver Creek 4	7.21	12.90	4.4	0.934	83.88	willow	2483	330	6.6
Beaver Creek 4.5	7.80	11.34	6.4	0.143	74.52	willow	2456	330	5.6
Beaver Creek 5	6.86	11.89	4.8	0.353	97.92	willow	2375	320	12.8
Berry Creek 1	2.28	3.07	2.6	0.645	100	willow	2550	180	6.3
Berry Creek 2	12.50	30.06	3.50	0.177	98.7	willow	2610	160	2.0
Berry Creek 4	7.17	16.05	3.8	0.0263	67.5	conif/grass	2899	220	9.2
Berry Creek 5	5.00	11.20	2.4	0.628	78.42	conif/grass	2897	250	6.9
Cross Creek 1	12.12	29.45	12.73	6.73	56.84	coniferous	2644	330	14.2
Cross Creek 2	12.47	27.34	12.1	1.11	45.92	coniferous	2739	30	20.3
Cross Creek 2.5	17.52	36.52	19.8	25.47	0.16	conif/grass	2729	30	9.8
Cross Creek 3	9.06	13.29	12.9	43.84	20.18	grass/sedge	2695	50	5.1
Grizzly Creek 1	6.99	13.44	9.3	31.99	48.26	conif/grass	2668	130	6.2
Grizzly Creek 2	6.96	10.98	11.7	9.1	52.94	coniferous	2720	160	4.2
Grizzly Creek 4	7.86	13.74	10.3	2.22	23.82	willow/conif	2998	90	4.1
Grizzly Creek 4.5	9.87	19.33	7.8	2.39	30.06	willow/conif	2993	90	5.5
Grizzly Creek 5	7.05	10.70	8.6	2.77	0.16	willow	3183	90	5.1
North Elk Creek 1	8.16	17.46	9.3	4.06	0.16	grass/sedge	2151	340	3.1
North Elk Creek 2	5.17	8.73	4.6	0.293	92.46	willow/conif	2497	250	9.7
North Elk Creek 3	7.50	13.31	7.2	0.721	88.3	conif/grass	2327	270	11.7
North Elk Creek 4	4.43	5.68	4.7	3.797	95.32	coniferous	2267	270	12.3
North Elk Creek 5	4.85	9.91	6.3	2.95	4.06	grass/sedge	2237	340	17.0
North Elk Creek 5.5	10.79	38.65	15.1	31.29	17.06	grass/sedge	2231	340	7.1
Up. Piney River 1	7.43	10.22	10.4	51.76	0.16	grass/willow	2846	120	11.6
Up. Piney River 1.5	9.73	20.07	10.7	13.4	0.16	grass/willow	2846	120	13.6
Up. Piney River 2	11.67	16.22	8.75	4.62	27.46	grass/sedge	2735	280	4.1
Up. Piney River 3	10.91	19.89	13.2	6.786	17.58	willow/conif	2550	320	2.2
Up. Piney River 4	10.45	14.46	12.75	12.69	0.16	willow	2613	310	5.1
Up. Piney River 4.5	7.27	11.85	15.2	28.79	0.16	grass/sedge	2613	310	4.3
Up. Piney River 5	10.82	18.25	10.6	1.32	65.42	conif/grass	3073	70	5.9

