Development of Stream Temperature Models for Selected Missouri Streams

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Table of Contents

List of Tables

List of Figures

Executive Summary

Effective management plans for river systems benefit from understanding the thermal patterns that contribute to water quality and dictate the organisms that live in these systems. Although long-term datasets are needed to capture stream temperature trends and patterns, shorter-term datasets can still provide insight into longitudinal patterns and geographic differences among streams that may indicate the species that can be supported.

We had three primary objectives for this project:

- Characterize water temperature patterns for Missouri Ozark Plateau streams using data from long-term monitoring of select streams within this aquatic subregion
- Develop a stream temperature model for wadeable streams throughout Missouri
- Determine the relationship between stream temperature and discharge based on streams in the Ozark Plateau and Central Plains

We utilized three datasets to assess trends and patterns in Missouri streams within the Central Plains (CP) and Ozark Plateau (OP) regions. As expected, for all datasets, air temperature was the metric that had the greatest influence on water temperature. The first dataset was a 13-year dataset of summer (July 1 – Sept 15; 2002-2014) water temperatures from 21 OP spring-fed streams that we used to assess similarities among streams, trends over time, and to project whether water temperatures were expected to change over the coming century. Based on hierarchical clustering and principal components analysis of stream characteristics, these streams formed six groups which potentially would respond similarly to management actions and may support similar species assemblages. We did not constrain the groupings by either geography or management boundaries to provide regional managers with opportunities for comparisons across these spatial units. As for a temporal trend, none of the sites exhibited either increasing or decreasing trends in water temperature over the 2002 to 2014 period. Projections of water temperature over the next 60 years indicate only slight increases; sites that currently have warmer and more variable temperatures are most likely to show larger increases in water temperatures and periods over the threshold of 21.1°C which is a critical upper temperature for the trout in these streams. Most sites exhibited resilience to forecasted climatic increases in air temperature. A caveat to these findings is that if groundwater temperatures rise in response to the warmer air temperatures, then these Ozark streams could be warmer than our predictions.

The second dataset was a collection of continuously collected stream temperature from 349 sites throughout the CP and OP of Missouri. We were unable to locate datasets from the Mississippi Alluvial Plains region. With this dataset, we developed a robust approach to model stream temperature in Missouri using variables known or expected to be drivers of stream temperature. Using our approach and separate models for each region, we obtained robust (predicted temperatures were within 0.6°C of actual temperature) daily water temperature predictions for stream segments throughout the CP and OP. Based primarily on research in smaller watersheds, predicted values within 2°C are considered good results for daily stream temperature models. Predictions for OP streams were poorest in the winter and summer, which is not surprising given the seasonal influence of groundwater on fluvial temperatures. The worst performing month for both models was July, which is a critical period when stream temperatures can exceed thermal tolerances of aquatic organisms. This limitation should be considered when using these July predictions; however, the deviation in predicted temperature was only slightly over 0.5°C in the CP and around 0.8°C in the OP. An important difference between our models and other efforts is that we have provided a tool to assess annual response or variation while the more typical approach has focused on the warmest period of the year. The OP and CP models can be used for quantifying general patterns and ranges of stream temperatures both spatially and temporally within

these aquatic subregions of Missouri, which can inform management for biotic resources and water quality.

For the third dataset, we collected water temperatures near USGS gage sites in the CP and OP regions that recorded discharge measurements to develop an approach to predict the change in water temperature relative to change in discharge. This provided a scientific basis for projecting how modifications to discharge levels could alter thermal patterns in Missouri streams. For this objective, we provided a few scenario assessments to demonstrate how this approach could be used depending on the region, season, or stream class of interest. We developed water temperature models separately for each region using a generalized additive approach. With the regional models we assessed thermal changes based on annual and late summer periods, and annually for stream flow classes. All models were relatively robust (adjusted $r^2 > 0.9$; one exception was the model for perennial groundwater super-stable flow class: adjusted $r^2 = 0.86$). The approach we used for this project provides a conservative estimate for change in water temperature if discharge levels were to increase or decrease. The estimates are conservative due to the coarse-scale nature of the data used in these models and that we are summarizing patterns across individual streams. A primary benefit of this approach is having the ability to make these estimates without needing the extensive habitat and water transport data (e.g., infiltration times, channel width and depth for the reach of interest, hypolimnetic flow rate), required for more standard approaches such as energy balance models. These robust stream temperature - discharge models provide a scientific basis for land managers and decision makers to evaluate how management actions and other activities that modify stream discharge may lead to alterations in stream temperature and thus aquatic biota.

Acknowledgements
Funding for this project was provided by the Missouri Department of Conservation. We thank Ryan Leukenhoff, Travis Schepker, Jackman Eischenroeder, Joseph Rasco, Matt Dolan, Emily Tracy-Smith, and Danielle Fox for field work and data management assistance. MDC biologists Dr. Paul Blanchard, Dr. Michael Roell, Michael Kruse, and USGS, University of Missouri Cooperative Faculty, Dr. Craig Paukert assisted in the development of the project design and provided guidance throughout the project. Dr. Amy Davis, MDC and Dr. Christopher Wikle, University of Missouri provided statistical guidance. We also thank Dr. Doug Novinger, MDC and the University of Missouri Writing Workshop group for constructive reviews of this report.

Report organization

This report is organized into three primary sections based on the intent of the objectives and similarity of methods used. For this reason, the objectives are not presented in the same order as listed in the proposal. Objectives 2 and 5 are addressed in the section titled “Characterize water temperature patterns of the Missouri Ozark Plateau streams”. Objectives 1, 3, and 4 are addressed in the section titled “Stream temperature model for Missouri watersheds”. Objectives 6 and 7 are addressed in the section titled “Influence of stream flow on water temperature in Missouri streams”. A general introduction is provided with more specific background information included within each section.

Goals

We had three primary goals for this project.

- Characterize water temperature patterns for Missouri Ozark Plateau streams using data from long-term monitoring of select streams within this aquatic subregion.
- Develop a stream temperature model for wadeable streams throughout Missouri.
- Determine the relationship between stream temperature and discharge based on streams in the Ozark Plateau and Central Plains

General Introduction

Water temperature is a fundamental driver of biological processes within fluvial systems. As such, this physical parameter is an important determinant of species occurrence in individual streams and location along a longitudinal stream gradient (Chu et al. 2008; Coutant 1999; Ebersole et al. 2001). Gradients in stream temperature have been long associated with shifts in community composition, most typically from cold-water species in higher elevations to warm-water species at lower elevations (Rahel and Hubert 1991). Metrics such as daily mean and maximum stream temperatures can aid in understanding of distributions, survival, and growth in aquatic organisms as even a few hours above a thermal limit can be detrimental to individuals of some species (Bjornn and Reiser 1991; Burgmer et al. 2007; Caissie et al. 2001; Galbraith et al. 2012; Ganser et al. 2013; Ganser et al. 2015). Therefore, understanding current and potential future thermal patterns in lotic systems is an important component of effective watershed management plans for individual species and biodiversity.

As ectotherms, freshwater fish depend on thermally suitable habitat to successfully grow, reproduce, and survive (Magnuson et al. 1979). Some species, such as many salmonids, have narrow thermal tolerances and are less viable when temperatures exceed about 20°C (Bjornn and Reiser 1991). However, these taxa can survive and even maintain perennial populations in generally warm waters where cooler thermal refugia (or pockets) exist (Ebersole et al. 2001; Ebersole et al. 2003; Hickling et al. 2006). Groundwater inputs from springs can provide thermal refugia from excessively warm or cold temperatures. In the summer, groundwater flows moderate the influence of high summer air temperatures on water temperatures spanning the area from the immediate outflow zone to substantial distances downstream depending on the volume and rate of discharge (Mugel et al. 2009). Conversely, in the winter, these springs also serve as refugia from cold extremes for species that prefer warmer temperatures such as Smallmouth Bass (Dauwalter and Fisher 2008; Peterson and Rabeni 1996; Westhoff et al. 2016). Sustained periods of high or low water temperature can have deleterious effects on individuals and populations.

Stream temperature is dictated by the interaction of environmental processes and anthropogenic disturbances (Caissie 2006; Ward 1985). Environmental drivers are primarily atmospheric factors and secondarily hydrologic and local factors such as groundwater, stream discharge, riparian cover, and elevation. Anthropogenic alterations including water withdrawals and clearing of riparian habitat typically disrupt daily and seasonal patterns that have driven patterns of species evolution and adaptation which may result in the extirpation of species.

The primary atmospheric driver of water temperature is air temperature. Above zero degrees Celsius, air temperature generally has a strong positive correlation with stream temperature (Stefan and Preud'homme 1993) although the relationship is actually more curvilinear (Mohseni and Stefan 1999). This linear relationship is tempered by evaporative cooling at high air temperatures and the influence of groundwater at low temperatures (Caissie 2006; Erickson and Stefan 2000). Stream and air temperatures fluctuate temporally in a sinusoidal pattern at both an annual and daily scale (Cluis 1972). In the northern hemisphere, the annual cycle generally is coolest in winter and warmest in the late summer to early fall. Minimum daily temperatures are usually reached in the early morning hours while maximums occur in late afternoon. Daily variation in temperature tends to be highest for mid-size shallow rivers and lowest for both large rivers and small streams (Caissie 2006). Thermal inertia creates a time lag between air and stream temperature that becomes more pronounced with increased stream depth (Stefan and Preud'homme 1993) and flow (Webb et al. 2003). For this reason, time lags for air temperature metrics can be key components in predicting stream temperatures particularly for short time scales (Benyahya et al. 2007; Letcher et al. 2016; Troia et al. 2016).

Other atmospheric drivers of water temperature include solar radiation and wind speed. Solar radiation can account for a substantial component of heat inputs to stream water (Webb et al. 2008) that may be tempered by local variations in topography and vegetation cover (Beschta and Taylor 1988; Brown and Krygier 1970). Although reduced wind speed plays a role in warming stream temperatures, particularly for smaller streams, this relationship is generally less influential than solar radiation (Webb et al. 2008).

The dominant hydrologic factors affecting stream temperature include relative contribution of groundwater, water source (e.g. precipitation runoff, spring flow), and discharge rate. In general, water temperature is similar to its groundwater source in headwaters and increases to be more similar to air temperature with downstream distance and corresponding stream size (Poole and Berman 2001). However local modifiers such as springs and geomorphology can disrupt this relationship (Burkholder et al. 2008; Ebersole et al. 2003; Westhoff and Paukert 2014). The greater the contribution from subterranean waters, the more stable the water temperature either in headwaters or along a waterway where springs make a substantial contribution to the total discharge (Westhoff and Paukert 2014). The volume and source of surface runoff water can rapidly change water temperature (Webb 1996; Webb et al. 2003). Discharge from storm drains and other urban point-source pollution also contribute to abrupt changes in stream water temperatures (Herb et al. 2008; Kinouchi et al. 2007; Poole and Berman 2001).

Topography also plays a role in regulating stream temperature at landscape and local scales. Escarpments such as expansive valley walls or localized stream banks can provide a shading effect on streams thereby decreasing water temperatures. Streams at high elevations or on steep slopes tend to be cooler than those in low-lying areas or with less topographical relief (Laizé et al. 2016; Mayer 2012). In addition, there tends to be a positive relationship between upstream watershed area, and both stream temperature and reduced variability (Álvarez-Cabria et al. 2016; Moore et al. 2015).