Site Name	Drainage Area (km^2)	QPK2 (cms)	MM Air Temp (°C)	7-Day Air Temp (°C)	PRISM July Max (°C)	PRISM July Mean (°C)	PRISM Annual Max (°C)	PRISM Annual Mean (°C)
Beaver Creek 1	6.06	1.41	13.18	23.52	20.15	14.07	7.55	1.33
Beaver Creek 2	12.87	2.38	15.28	31.39	22.29	15.66	9.84	3.78
Beaver Creek 4	13.83	2.46	17.37	40.59	22.29	15.66	9.84	3.78
Beaver Creek 4.5	13.86	2.46	17.37	40.59	24.45	17.85	11.09	5.42
Beaver Creek 5	17.12	2.69	19.58	46.40	25.70	18.41	12.18	5.93
Berry Creek 1	10.33	1.48	16.29	40.78	24.34	16.06	11.27	4.21
Berry Creek 2	9.71	1.44	15.20	39.61	23.29	15.98	10.79	4.29
Berry Creek 4	2.20	0.51	12.85	31.37	21.95	14.66	9.21	2.89
Berry Creek 5	3.26	0.69	12.73	26.58	22.83	15.62	10.18	3.85
Cross Creek 1	83.92	10.28	15.47	29.02	24.25	15.01	11.27	3.34
Cross Creek 2	80.03	10.08	15.19	35.05	23.58	14.51	10.53	2.78
Cross Creek 2.5	80.29	10.08	15.20	35.05	23.58	14.51	10.53	2.78
Cross Creek 3	83.14	10.23	16.46	30.78	23.58	14.51	10.53	2.78
Grizzly Creek 1	72.26	12.63	14.62	28.48	21.45	15.10	8.85	2.96
Grizzly Creek 2	58.53	11.05	14.74	35.74	23.09	15.69	10.58	4.03
Grizzly Creek 4	27.45	6.32	13.08	28.51	19.59	12.87	7.54	1.41
Grizzly Creek 4.5	27.45	6.35	13.08	28.51	19.59	12.87	7.54	1.41
Grizzly Creek 5	16.47	4.16	15.29	39.97	18.91	12.36	7.00	0.93
North Elk Creek 1	103.08	9.38	18.16	47.45	27.19	17.60	13.60	5.72
North Elk Creek 2	9.89	1.90	16.29	35.96	23.75	15.77	11.27	4.09
North Elk Creek 3	36.26	4.99	17.57	31.66	25.24	16.55	12.29	4.64
North Elk Creek 4	39.11	5.16	17.38	28.61	25.40	16.71	12.41	4.79
North Elk Creek 5	69.41	7.79	17.05	27.32	26.25	17.49	12.99	5.46
North Elk Creek 5.5	69.41	7.79	17.05	27.32	26.25	17.49	12.99	5.46
Up. Piney River 1	26.68	4.25	12.35	25.44	23.32	13.85	10.05	2.09
Up. Piney River 1.5	26.94	4.25	12.35	25.44	23.32	13.85	10.05	2.09
Up. Piney River 2	34.19	4.65	14.45	31.28	23.89	14.86	10.54	2.97
Up. Piney River 3	90.91	8.44	14.20	26.52	24.42	14.79	11.15	2.94
Up. Piney River 4	56.98	6.20	14.20	26.52	24.54	14.82	11.23	2.96
Up. Piney River 4.5	56.98	6.20	14.20	26.52	24.54	14.82	11.23	2.96
Up. Piney River 5	15.10	2.86	12.19	24.00	22.10	13.67	8.67	1.83

6.3 Appendix C: Summary statistics of the original field and GIS data

Watershed	# Sites n	Summary Statistic	D_{50} (mm)	D_{84} (mm)	Slope	W/Dmax	W/Dmean	BF Width (m)	Residual Pool Volume (m^3)
All	31	Mean	76.19	152.50	0.031	8.61	16.21	8.77	9.45
		Maximum	290.00	508.00	0.219	17.52	38.65	19.80	51.76
		Minimum	16.00	32.00	0.0015	2.28	3.07	2.40	0.026
		Std. Dev.	51.47	85.20	0.042	3.11	8.41	4.28	14.04
Beaver Creek	5	Mean	80.60	155.20	0.083	8.14	12.53	5.11	0.67
		Maximum	120.00	190.00	0.219	12.50	18.13	6.40	1.25
		Minimum	64.00	128.00	0.0053	6.37	8.41	3.95	0.14
		Std. Dev.	24.94	28.87	0.080	2.49	3.55	1.05	0.44
Berry Creek	4	Mean	33.25	95.25	0.055	6.74	15.10	3.08	0.37
		Maximum	45.00	130.00	0.088	12.50	30.06	3.80	0.65
		Minimum	16.00	32.00	0.032	2.28	3.07	2.40	0.026
		Std. Dev.	14.29	45.82	0.028	4.33	11.32	0.68	0.31
Cross Creek	4	Mean	127.20	228.50	0.014	12.79	26.65	14.38	19.29
		Maximum	290.00	508.00	0.031	17.52	36.52	19.80	43.84
		Minimum	64.00	128.00	0.003	9.06	13.29	12.10	1.11
		Std. Dev.	109.24	186.62	0.013	3.50	9.73	3.63	19.40
Grizzly Creek	5	Mean	76.40	160.80	0.019	7.75	13.64	9.54	9.69
		Maximum	91.00	199.00	0.029	9.87	19.33	11.70	31.99
		Minimum	45.00	128.00	0.0015	6.96	10.70	7.80	2.22
		Std. Dev.	21.09	36.01	0.012	1.24	3.47	1.52	12.79
North Elk Creek	6	Mean	59.67	119.80	0.010	6.82	15.62	7.87	7.19
		Maximum	76.00	190.00	0.027	10.79	38.65	15.10	31.29
		Minimum	45.00	91.00	0.0024	4.43	5.68	4.60	0.29
		Std. Dev.	12.27	38.86	0.011	2.46	11.98	3.95	11.91
Upper Piney River	7	Mean	82.43	162.10	0.014	9.75	15.85	11.66	17.05
		Maximum	155.00	260.00	0.055	11.67	20.07	15.20	51.76
		Minimum	16.00	32.00	0.0027	7.27	10.22	8.75	1.32
		Std. Dev.	55.14	88.78	0.018	1.74	3.87	2.17	17.71