Riparian vegetation moderates stream temperature primarily through the filtering of solar radiation. Short- and long-term research has shown a direct relationship between intact riparian cover and stream temperature (Beschta and Taylor 1988; Brown and Krygier 1970). Removing this natural source of shade increases exposure to solar radiation and has been shown to increase water temperature as much as 15°C in a small watershed (Brown and Krygier 1970).

Effective management plans for lotic systems benefit from understanding the thermal patterns that contribute to water quality and dictate the organisms that live in these systems. Although long-term datasets are needed to capture stream temperature trends and patterns, shorter-term datasets can still provide insight into longitudinal patterns and geographic differences among streams that may indicate the species that can be supported. In this report, we utilized three datasets to assess trends and patterns in Missouri streams. We used a 13-year dataset of summer water temperatures from Ozark Plateau spring-fed streams to assess trends over time and project whether water temperatures were expected to change over the coming century. The second dataset was a collection of continuously collected stream temperature from sites throughout Missouri. With this dataset, we developed a robust approach to model stream temperature in Missouri using 20 variables known or expected to be drivers of stream temperature in the region. For the third dataset, we collected water temperatures near USGS gage sites that recorded discharge measurements. We used this dataset to develop an approach to predict the change in water temperature relative to change in discharge. This provides a scientific basis for projecting how modifications to discharge levels could alter thermal patterns in Missouri streams. The collective analyses and relationships identified between water temperature and its drivers can be used when developing management plans for aquatic species or to assess water quality from a thermal standpoint.

Study Area

Three aquatic subregions have been delineated for Missouri: Central Plains, Ozark Plateau, and Mississippi Alluvial Plain (Figure 1; Pflieger 1989; Sowa et al. 2005). These regions represent relatively distinct configurations of geology, physiography, aquatic communities and groundwater influence (Sowa et al. 2007; Sowa et al. 2005). A brief review of characteristics important to stream temperature is provided here; however, detailed descriptions for these subregions can be obtained in Sowa et al. (2005).

The Central Plains (CP) encompasses watersheds in northern Missouri with rolling topography consisting of deep loess and glacial till soils (Pflieger 1989). The few springs that exist in this subregion (Figure 1; (Missouri Department of Natural Resources 2010) tend to exhibit highly variable flows with many becoming dry in the summer (Kennen et al. 2009; Pflieger 1989). Average slope is 5% with elevation falling between 180 – 370 meters and local relief between 15 – 60 meters (Sowa et al. 2005). Agriculture and pasture dominate the landscape (Table 1) replacing the once common prairie habitat. Mean annual air temperatures generally range between 11 – 12°C with maximum July temperature around 32°C (Sowa et al. 2005). Winter precipitation tends to be lower (<5 cm mean monthly) than in the other two subregions while snowfall is higher (50 cm mean annual). Streams in this subregion are generally classified as warm-water (Annis et al. 2010).

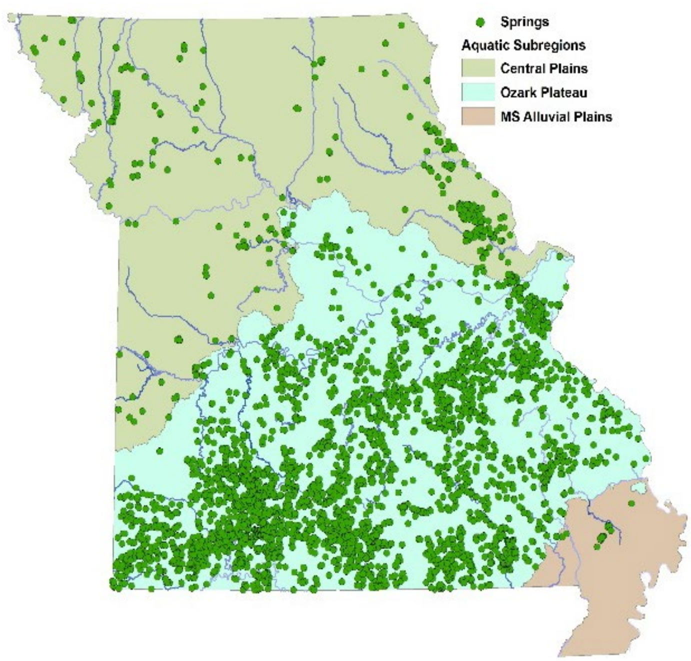


Figure 1. Map depicting the disparate distribution of documented springs in Missouri relative to aquatic subregions.

The Ozark Plateau (OP) spans an area from the southwest corner of Missouri to the central-eastern border. It has greater topographic relief (Sowa et al. 2005) and is heavily forested (55%) compared to the other subregions (Table 1). Elevations range from 120 m to the highest elevation in Missouri of 550 m. The mean slope is around 9% however slopes >20% are common locally. Stream flow is generally stable due to the presence of numerous springs and karst topography of this subregion. Mean annual air temperature (12 - 13°C) tends to be slightly warmer than in the CP with maximum July temperature around 32°C (Sowa et al. 2005). Precipitation mean annual measurements range from 100 to 122 cm with snowfall contributing 25 to 50 cm annually (Sowa et al. 2005). Unlike most CP streams, water clarity is high even in deep pools. Stream temperatures are predominantly warm excluding where highly influenced by groundwater inputs (Annis et al. 2010).

Table 1. Percent land cover for each aquatic subregion based on the 2011 National Landcover Dataset (Homer et al. 2015).

	Land Cover (%)					
Aquatic Subregion	**Urban**	**Agriculture**	**Forest**	**Shrub**	**Grassland**	**Pasture**
Central Plains	7	37	15	1	4	34
Ozarks	7	5	55	0	2	29
Mississippi Alluvial Plains	6	75	5	0	0	3

The Mississippi Alluvial Plain encompasses the far southeast corner of Missouri where streams have been highly modified through channelization. The intent of the channelization was for flood control and to convert this predominately flooded, bottomland hardwood forest to farmable land for crops (Stanturf et al. 2000). Mean annual air temperature (14°C) and rainfall (130 cm) are the highest of the three subregions (Sowa et al. 2005). There is little topographic relief (mean < 3 m; (Pflieger 1989) which is reflected in our measured mean slope of 1%.

Spatial Framework

We used the Missouri Streams Dataset as our base stream layer which is a 1:100,000 scale spatially-referenced file modified from the National Hydrography Dataset V1 (Sowa et al. 2007). Modifications included connecting incorrectly isolated streams, correcting direction of stream flow, and also removing hydrologically incorrect stream segments. Throughout this report, stream segments are defined as individual sections between confluences or sections representing headwaters (Figure 2). Each stream segment is associated with a catchment area which represents the spatial region most directly influencing a given stream segment. Watershed is defined as all catchments influencing a focal stream segment. All data used in this project were spatially referenced to this framework.

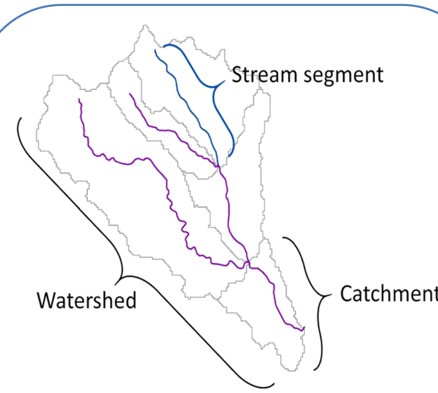


Figure 2. Spatial scales used for this project. See text for descriptions.

Characterize water temperature patterns for Missouri Ozark Plateau streams

Objectives addressed:

Objective 2: Report on stream temperature patterns identified through analysis of stream temperature monitoring performed by MDC staff from 2002 – 2014 in Ozark Plateau streams.

Objective 5: Predict future patterns of stream temperature using climate forecasts.

Our objectives were to investigate patterns in water temperature within Ozark Plateau streams using a long-term dataset of summer stream temperatures collected by MDC biologists and to evaluate whether contemporary thermal regimes might shift under future climatic conditions. To this end we described the patterns in stream temperature documented within the 21 monitored streams and identified sites with similar thermal patterns. Using these data we also evaluated whether stream temperature had been stable over the 13-year period of monitoring and modeled predicted temperatures in the coming century.

Background

The Ozark Plateau is liberally interspersed with springs that provide thermal refuge to fish during seasonal periods of hot and cold stream temperatures. Two of these species are popular sport fish and indicators of habitat condition: Smallmouth Bass (*Micropterus dolomieu*) and Rainbow Trout (*Oncorhynchus mykiss)* (Schramm Jr et al. 1991). Rainbow Trout are considered a cold-water species while Smallmouth Bass are considered a cool- to warm-water species. Summer temperatures in Missouri Ozark Plateau streams often exceed 27°C which surpasses thresholds of survival, optimum growth, and may impair recruitment for these species (Bjornn and Reiser 1991; Brewer 2013; MacCrimmon 1971; Whitledge et al. 2006). Rainbow Trout are known to seek cooler refugia under thermal conditions that exceed 18 - 25°C (Ebersole et al. 2001). Of necessity, management plans for these species focus on suitable habitat with water temperature being a primary component (Kruse et al. 2003; Meneau 2009).

Suitable habitat for cold- to cool-water species may become limited to regions with substantial groundwater inputs due to climatic changes (Meisner 1990). Contemporary observations have already revealed shifts in the distributions of fish species that correspond with climatic changes and are potentially exacerbated by additional factors (Comte et al. 2013). If atmospheric carbon dioxide doubles, cold-water fishes in the conterminous U.S. are predicted to decline by up to 50% and lose over a third of suitable thermal habitat (Eaton and Scheller 1996; Mohseni et al. 2003). Because springs typically provide stable levels of discharge and water temperature, these and their associated systems may buffer suitable habitat for aquatic organisms from detrimental changes in climatic conditions (Brewer 2013; Chu et al. 2008; Westhoff and Paukert 2014). Identifying streams that are resilient to changes in climate will be important in future management plans of aquatic systems.

Information on daily mean and maximum water temperatures in stream segments can be useful for understanding distributions, survival, and growth of aquatic organisms as even a few hours above a thermal limit can be detrimental to species (Bjornn and Reiser 1991; Burgmer et al. 2007; Caissie et al. 2001; Galbraith et al. 2012; Ganser et al. 2013; Ganser et al. 2015). Thus, understanding current and potential future thermal patterns within a watershed is an important component of effective management for aquatic biota that occurs or could occur there.

Methods

Study area

The study area for this section is the Ozark Plateau subregion in southern Missouri. This subregion is dominated by forested habitat of oak, hickory, and ash. The mean maximum air temperatures in July hover around 32°C across the Ozark Plateau (Sowa et al. 2005). Stream systems are highly influenced by springs which occur throughout the plateau due to a dominant karst geology composed of limestone and chert. The groundwater influence allows for blue-ribbon class trout streams scattered across the plateau that are highly prized by fishermen. Some of these trout populations are maintained through stocking but some populations are self-sustaining due to the presence of thermal refugia provided by the spring flows. See General Introduction for more details on this subregion.

Datasets

Stream temperature

Missouri Department of Conservation (MDC) staff collected summer (July 1 – Sept 15) air and water temperature data across streams in the Missouri Ozarks using continuously recording temperature loggers over the time period from 2002 through 2014 (Figure 3; Appendix A). Spatial and temporal continuity of data varied among systems with some locations having as little as one year of data, and others with records for all 13 years (Tables 2 and 3). More sites were sampled during the first few years of this dataset. In addition, for any given year, most sites did not have data for the entire summer period. Typically, a block of days at the beginning or end of the summer was missing, though in rare cases an isolated day in the middle of the summer was missing due to erroneous measurements. Many river systems had multiple data loggers at different locations to capture spatial variation in temperature across the system. Additionally, not every temperature logger remained in the exact same location from year to year. We defined 21 separate river systems (Table 2), whereby a stream or a large spring feeding a stream was considered a unique system (e.g., Greer Spring Branch and the Eleven Point River were each considered unique systems). We further refined datasets to focus on the summer season of July 1st through September 15th (hereafter referred to as summer) as this is the period of primary management concern for the fisheries of this subregion.