Watershed	# Sites n		Overstory Density (%)	Elevation (m)	Valley Aspect (degrees)	V/C Width	Drainage Area (km^2)	QPK2 (cms)	Mean Monthly Air Temp (°C)	7-Day Air Temp (°C)
All	31	Mean	46.66	2651	220.80	6.61	40.4	5.50	15.17	32.13
		Maximum	100.00	3183	360.00	20.32	103.1	12.63	19.58	47.45
		Minimum	0.16	2151	30.00	2.00	2.2	0.51	12.19	23.52
		Std. Dev.	37.04	262	111.82	4.47	30.8	3.49	1.94	6.55
Beaver Creek	5	Mean	83.00	2571	339.00	9.04	12.75	2.28	16.55	36.56
		Maximum	97.92	2941	360.00	12.77	17.12	2.69	19.58	46.40
		Minimum	74.52	2375	320.00	5.58	6.06	1.41	13.18	23.52
		Std. Dev.	9.03	222	17.46	3.23	4.07	0.50	2.43	9.03
Berry Creek	4	Mean	86.16	2739	202.50	6.11	6.38	1.03	14.27	34.58
		Maximum	100.00	2899	250.00	9.23	10.33	1.48	16.29	40.78
		Minimum	67.50	2550	160.00	2.00	2.20	0.51	12.73	26.58
		Std. Dev.	15.88	185	40.31	3.02	4.24	0.50	1.77	6.78
Cross Creek	4	Mean	30.77	2702	110.00	12.36	81.80	10.17	15.58	32.48
		Maximum	56.84	2739	330.00	20.32	83.90	10.28	16.46	35.05
		Minimum	0.16	2644	30.00	5.10	80.00	10.08	15.19	29.02
		Std. Dev.	25.55	43	146.97	6.48	1.97	0.10	0.60	3.06
Grizzly Creek	5	Mean	31.05	2912	112.00	5.03	40.40	8.10	14.16	32.24
		Maximum	52.94	3183	160.00	6.17	72.30	12.63	15.29	39.97
		Minimum	0.16	2668	90.00	4.15	16.50	4.16	13.08	28.48
		Std. Dev.	21.11	214	31.94	0.86	23.70	3.57	1.02	5.34
North Elk Creek	6	Mean	49.56	2285	301.70	10.15	54.50	6.17	17.25	33.05
		Maximum	95.32	2497	340.00	17.02	103.10	9.38	18.16	47.45
		Minimum	0.16	2151	250.00	3.10	9.90	1.90	16.29	27.32
		Std. Dev.	46.91	118	42.62	4.76	32.80	2.69	0.63	7.79
Upper Piney River	7	Mean	15.87	2754	218.60	6.67	44.00	5.26	13.42	26.53
		Maximum	65.42	3073	320.00	13.58	90.90	8.44	14.45	31.28
		Minimum	0.16	2550	70.00	2.17	15.10	2.86	12.19	24.00
		Std. Dev.	24.43	182.77	109.76	4.25	26.00	1.83	1.06	2.29

6.4 Appendix D: Simple scatterplot matrix of potential model variables

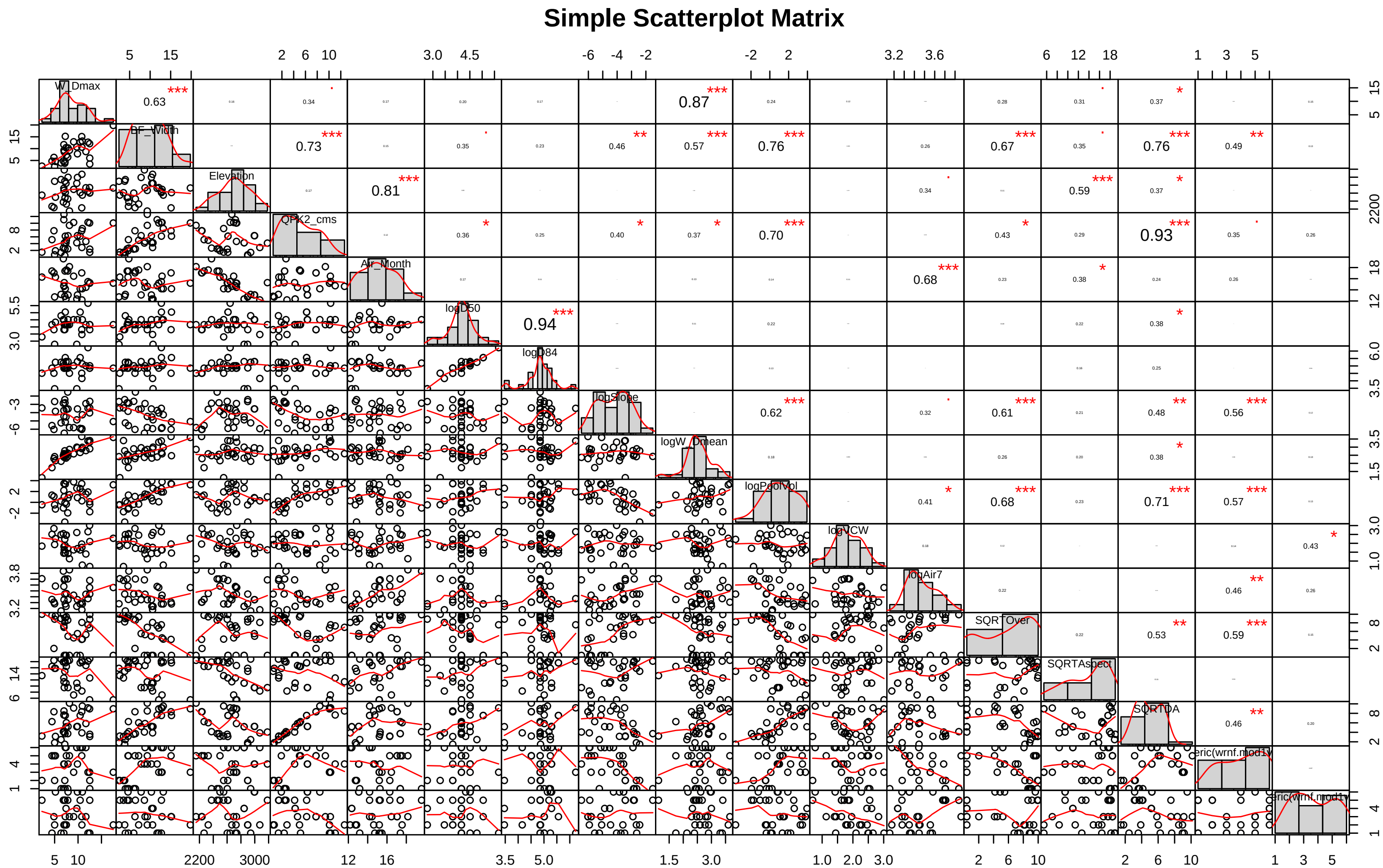

Figure 37: Scatterplot matrix showing correlations between the potential model variables. Variables are listed diagonally from top-left to bottom-right, over a histogram plot. To the left of the histograms are scatter plots of each pair of variables. To the right of the histograms are r^2 correlation coefficients for each pair of variables.