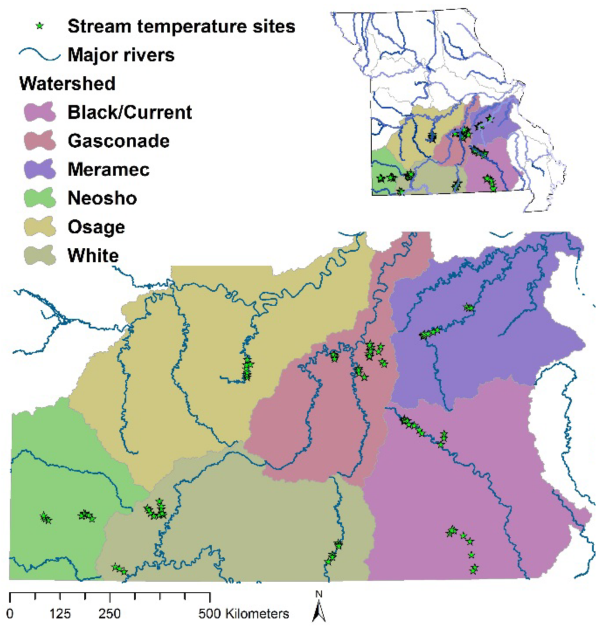


Figure 3. Distribution of Missouri Department of Conservation water temperature monitoring sites in Ozark Plateau watersheds.

Our initial intent was to analyze ambient air temperature recorded in association with the water temperature records. However, air temperature was only collected for more than three years at two sites so this assessment component was dropped from analyses (Table 3).

Table 2. Temporal distribution of water temperature records taken in Ozark Plateau streams of Missouri. Site ID designated by Missouri Department of Conservation reflects unique locations (n = 106) within each river (X = data records were collected between June 1 and Sept 15 for that year).

River System	Site ID	Year												
		2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Barren Fork	P1	X	X	X		X	X							
	P2	X	X	X	X	X	X	X						
Bennett Spring Branch	P1	X	X	X	X	X	X	X	X		X	X	X	X
	P2	X	X	X	X	X	X				X	X	X	X
Blue Spring Creek	P1	X	X	X	X	X	X	X	X	X	X	X	X	X
	P1A				X	X	X	X	X	X	X	X	X	X
	P2	X	X	X	X	X	X		X	X	X	X	X	
Capps Creek	P1	X	X											
	P2	X	X											
	P3	X	X											
	P4	X	X	X										
	P5	X	X			X	X		X					
	P5A			X	X	X	X		X					
	P6	X	X	X	X	X	X		X					
Crane Creek	P1	X	X	X	X	X	X		X	X	X	X	X	X
	P2	X	X	X	X					X				
	P3	X	X	X	X		X		X	X				X
	P4	X	X	X	X	X	X		X	X	X	X	X	X
	P5	X	X	X	X	X	X		X	X			X	X
	P6											X		
	P7										X	X		X
Current River	P1	X	X											
	P2	X												
	P2A		X											
	P2B	X	X											
	P2C	X	X											
	P3	X	X											
	P4	X	X	X	X	X	X		X	X				
	P4A			X	X	X	X	X	X	X				
	P4B			X	X	X	X							
	P5	X	X	X			X	X	X					
	P6	X	X	X	X	X	X	X	X	X				
	P7	X	X	X	X	X		X	X	X				
	P8	X	X	X	X	X		X						
	P9							X						
Dewitt-Wilkins Spring	P1		X	X	X	X	X	X	X	X	X			
	P2		X	X	X		X	X						
Dewitt-Wilkins Spring (cont)	P3		X		X	X	X	X						

River System	Site ID	Year												
		2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Eleven Point River	P1	X	X				X	X						
	P2	X	X	X	X	X	X	X	X	X				
	P3	X	X		X	X	X	X	X	X				
	P4	X	X											
	P5	X	X	X	X	X	X	X						
	P6	X	X											
	P7	X	X	X	X	X								
Greer Spring Branch	P1	X	X	X	X	X	X	X	X					
	P2	X	X	X	X	X	X							
Hickory Creek	P1	X	X											
	P1A			X	X	X	X		X					
	P3		X	X	X	X	X		X					
	P4		X											
Little Piney Creek	P1	X	X											
	P2	X	X	X	X	X	X	X		X	X	X		
	P3	X	X	X	X	X	X	X	X	X	X	X		
	P4	X	X	X	X	X		X		X	X			
	P5	X	X											
Meramec Spring Branch	P1	X	X	X	X	X	X	X	X					
	P2	X	X	X										
Meramec River	P1	X	X											
	P2	X	X	X	X	X	X	X	X	X	X	X	X	X
	P3	X	X											
	P3AA									X	X	X	X	X
	P3AAA										X	X	X	X
	P4	X	X	X	X	X	X	X	X	X	X	X	X	X
	P5	X	X											
Mill Creek	P1	X	X		X	X	X							
	P10											X		
	P1A		X		X		X							
	P2	X	X	X	X	X	X		X	X	X	X		
	P2A		X							X	X	X		
	P3	X		X	X		X	X						
	P3A				X	X	X	X						
	P4	X	X	X	X	X	X	X	X	X	X			
N Fork White River	P1	X												
	P2		X											
	P3	X	X											
	P4	X	X	X	X	X								
N Fork White River (cont)	P5	X	X	X	X	X	X	X	X					
	P6	X	X											

River System	Site ID	Year												
		2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	P7	X	X											
	P8	X	X	X	X		X	X	X					
Niangua River	P1	X	X											
	P2	X	X				X							
	P3	X	X	X	X	X			X	X	X			
	P3A			X	X	X	X	X	X	X		X		
	P4	X	X	X	X	X								
	P5	X												
Roaring River	P1	X	X	X		X	X		X					
	P2	X	X	X	X	X	X							
	P3	X		X		X	X		X					
Roubidoux Creek	P1	X	X											
	P2		X	X	X		X							
	P4	X	X							X	X	X		
	P5	X	X	X	X		X		X	X	X	X		
	P6	X	X											
Roubidoux Spring Branch	P1	X	X	X			X			X				
Spring Creek Phelps	P1	X	X	X										
	P2	X	X	X	X	X	X	X	X	X	X			
	P3	X	X		X	X	X	X	X	X	X	X		
	P8									X	X	X		
	P9											X		
Spring Creek-Stone	P1	X	X								X	X		X
	P2	X	X										X	X
	P2A						X							
	P3										X			X
	P4												X	X

We identified outliers and erroneous measurements, and recorded changes to the dataset (Appendix B). We also created violin plots of the hourly water temperature data for all 106 locations and displayed them grouped by the 21 river systems (Appendix C). Violin plots display data by plotting kernel density of observations in much the same way a histogram displays abundance. Mean temperature was also displayed in conjunction with each violin plot.

We used the R package StreamThermal 1.0 (Tsang et al. 2016) to calculate 99 different summary metrics (Appendix D) from hourly water temperature records collected from 57 of the temperature monitoring locations. These 57 sites included only locations that had five or more years of data. Each metric summarized for the summer period represents a composite of the data from that location covering all years of record. Calculated metrics fell into five broad categories comprising frequency, magnitude, duration, timing, and rate of change.

Table 3. Temporal distribution of air temperature records taken near locations where water temperature also was being recorded for streams in the Ozark Plateau of Missouri (X = data records exist for associated year).

River System	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bennett Spring Branch	X	X	X	X	X	X	X	X	X	X	X	X	X
Capps Creek	X	X				X							
Current River	X	X	X	X	X	X	X	X	X				
Eleven Point River	X	X											
Meramec Spring Branch						X	X	X					
Meramec River	X	X											
N Fork White River	X	X											

Predictor metrics of stream temperature

We obtained daily total precipitation (mm), total incident solar radiation (W/m^2), and minimum and maximum air temperature (°C) data for the Ozark subregion of Missouri from 2002 – 2014 from the Oak Ridge National Laboratory Daymet dataset (Thornton et al. 2016). This dataset has daily climatological variable estimates as a 1-km grid throughout the conterminous United States, modeled using interpolation and extrapolation of meteorological station data. Solar radiation and air temperature were obtained using the Daymet multiple coordinate extractor whereby coordinates for each water temperature monitoring site were used to extract values specific to that location. Air temperature was provided as minimums and maximums which we summarized as average daily values. We used the Daymet tile selection tool to download precipitation data layers so we could calculate the total daily area-weighted precipitation within the upstream watershed of each water temperature monitoring location. We also used Daymet estimates of the uncertainty (cross-validation statistics) for the daily temperature and precipitation metrics (Thornton and Thornton 2016) to obtain measures of uncertainty for our study region.

In addition to climatological data, we incorporated several site characteristics that we considered fixed over time and could influence the effects of climatological variables on water temperature: groundwater influence, elevation, stream slope, upstream watershed area, and Strahler order (Caissie et al. 1998). We estimated groundwater influence using a Missouri spring location dataset (Missouri Department of Natural Resources 2010). Although this was the best available data, information on spring discharge was incomplete and there are many unrecorded springs in Missouri. To approximate groundwater influence for a given site, we created a list of all known springs upstream of each sampled site. For each upstream spring, we divided the mean annual spring flow by the distance from the spring to the site. For springs with unknown flow rate, we used 0.0003 cms (0.01 cfs) as a conservative approximation. Finally, the groundwater influence measure for a site was the flow divided by distance, summed over all upstream springs. Values ranged from 1.4810^{-8} to 4.1 cms/m ($1.6*10^{-6}$ to 472 cfs/f). This provided a coarse measure of groundwater influence. Elevation, slope, and Strahler order were already in the Missouri stream dataset. We used the RivEx toolset (Hornby 2015) to calculate upstream watershed area and to measure distance from each site to all upstream springs.

Forecasted climate

To predict future stream temperatures, we obtained daily air temperature, solar radiation, and precipitation from a dynamically downscaled climate model (Hostetler et al. 2011). The downscaling was performed using RegCM3, a regional climate model, on simulations from three global climate models

(GCMs) with the A2 time series scenario: GFDL CM2.0 (Delworth et al. 2006), MPI ECHAM5 (Roeckner et al. 2003), and USGS GENMOM (Alder et al. 2010). These models were available as a 15-km grid. As with the Daymet dataset, we obtained air temperature and solar radiation values associated with the point coordinate of each monitoring site and precipitation as an area-weighted average of the total daily precipitation in the upstream watershed (mm). For mean daily air temperature, we used the mean of average minimum daily temperature and average maximum daily temperature (°C). For solar radiation, we used total daily incident solar radiation (W/m^2). We acquired these data for three future time periods: 2040 – 2044, 2060 – 2064, and 2085 – 2089. However, for the GFDL scenario, climate predictions were not available for the 2085 – 2089 time step.

Analysis

Water-climate patterns

We summarized weather data and water temperature independently of each other to look at variation in air temperature, precipitation, and stream temperature across years. Although air temperature is often a good predictor of stream water temperature, we fit a simple linear regression to assess whether a linear relationship existed between mean daily air temperatures and mean daily water temperature in this groundwater driven subregion. To evaluate the accuracy of the modeled air temperature and precipitation, we used the Daymet cross-validation statistics data to calculate mean absolute error and bias for daily minimum and maximum air temperatures and precipitation for the area covered by the stream temperature sites. The cross-validation statistics were not available for solar radiation.

In addition, we used ANOVA and linear regression to examine whether summer water temperatures varied significantly from year to year and whether there was an overall increasing or decreasing trend in summer water temperatures from 2002 to 2014. Some sites did not have water temperature data at the beginning and end of the summer observation period. To avoid the bias that such missing data could cause, we bracketed the data set for this analysis to July 9 – September 8, and removed any site-year pairs that had any missing data between July 9 and September 8. The reduced data set contained 103 of the 106 sites – all except Current River P9, Mill Creek P10, and Spring Creek Phelps P9. To examine the effect of each year on the mean, minimum, and maximum daily water temperatures, we performed a two-way ANOVA with site and year as fixed effects. We ran pair-wise comparisons among years using a Tukey 95% experiment-wise confidence level. We used three linear regression models with site as a categorical variable and year as a continuous variable to test for an overall increasing or decreasing trend in mean, minimum, and maximum daily water temperatures.

Thermal similarities of monitoring sites

The numerous approaches to classify study units based on similarities and dissimilarities can themselves be grouped as non-hierarchical or hierarchical clustering. Non-hierarchical approaches develop an optimum structure based on a pre-determined number of groups and are biased by which units are selected to initiate the clustering process (Johnson 1998; McCune et al. 2002). Hierarchical clustering methods employ a bottom-up approach to iteratively aggregate units based on similarities and unlike non-hierarchical approaches provide a means to elucidate relationships among units without designating a pre-determined number of clusters (McGarigal et al. 2000).

To determine similarities among sites based on water temperature patterns, we conducted a hierarchical cluster analysis mostly because we did not have a justification for setting a pre-determined number of groups and also wanted to be able to examine the relationships. Clusters were based on (dis)similarities among selected StreamThermal metrics and stress day indicators (Table 4). Stress days were defined as continuous periods of at least 24-hours where water temperature met or exceeded a threshold of 21.1°C (70°F; Mike Kruse, retired Resource Science Division Chief, MDC, personal comm.).

Table 4. List of 11 thermal metrics in five categories used in the hierarchical cluster analysis. Excluding the frequency category, metrics were calculated using the "StreamThermal" package v1.0. The acronyms match the headers in the supplied data spreadsheets and databases.

Category	Metric	Definition
Magnitude	AvgDmeanSU	Average daily mean temperature (°C)
Frequency	AvgPercStrD_Ttl	Average number of stress days (% of total summer days)
	AvgPercStrD_GE15	Average number of days when temperatures equaled or exceeded 15°C (% of total summer days)
	AvgPercStrD_GE25	Average number of days when temperatures equaled or exceeded 25°C (% of total summer days)
Variability	RMaxSu	Range of daily maximum temperature (°C)
	Max7MovingADRT	Maximum of 7-day moving average of daily range (°C)
	DiffExtreme2.7	The 2-day average high minus the 2 day average low over the warmest 7-day window (°C)
Timing	JDmaxMaxTSu	Julian day of maximum daily maximum temperature (day)
	JDminMinTSu	Julian day of minimum daily minimum temperature (day)
	JDM7MAMaxT	Julian day of maximum daily maximum of 7-day moving window (day)
Rate of change	RCsu	Difference in maximum and minimum daily mean temperature divided by the number of days between events (°C/day)

Subsequent hours above the threshold temperature were included as fractions until reaching a second 24-hour period and so forth. We eliminated many of the 99 StreamThermal metrics by removing metrics summarized by month, but kept those summarized for the summer season. We then identified remaining variables with Pearson Correlation Coefficients > 0.9 and removed correlated variables we believed to be the least informative. All of the frequency metrics output by StreamThermal were removed in favor of metrics we calculated separately related to the number of days that exceeded temperature thresholds. Eleven variables were used to conduct the hierarchical cluster analysis (Table 4). Prior to conducting the analysis, each of the eleven variables was standardized using Z-scores (value – mean/standard deviation) to ensure different measurement scales did not bias importance in determining cluster placement. We only used data from the 57 temperature monitoring locations with at least five years of data. This was done to ensure adequate temporal representation for sites and avoid classifying a site based on one or two years that may not have been representative. We evaluated several clustering approaches (average, single linkage, complete linkage, and Ward's methods) using the agglomerative coefficient (AC), which measures strength of the clustering structure (coefficient values could range from 0 to 1 with values closer to 1 indicating stronger support for the developed structure). The distance matrix was determined using Euclidean distance and Ward's method was the clustering method. We further explored relationships between clusters by visualizing the clusters with a principal components analysis. Hierarchical cluster analysis was performed in Program R using the cluster and dendroextras libraries. Principal components analysis was conducted and visualized with the factoextra library.

Stream temperature model

Our main goal was to accurately and precisely predict water temperature to unsampled years using climatological variables, acknowledging that the impact of climatological variables on water temperature differs from site to site, due to site-specific differences such as amount of groundwater influence. In developing this predictive model, we were also able to describe how site characteristics, such as groundwater influence, impacted the relationships between climatological variables and water temperature. Our model did not account for uncertainty in air temperature, solar radiation, or precipitation values because of the increased model complexity and lack of uncertainty data for solar radiation. However, using the cross-validation summary statistics for air temperature and total daily precipitation (Thornton and Thornton 2016), we examined the mean absolute error (MAE) and bias statistics.

During initial exploration of predictor climatological metrics, we used straightforward, non-Bayesian regression to explore which to use. In addition to daily values for air temperature, solar radiation, and precipitation we also considered lagged variables (values of the same variables from previous days), squared air temperature (to model possible curvature in the relationship between air and water temperature), and categorical versions of the precipitation variable (<3 versus ≥3, <5 versus ≥5, and <25 versus ≥25 mm). We fit a separate regression equation at each site and used best subset selection to select the best predictors at each site. We then summarized the results across each of the sites. We then noted the metrics which tended to be good predictors across the most sites.

Our Bayesian model was built upon a basic regression model using climatological variables as predictors of mean daily water temperature. Using a hierarchical structure, we estimated how much site characteristics, such as groundwater influence, were responsible for variability in the effect of climatological variables between sites. Thus the effects of the climatological variables were estimated separately for each site (like a separate regression equation for each site), but were influenced by information gained from all of the sites. Sites with relatively little data were the most strongly affected; their estimates were drawn closer to the typical values for sites with similar site characteristics. We considered a few variations on this basic model structure, as well as different sets of predictor variables based on those suggested by the initial exploration.

Model 1

The first or "top" part of our initial model using only air temperature and precipitation as predictors was written as:

$$y_{itd} = \beta_{0_i} + \beta_{1_i} a_{itd} + \beta_{2_i} p_{itd} + \epsilon_{itd} \tag{1}$$

In this equation, y_{itd} was mean daily water temperature at site i, in year t, on day d, β_{0_i} was an intercept, a_{itd} and a_{itd} were air temperature and precipitation for the same site, year and day, β_{1_i} and β_{2_i} were coefficients describing the linear relationships between the climatological covariates and water temperature, and ϵ_{itd} was the residual error or variability in water temperature not accounted for by the regression equation. The intercept and coefficients have a subscript i, indicating that different intercepts and coefficients were estimated for each site. The error terms were assumed to be independent normal random variables with variance σ_i^2. Once again, the use of the subscript i indicated that a separate error variance was estimated at each site. This model can very easily be modified to include more or fewer predictors. When fitting the model, we considered several other predictors, including solar radiation and lagged air temperature data: air temperature data from previous days. We discussed variable selection at the end of this section.

One level "down" in the hierarchical model, each of the climatological variable coefficients was modeled as functions of site characteristics. We included groundwater influence and Strahler order as predictors in the following model:

$$\beta_{k_i} = \alpha_{0_k} + \alpha_{1_k} g_i + \alpha_{2_k} s_i + \eta_{k_i} \tag{2}$$

where k was either 1 for air temperature or 2 for precipitation, g_i and s_i were the groundwater influence and Strahler order at site i, and η_{k_i} was the residual error or variability in β_{k_i} not accounted for by the site characteristics. The three α coefficients must be estimated to describe the impact of the site characteristics on the effect of climate variable k. The coefficient level errors were assumed to be independent Normal random variables with variance $\sigma^2_{\eta_k}$. The subscript k indicated that there are separate coefficients and variance estimate for each of the two climatological variables. Additional site characteristics could be added or removed from this model.

Model 1 with quadratic seasonal trend

After fitting models of this form with different choices for predictors, we noted a curved trend in the residuals plotted as a function of day. This indicated systematic variability in water temperature not accounted for by the climatological variables, which violates the independent errors assumption. This observation led us to realize a problem with the model as specified: Imagine two 20°C days, one in late April and one in late July. Intuitively, you would not expect water temperature to be the same on those two days. Since the model used only the current day's climatological data (plus potentially some air temperature data from the past week), it must predict that those two days will have roughly the same water temperature. Additional variables such as the average air temperature for the previous 30 days were unable to account for this large-scale seasonal trend: For many sites, the model estimated that increasing the average air temperature over the previous 30 days would decrease water temperature. The seasonal trend may be influenced by other factors such as changes in water flow over the summer. Without flow information to evaluate this theory, we chose to model the trend as a quadratic function of day, with a different quadratic function for each site. This modification resulted in better predictive ability for the observed time period, but does have a drawback: The actual causes of the trend, possibly seasonal climatological variable patterns and other factors such as changes in flow, are likely to be affected by climate change. Since the quadratic function does not change from year to year, the model predictions may be overly confident for future time periods if the estimated curve is no longer appropriate in the future. However, we justify its inclusion because of the improved model fit for the current time period and because there is no reason to believe that a model without the quadratic curve would do any better at future prediction. Therefore, for each site we incorporated a quadratic curve into the model:

$$y_{itd} = \beta_{0_i} + \gamma_{1_i} d + \gamma_{2_i} d^2 + \beta_{1_i} a_{itd} + \beta_{2_i} p_{itd} + \epsilon_{itd} \tag{3}$$

Here, γ_{1_i} and γ_{2_i} correspond to b and a in the standard quadratic function $y = ax^2 + bx + c$. For example, we would expect γ_{2_i} ("a") to be negative so that the seasonal trend would be a concave down (hill-shaped) curve.

Model 2: Random yearly variability

In the Model 1 residual plots, we observed clear yearly variability in water temperature not accounted for by the model. Again, it is possible to propose many causes, including the effect of fall, winter and spring climate. For example, average air temperature varies from year to year, and this could adjust the seasonal curve. As another example, stream flow varies from year to year due to long-term precipitation variability. Streams with greater flow volume will be more thermally stable and less strongly affected by changes in air temperature or precipitation. Thus, yearly variability in stream flow would likely affect water temperature by altering the impact of climatological variables like air temperature and precipitation.

The most obvious approach to capture this variation was to use information about the climatological variables to shift the seasonal curve up or down. However, despite trying different combinations of climatological variables averaged over several different time intervals (spring, summer, previous eight months, etc.), we were unable to find a set of predictors that accounted for the yearly variability.