6.5 Appendix E: Diagnostic plots for ANOVA and Kruskall-Wallis tests

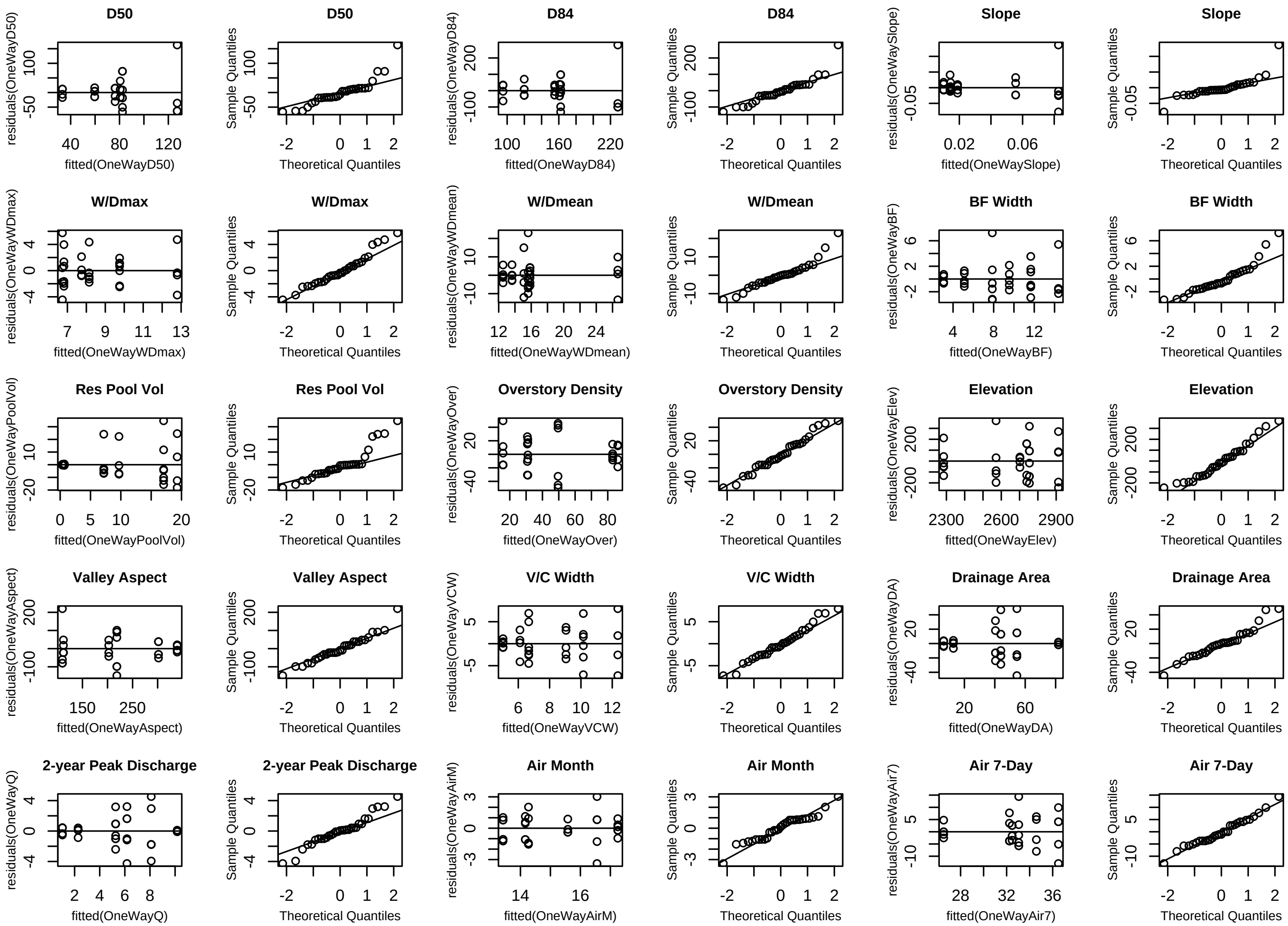

Figure 38: Residual versus fitted values plots, and QQ plots of the residuals for determining whether the ANOVA or Kruskall-Wallis tests for comparing means should be used.