Since we do not know the actual cause of the variability, we chose to model it as random yearly variability in the coefficients. This change improves model fit (leading to more accurate confidence intervals) but will not improve prediction for future years. Thus in Model 2, assuming we include the quadratic seasonal trend, we have the following model equations:

Top level: $$y_{itd} = \beta_{0_i} + \gamma_{1_i} d + \gamma_{2_i} d^2 + \beta_{1_{it}} a_{itd} + \beta_{2_{it}} p_{itd} + \epsilon_{itd} \quad (4)$$

Year variability level: $$\beta_{k_{it}} = \beta_{k_i} + e_{k_{it}} \quad (5)$$

Bottom level: $$\beta_{k_i} = \alpha_0 + \alpha_{1_k} g_i + \alpha_{2_k} s_i + \eta_{k_i} \quad (6)$$

The subscript t on the coefficients for air temperature and precipitation in equation (4) indicated that they are estimated separately for each year as well as for each site. For example, if there were an increased stream flow at site i in year t, it might decrease the impact of air temperature (so $\beta_{1_{it}}$ would go up). Thus the error term $e_{1_{it}}$would be negative. The value β_{k_i} represents the average value of coefficient k at site i over all of the years. The year variability level errors were assumed to be independent Normal random variables with variance $\sigma^2_{e_k}$. The subscript k indicated that there is a separate variance estimate for each of the k coefficients.

We chose to use a Bayesian hierarchical approach to fitting the models. This approach works well because of the hierarchical nature of our model. It also makes estimation of β coefficients at sites with little data more stable by drawing on information from other sites. In the Bayesian paradigm, prior distributions are specified for all of the model parameters, describing the prior beliefs about the values of the parameters. The data are used to update beliefs about the parameters, resulting in a posterior distribution. The posterior distribution is used to obtain parameter estimates (typically the posterior mean, or Bayes' estimate), and to obtain predictions and prediction uncertainty estimates.

We chose non-informative priors, reflecting a lack of any prior information about parameters. In particular, for each of the α, β, and γ coefficients, we chose independent Normal priors with mean 0 and standard deviation 100. For the variance parameters, we chose independent Inverse-Gamma priors with shape 0.01 and rate 0.01.

We used several objective measures to compare models: two AIC-type measures, deviance information criterion (DIC) and Watanabe-Akaike information criterion (WAIC) (Gelman et al. 2014), and two cross-validation measures, mean prediction error or bias (MPE) and root mean squared prediction error

(RMSPE). DIC and WAIC are Bayesian model comparison criteria that attempt to evaluate out-of-sample predictive accuracy. Similar to Akaike information criterion (AIC), each uses a measure of goodness of fit penalized by a measure of the effective number of parameters. It is possible for a statistical model to over-fit data if the model is flexible enough to fit sample noise. If a model over-fits to the sample data, then it will perform more poorly on new data than one would expect based on the in-sample results. We used a cross-validation approach to evaluate how the model performed on data from unobserved years. To calculate MPE and RMSPE, for each site with 5 or more years of data, we randomly chose one year to remove. The model was fit on the remaining data and mean predictive error (MPE) and square root of mean squared predictive error (RMSPE) were calculated for the data that were left out. This process was repeated four more times, each time removing one of the other 4 years; we report the MPE and RMSPE averaged over the five model fittings. The amount of bias is indicated by MPE and the magnitude of typical errors is indicated by RMSPE. For all of these measures, smaller numbers indicate a better model.

Forecasted stream temperature

To predict future water temperatures, we used the best fitted stream temperature model with future climate estimates as the climate covariates of the stream temperature model. Specifically, we used mean daily air temperature, total daily incident solar radiation, and area-weighted total daily precipitation in the upstream watershed as time-varying covariates of daily mean water temperature. For brevity, we refer to these three covariates as air temperature, solar radiation, and precipitation, respectively.

It was important to know how confident we were in the predictions produced by the model. Confidence and prediction intervals for the future time periods account for model uncertainty based on the model fit to the 2002 – 2014 data (i.e., uncertainty in model parameter estimates as well as residual variability in water temperature not accounted for by the model). To a lesser extent the confidence and prediction intervals also took into account uncertainty in the climate model predictions of climate variables. Only one simulation was available for each GCM of the USGS downscaled climate model. For each future time period, we used five consecutive years of climate model predictions, which act approximately like five simulations and provide some sense of prediction variability. Additional information about climate model uncertainty was accounted for by incorporating predictions from three different GCMs: GFDL, ECHAM5 and GENMOM.

To assess the strength of the forecasted climate data relative to the Ozark Plateau and to account for differences in predicted versus observed air temperatures and precipitation, we calibrated climate model predictions using hindcast data. Predictions from the climate models for the 1990 to 1999 time period were compared to Daymet values. Any bias present in the hindcast data was assumed to reflect bias in the model generally, and so climate model predictions for future time periods were adjusted to remove this bias. With the exception of precipitation (discussed below), we applied calibrations at each site separately, allowing for differences in weather patterns across sites. The predicted air temperatures and precipitation for the 1990 – 1999 period did not vary greatly between water temperature sites so although we reported metrics from all sites, we only showed plotted results for Current River P1 (Figure 4).

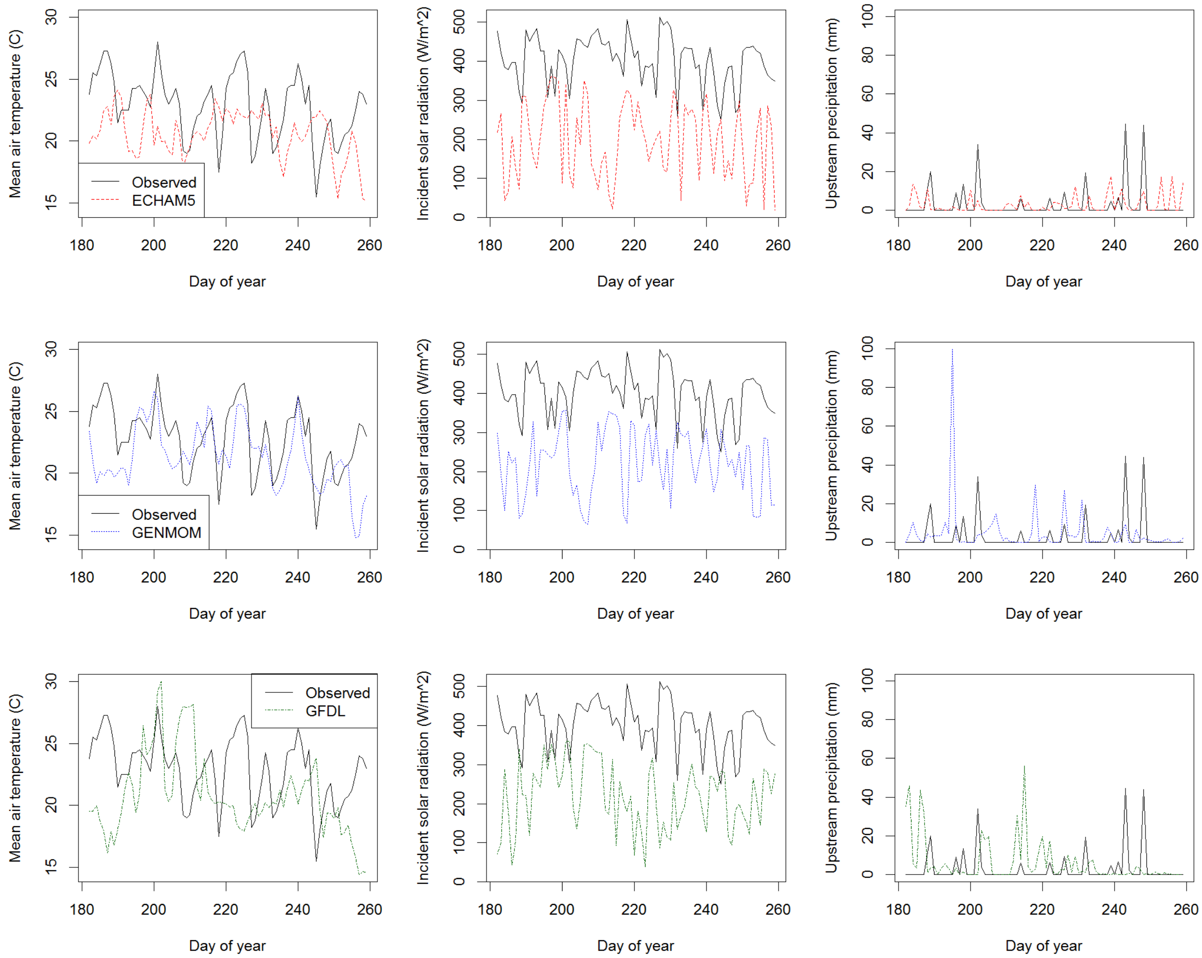


Figure 4. Hindcast and observed climate variables at Current River P1 for 1994 for ECHAM5, GENMOM and GFDL. All three models under-predicted solar radiation.

We primarily used the Doksum shift function (Bolin et al. 2016) to calibrate the climate model predictions. There are, however, several possible approaches to calibration. A simple method is to shift future predictions by the difference between the mean of the hindcast and observed values. A second approach is to compare daily (or weekly) means, rather than the overall means. This second approach removes differences in trends over the summer between the hindcast and observed data. For mean daily air temperature, some of the hindcasted climate model data did appear to have a different trend over the summer than the observed data. However, the data were relatively noisy, so that a daily or even weekly adjustment might have reflected noise rather than true model bias (Figure 5). Therefore, for mean daily air temperature, we used a smoothing spline with 3 degrees of freedom to estimate a smooth trend for the hindcast and observed mean daily air temperature (Figure 5). Then, the daily differences between the hindcast and observed trends were used to calibrate the future climate model predictions. Finally, a third approach is to use the Doksum shift function, which adjusts the distribution of predicted values to match the observed distribution, rather than only matching means. Examination of histograms (Figure 6) revealed a significant difference in the shape as well as the location of the

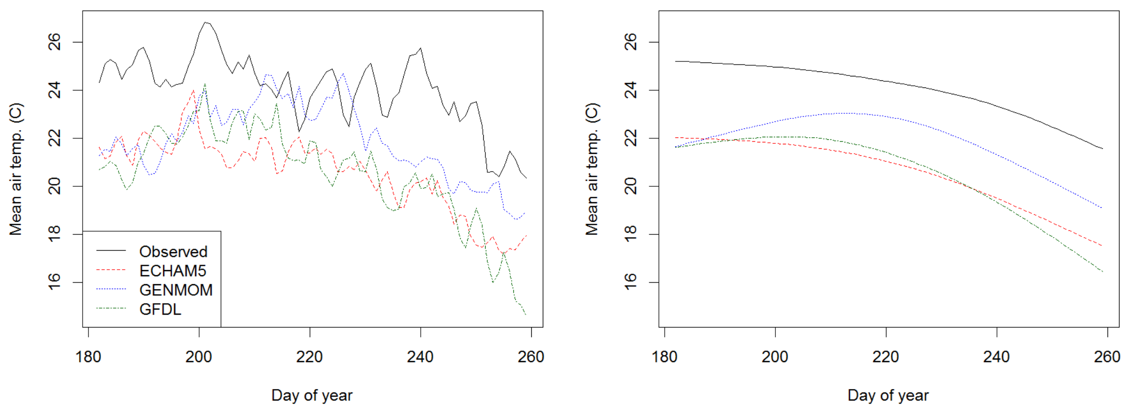


Figure 5. The left plot shows observed and hindcast (ECHAM5, GENMOM and GFDL) mean daily air temperature at Current River P1, averaged across years from 1990 to 1999. The right plot shows the results of applying a smoothing spline with three degrees of freedom to the observed and hindcast averages. Each climate model is adjusted using the daily differences between the smoothed hindcast data and smoothed observed data.

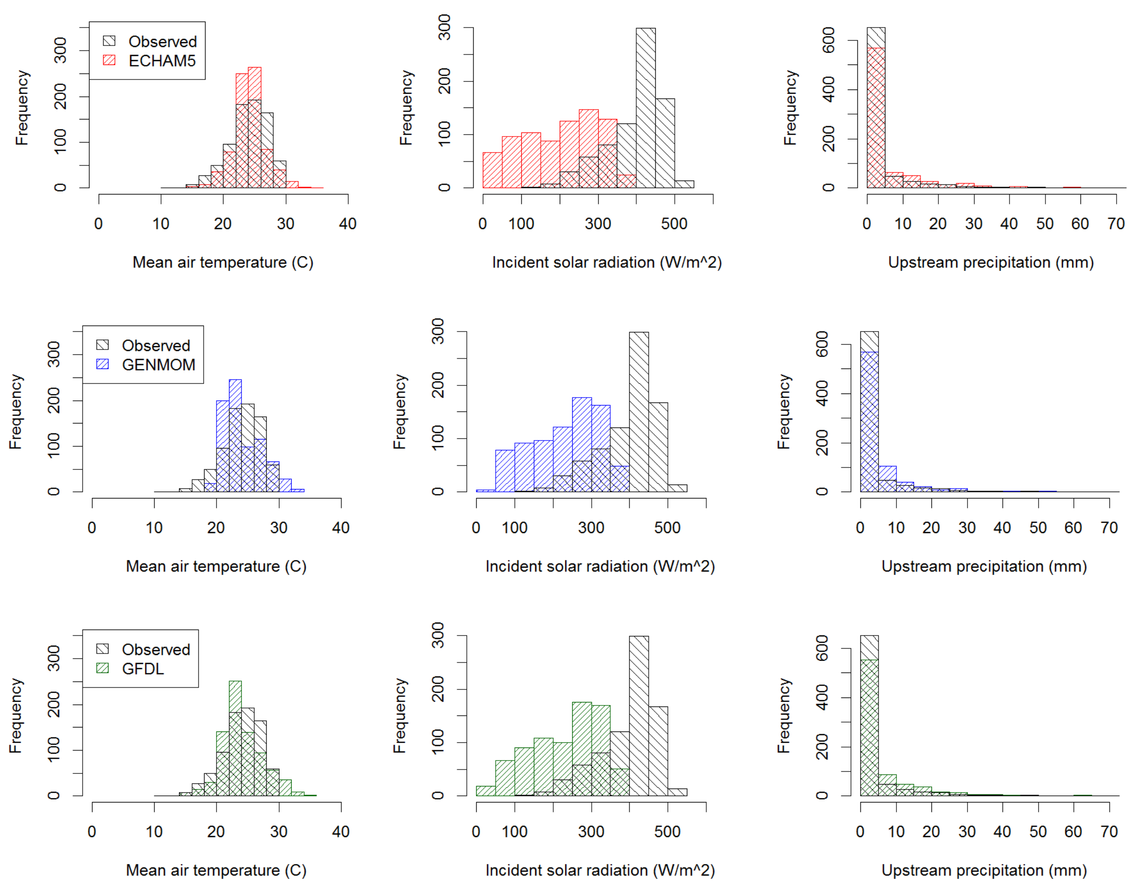


Figure 6. Histograms of hindcast and observed climate variables at Current River P1 from 1990 to 1999 for ECHAM5, GENMOM and GFDL. The shape and location of the hindcast distributions of the GCM models differ from the observed data. For air temperature, the hindcast data has already been adjusted

with a shift for each day of the year using the difference between the smoothed observed values and the smoothed hindcast values (smoothed using a smoothing spline with three degrees of freedom).

distributions, suggesting that a distributional calibration method would be valuable. Given these patterns in climate metrics, we applied the Doksum shift function to the solar radiation and precipitation data directly. For air temperature, the daily mean corrections from the smoothing splines were applied first, followed by the Doksum shift function.

The Doksum shift function assigns a shift amount to each possible prediction value, and is chosen so that when applied to the hindcast data the calibrated hindset data will have the same distribution as the observed data. Let $F(x)$ represent the empirical cumulative distribution function (ECDF) of the model hindcast data, and let $G(x)$ represent the ECDF of the observed data. Then the Doksum shift function is $G^{-1}(F(x)) - x$. Examples of the shift functions for our dataset are shown in Figure 7. For air temperature and solar radiation, we were able to calculate a separate shift function for each site. However, due to the highly-skewed distribution of precipitation values, a larger sample was needed to produce a reasonably stable shift function, and so we created one shift function for all sites. A plot (not shown) of the observed and model hindcast precipitation ECDF functions for each site individually suggested that these were similar across sites and that a single shift function was reasonable.

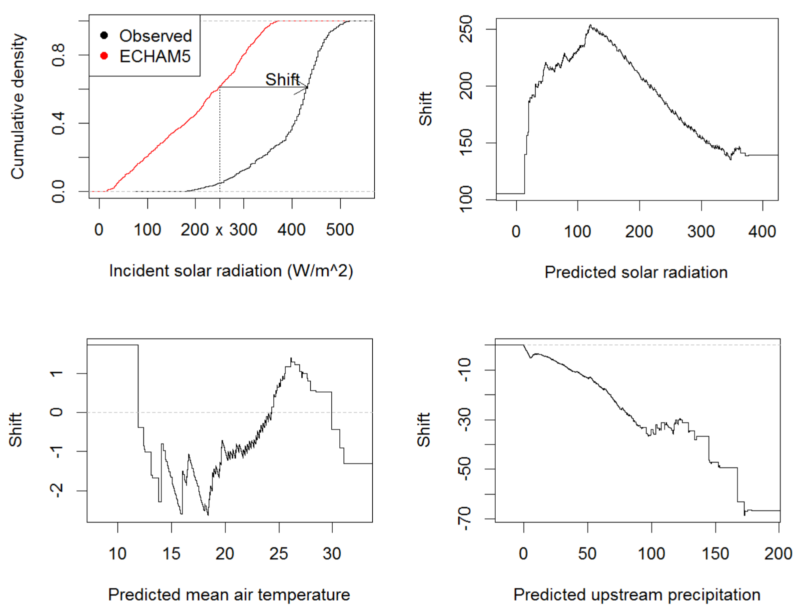


Figure 7. Doksum shift functions for mean air temperature, incident solar radiation, and mean upstream precipitation, for the ECHAM5 global climate model. At top left, the empirical cumulative distribution function (ECDF) for the observed and model hindcast incident solar radiation data are shown for Current River P1. A model incident solar radiation of 250 W/m^2 should be shifted up by 167 W/m^2 to create a distribution matching the observed incident solar radiation data. The corresponding Doksum shift function is shown at top right. The shift functions for mean air temperature and upstream total precipitation are in the bottom row. Note that the precipitation shift is calculated across all sites, whereas there is a separate shift function for each site for air temperature and solar radiation.

These calibration methods do not fix all possible problems with climate model predictions. A major shortcoming of the mean shift and Doksum shift function methods is that these do not take into account day-to-day patterns. As an extreme example, the model could predict a pattern where air temperature fluctuated rapidly, alternating between high and low values from one day to the next. We know intuitively that it is not reasonable for air temperature to be continually changing from hot one day to cold the next – most of the time, daily air temperatures fluctuate more slowly. However, neither the daily mean shift nor the Doksum shift function is designed to address this temporal pattern issue. Unfortunately, we are not aware of a good approach for dealing with this issue. Therefore, it is simply a potential problem with the climate model data. It is most likely to be an issue in producing realistic time series of water temperature predictions and in estimating consecutive day statistics, such as the number of consecutive days above 21.1°C (70°F). However, we do not use the model for consecutive day statistics. With this model, we predicted mean daily water temperature and number of 24-hour periods above 21.1°C (70°F) for 2040 – 2044, 2060 – 2064, and 2085 – 2089 using climatological variable predictions from the three global climate models: GFDL CM2.0, MPI ECHAM5, and USGS GENMOM.

Results

Data summary

Data for several sites and years were discarded because they were outliers, mislabeled, or had no spatial information that could be used to associate the site with landscape metrics (Appendix B). The resulting water temperature database contained data from 106 different locations, covering 21 river systems of interest, and resulting in unique sites by year combinations.

Water-climate patterns

Based on the Daymet climate metrics for the stream temperature sites, the mean summer air temperature ranged from 22.6°C (2009) to 25.9°C (2011; Figure 8a) while mean summer precipitation ranged from 2.3 mm/day (2014) to 5.7 mm/day (2008; Figure 8b). Precipitation had higher mean absolute error (MAE) and bias values than air temperature metrics (Table 5). With the exception of maximum air temperature, the climate metrics tended to have a positive bias indicating an overestimation of values. The maximum bias is relatively small (<0.3 mm for precipitation and <0.15°C for air temperature metrics) and only slightly higher than the mean values (<0.15 mm for precipitation and <0.08°C for air temperature metrics). Maximum MAE ranged from 2.7 mm for precipitation to <1.9°C for air temperature metrics. When mean daily summer air temperature and precipitation were plotted together, 2011 and 2012 were the warmest and driest years, whereas 2008 and 2013 were the cooler and wetter years (Figure 8c).

Table 5. Cross-validation-based mean absolute error (MAE) and bias for Daymet estimates of minimum and maximum daily air temperature and total daily precipitation. We report the mean and maximum MAE and bias for the period from 2002 to 2014 between 90 and 94 degrees west and between 36 and 38 degrees north.

Variable	Units	MAE		Bias	
		Mean	Max	Mean	Max
Minimum air temperature	°C	1.47	1.70	0.06	0.13
Maximum air temperature	°C	1.40	1.90	-0.03	0.05
Precipitation	mm	2.10	2.66	0.12	0.27

Mean daily summer air temperature alone did not explain much variation in mean water temperature (r^2 = 0.09). Mean daily recorded water temperature ranged from 17.5°C (2004) to 19.1°C (2006; Figure

9). Looking at variation in mean, minimum, and maximum daily water temperatures for each summer, 2003 and 2006 were significantly warmer than all years except 2005, while 2004, 2009, and 2013 were significantly cooler than all other years (Figure 9).