6.6 Appendix F: Additional boxplots

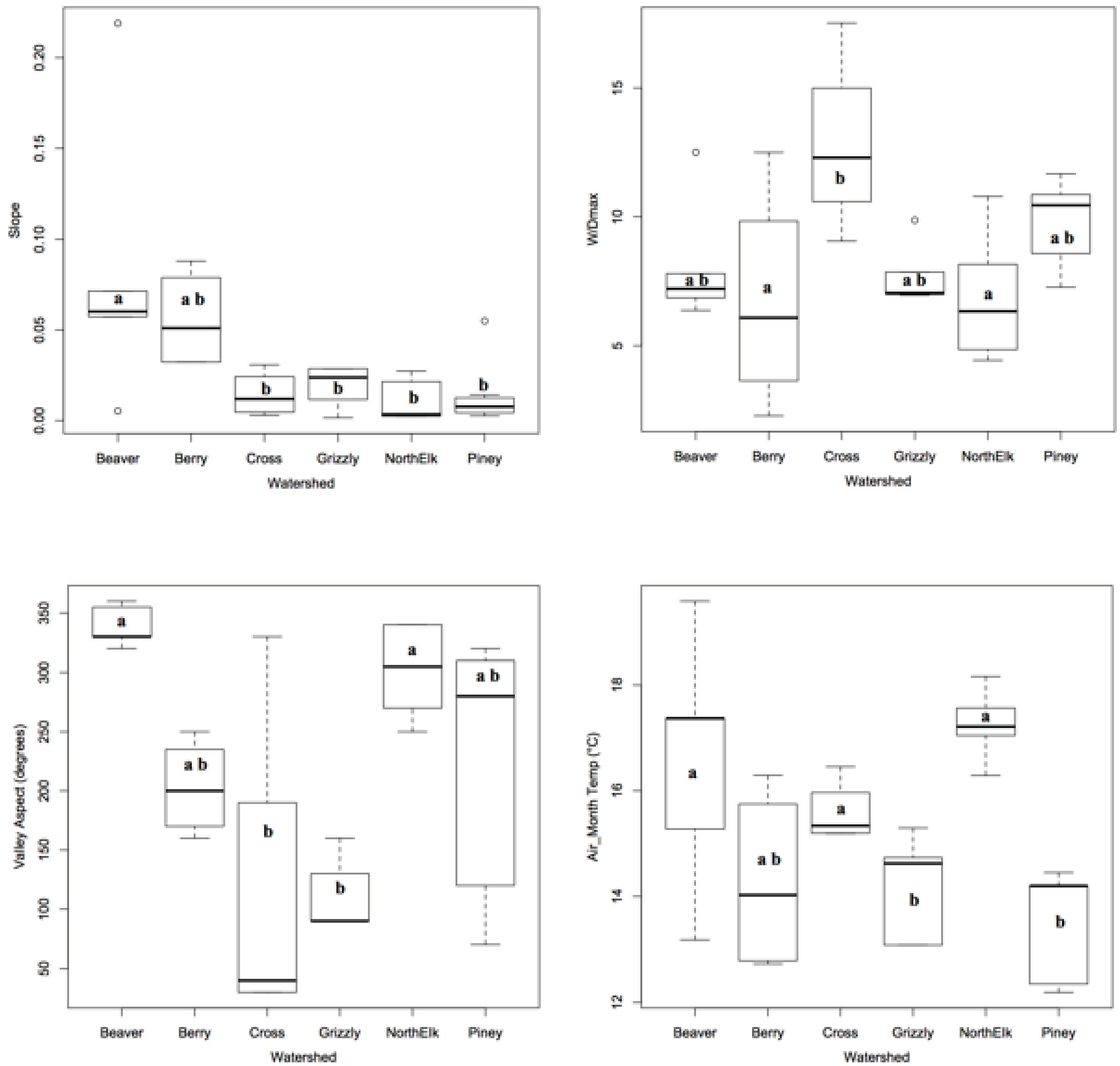

Figure 39: Boxplots of variables slope, W/Dmax, valley aspect and Air_Month. Watersheds with the same lower case letter do not have significantly different means for the variable.