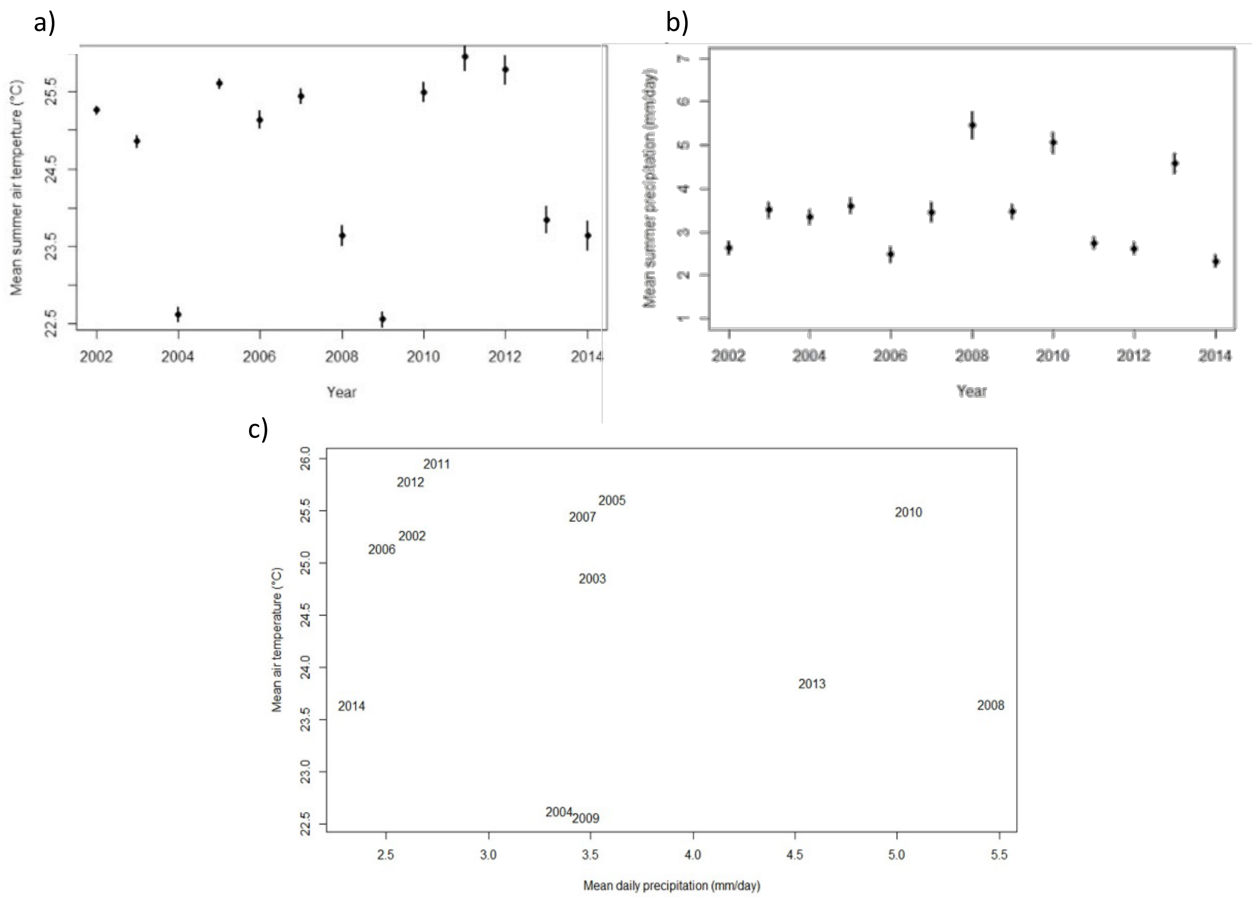


Figure 8. Mean summer air temperature and precipitation and the relationship between these from 2002 to 2014. a) Mean (95% confidence interval) summer air temperature, b) mean (95% confidence interval) summer precipitation rates, and c) comparison of mean air temperature and mean daily precipitation rates from 2002 – 2014 across the entire subregion where water temperatures were monitored in the Missouri Ozarks.

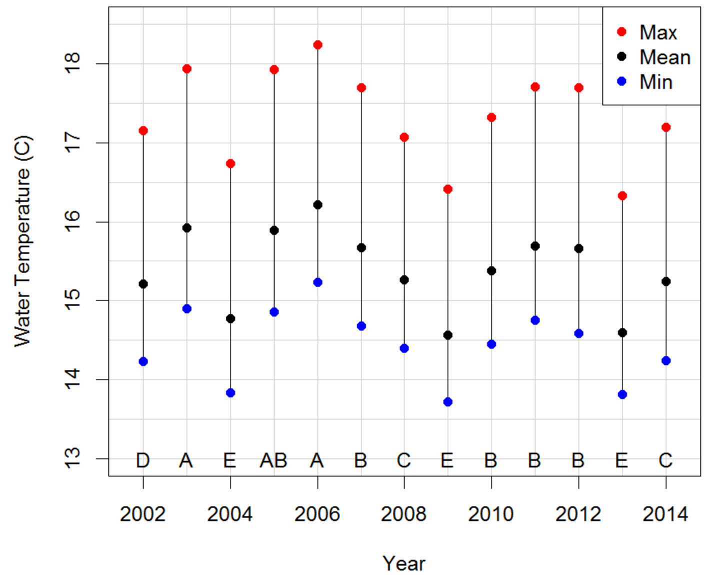


Figure 9. Each water temperature point in the plot is an estimated yearly average for the period from July 9 to September 8 from a two-way ANOVA of minimum, mean, or maximum daily water temperature with site and year as factors. The yearly average water temperature was estimated using ANOVA rather than simply reported from the sample because different years of data were missing at each site. The letters at the bottom of the plot provide Tukey 95% experiment-wise confidence level pairwise comparisons of the years. Years with a letter in common are not significantly different for at least one of the three measures (min, mean, or max).

We ran pairwise correlations between the climatological variables and water temperature measurements using the original data with daily observations rather than yearly averages (Table 6). For correlations with water temperature variables, only days with observed water temperature were used. For correlations involving only climate variables, all summer days from 2002 to 2014 were used. All correlations were highly significant ($p < 2.2\text{e-}16$) at any reasonable significance level, except for the correlation between minimum water temperature and precipitation ($p = 0.194$). Not surprisingly the mean values of the climate variables air temperature, solar radiation, and precipitation do not explain all of the variability in water temperature. For example, 2002 was a relatively warm and dry year, but water temperatures were fairly low. Although 2011 was warmer than and about as dry as 2006, water temperatures were warmer in 2006. As expected, solar radiation was negatively correlated with precipitation, since rain requires cloud-cover. We explored a number of simple regression models to predict the mean summer water temperatures for each year shown in Figure 5 using air temperature, solar radiation, and precipitation data. Although the best models accounted for about 50 – 60% of the variability in water temperatures, none of the climate metrics adequately captured enough of the variability to use as a covariate for yearly variability.

While the ANOVA analysis allowed us to estimate yearly changes in mean summer water temperature (i.e., fixed effects of years), we also examined whether there was an overall trend (increasing or decreasing) in water temperature (WT) from 2002 to 2014. For each of three variables (mean WT, mean minimum WT, and mean maximum WT), we performed linear regression with fixed effects for site but treating year as a continuous variable. For all three variables, the estimate was slightly negative, but

Table 6. Pairwise correlations between the climatological variables and water temperature (WT) measurements using the original data with daily observations rather than the yearly averages. For correlations with water temperature variables, only days with observed water temperature were used. For correlations involving only climate variables, all summer days from 2002 to 2014 were used. AT = air temperature. All correlations were significant ($p < 2.2e-16$), except for the correlation between minimum water temperature and precipitation ($p = 0.194$).

	Min WT (°C)	Max WT (°C)	Mean WT (°C)	Mean AT (°C)	Mean Precipitation (mm)	Mean solar radiation (W/m^2)
Min WT	1	0.885	0.969	0.322	0.006	-0.055
Max WT		1	0.968	0.282	-0.075	0.082
Mean WT			1	0.300	-0.040	0.025
Mean AT				1	-0.020	-0.051
Precip.					1	-0.620
Solar rad.						1

only significant for the mean maximum WT (mean WT: slope coefficient = -0.027, p = 0.053; mean minimum WT: slope coefficient = -0.019, p = 0.164; mean daily maximum WT: slope coefficient = -0.034, p = 0.026). Mean summer air temperature, solar radiation, and precipitation only partially accounted for the decrease in mean maximum WT. All three climate metrics tended to increase (if anything) during 2002 – 2014 (air temperature: slope coefficient = 0.016, p = 0.1082; solar radiation: slope coefficient = 0.488, p = 1.14*e-10; precipitation: slope coefficient = 0.032, p = 0.0002). Based on a regression of the only water temperature variable with a significant trend, mean maximum WT for summer, as a function of air temperature, solar radiation, and precipitation, we found that air temperature was significantly positively related to water temperature (slope coefficient = 0.312, p < 2*e-16) while solar radiation (slope coefficient = -0.007, p = 0.146) and precipitation (slope coefficient = -0.045, p = 0. 375) were both negatively related to water temperature, but not significantly. After accounting for these variables there was still an overall decrease in mean summer water temperature. A separate linear regression on the residuals as a function of year had a slope of -0.016, p=.053. Thus, there is weak evidence of an overall decreasing trend in water temperatures over the period from 2002 to 2014, and this trend cannot be fully accounted for by mean summer air temperature, solar radiation, and precipitation.

Thermal similarities of monitoring sites

The results of the hierarchical cluster analysis were displayed as a dendrogram (produced using Ward's method) in Figure 10 with sites divided into six color-coded and numbered groups based on cluster breaks. Of the four distance measures assessed, Ward's method resulted in the highest agglomerative coefficient value (0.89; Table 7) indicating the strongest support for the partitioning of sites based on this approach. These six groups contained from three to 20 sites.

In viewing the dendrogram it is important to understand that the proximity of labels to each other is not an indication of similarity. For example, group two could have been drawn such that the order of sites top to bottom would read: Greer Spring Branch – P2, Crane Creek – P1, Crane Creek – P3. The length of lines between branches and site names are important for interpretation and reflects the relative distance or degree of similarity among sites. Sites that cluster together with short distances between them (as depicted by a relatively short line from a branch to the site label) are more similar than clustered sites with longer lines (distances) between them. So in group 6 the paired sites, Greer Spring Branch – P1 and Dewitt-Wilkens Spring – P1 are more similar to each other than the paired sites, Maramec Spring Branch – P1 and Bennett Spring Branch – P1 are to each other.

Table 7. Measurement of strength of cluster structure for 4 methods to conduct a hierarchical clustering analysis. Scale is 0 – 1; values closer to 1 indicates more support for the resulting cluster structure.

Hierarchical clustering Method	Agglomerative coefficient
Average	0.74
Single linkage	0.53
Complete linkage	0.84
Ward's	0.89

Of the eleven metrics used to differentiate sites (Table 4), seven appeared to provide the majority of the differentiation based on range of values (Table 8). These metrics included the magnitude and rate of change metrics, one of the variability metrics, two timing metrics, and all metrics in the frequency of stress days category. Group 5 had the warmest temperatures, highest frequencies of stress days, and days exceeding 25°C while group 6 had the coolest summer temperatures with fewest stress days.

Table 8. Examples of variation among water temperature monitoring sites that were differentiated based on water temperature metrics using hierarchical clustering. These are based on range of values for each metric and are not meant to reflect the totality of differences among these groups. Refer to Table 4 for acronym definitions

		Hierarchical Cluster Groups					
Category	**Metric**	**1**	**2**	**3**	**4**	**5**	**6**
Magnitude (˚C)	AvgDmeanSU	14 - 17		16 - 21		≥ 20	≤ 15
Frequency (%)	AvgPercStrD_Ttl	0	≤ 0.22	≤ 3.2	≤ 1.3	≥ 1.6	0
	AvgPercStrD_GE15	37 - 100		> 98	78 - 100	> 99	< 8
	AvgPercStrD_GE25	0	0 - 2	0	0 - 2	0	3 - 17
Variability (˚C)	RmaxSu	2 - 5		4 – 8		> 7	0 - 3
Timing (Julian Day)	JDmaxMaxTSu	193 - 221	205 - 218	204 – 250	204 - 217	227 - 240	204 - 226
	JDM7MAMaxT	≤ 228	≥ 235	190 - 237		202 - 251	
	JDminMinTSu	185 - 228	235 - 251	184 - 197	190 - 236	224 - 236	226 - 237
Rate of change	RCsu	0.03 – 0.17	≤ 0.04	0.1 – 0.3		0.2 – 0.4	≤ 0.04

The six groups identified using the hierarchical clustering were further examined with a principal components analysis (PCA). The first two principal components axes explain 84.4% of the variation among these groups. Based on the environmental distance depicted in Figure 11, groups 3 and 4 have a fair amount of overlap, whereas the other four groups show distinct separation, although groups 1 and 2 adjoin one another. Axis PC1 represents a gradient for the breadth in timing of minimum summer