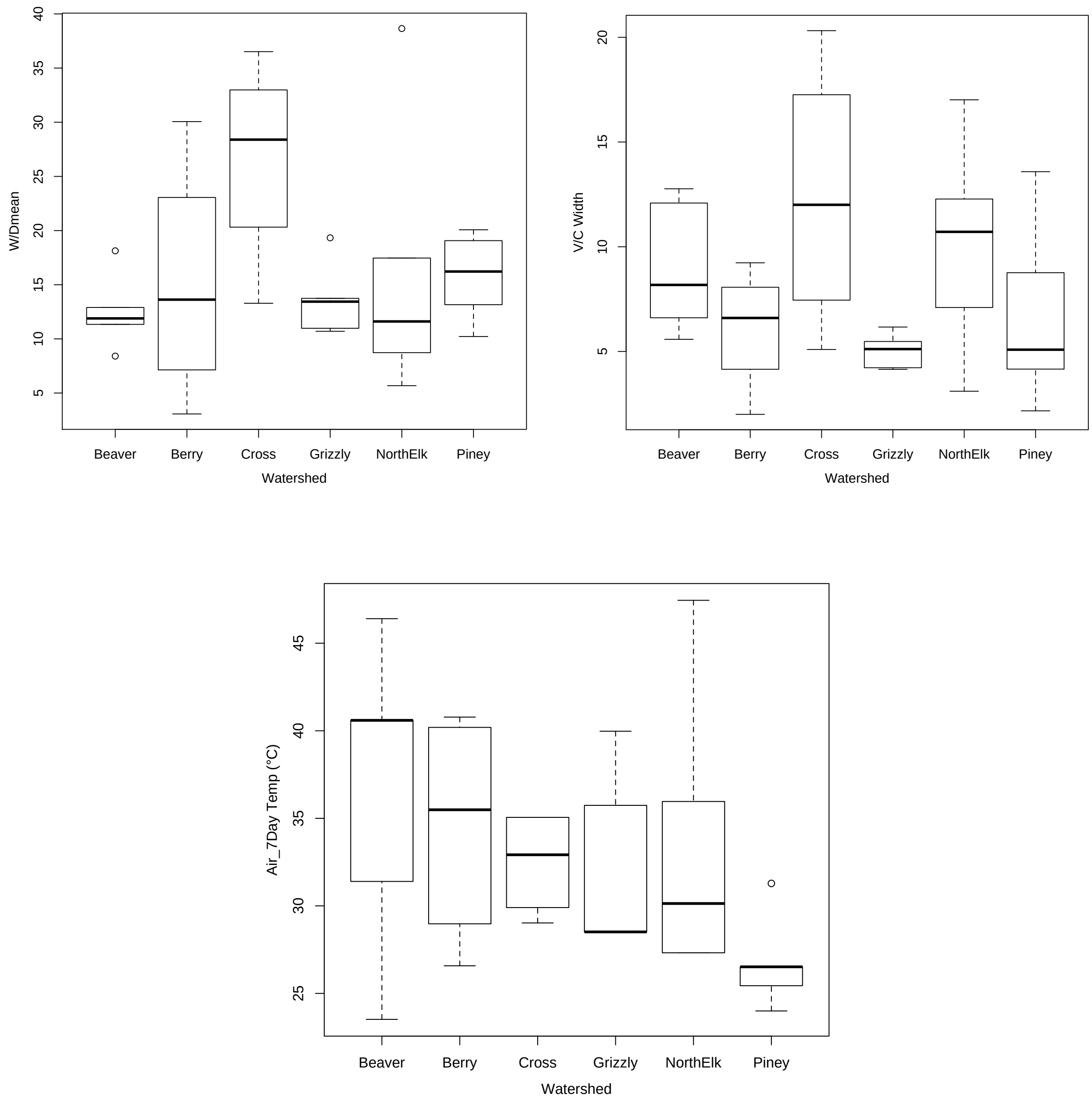

Figure 40: Boxplots of variables W/Dmean, valley-channel width and Air_7Day. There were no significant differences between the means of these variables across the watersheds.