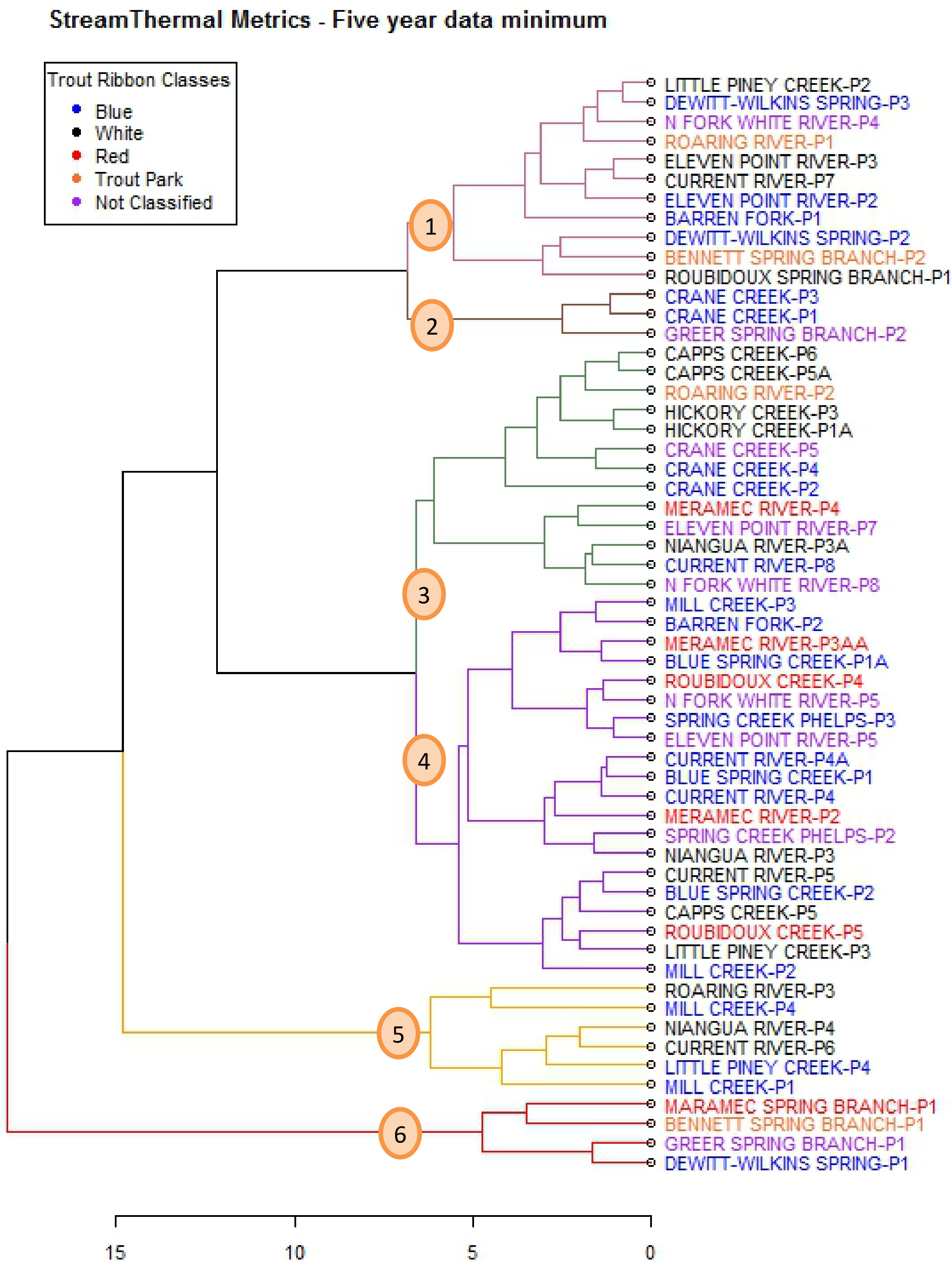


Figure 10. Dendrogram of hierarchical cluster analysis results obtained from the 57 temperature monitoring locations with at least five years of data covering the period of July 1st through September 15th. The analysis was based on 11 metrics from Table 2-3. Line colors represent six clusters of sites where water temperature was recorded for a minimum of 5 years and are numbered 1 – 6 for discussion purposes. Label colors represent the Missouri Department of Conservation Trout Stream Ribbon Area Classifications.

temperature combined with the number of stress days greater than or equal to 25˚C. Groups 1 and 4 have the widest range of dates (>28 days) for the occurrence of minimum temperature while the other groups had narrower windows (<18 days). Although the eigen value for AvgPercStrD_GE25 was roughly equivalent but opposite of the JDminMinTSu eigen value, we were unable to discern a pattern that explained the distribution of groups along PC1 based on this metric. The second axis, PC2, is a gradient of the mean temperatures and timing of maximum temperatures. Sites in groups 1, 2, and 6 tend to have lower mean summer temperatures, less annual variation in maximum temperature, and a lower rate of change within summers whereas those in group 5 have the highest of these metrics with the remainder of sites falling along a gradient between these groups.

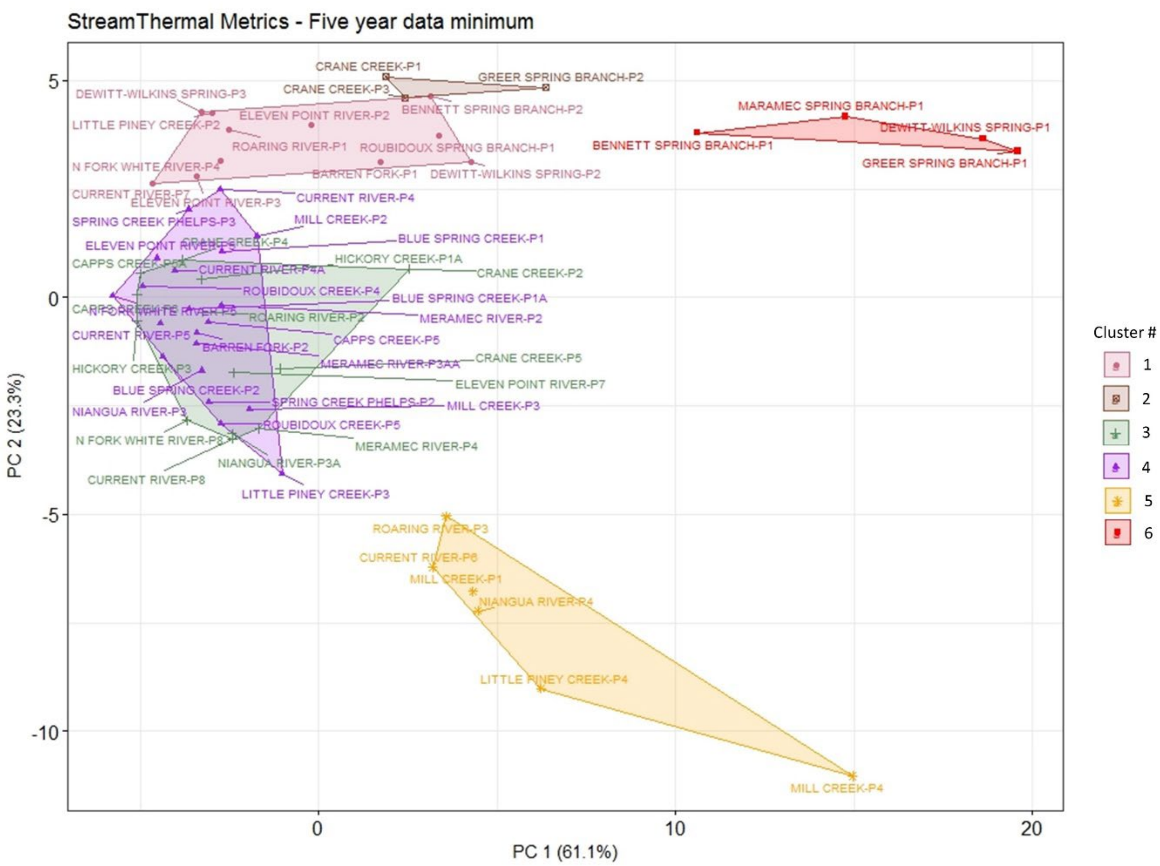


Figure 11. Principal components (PC) scatter plot showing the environmental distance between stream temperature monitoring sites with cluster groups based on a hierarchical clustering analysis. The axes correspond to the first two principal components axes and display the percent of variation explained by each axes. Cluster numbers and colors correspond to those in Figure 10.

Stream temperature model

Fitting the Bayesian hierarchical model confirmed that air temperature was the most important predictor. The best additional variables were squared air temperature, air temperature three and five days previous, precipitation categorical variable with cut-off at 3mm, and solar radiation. However, in the end we chose not to use the squared air temperature variable for several reasons: first, the mean value across years was typically very near to 0, indicating that the variable was in part allowing the model to fit yearly variability rather than accounting for the consistent, curved relationship observed between air and water temperatures. The estimated quadratic relationships between air and water temperatures for each site are shown in Figure 12. Overall, there is very little departure from linearity even when air temperature exceeded the ~20˚C threshold for linearity reported by Mohseni et al. (1998) or the ~25˚C threshold for Oklahoma streams reported by Erickson and Stefan (2000). Finally, the squared term makes interpretation of the air temperature coefficient significantly more complicated.

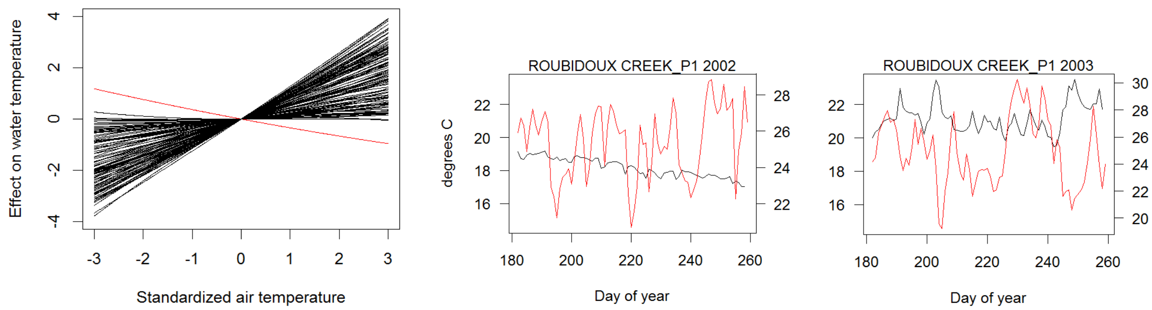


Figure 12. At left, quadratic curves for each site describing the effect of air temperature on water temperature. Overall, departures from linearity within the range of observed air temperature values is minimal. Roubidoux Creek P1 has an estimated negative effect of air temperature, shown in red on the plot at left. In the right two plots we show all data for Roubidoux Creek P1. Water temperature is in black and uses the left axis, while air temperature is in red and uses the right axis.

We report the results from the proposed stream temperature models in Table 9. Model option 1 (no yearly variability) fit more poorly than models with proposed option 2 (in which coefficients vary from year to year to accommodate yearly variability) as measured by DIC and WAIC. The quadratic seasonal trend clearly was important. In comparing model options with different climatological variables, the precipitation category (precip>3mm [P>3]) was preferable to alternate precipitation category, and air temperature three and five days previous (AL3 and AL5, respectively) were beneficial although the model without them does have the least bias (MPE).

In evaluating the site characteristics, Strahler order, upstream watershed area, elevation, and gradient tended to be fairly highly correlated, so we selected just one of those variables for inclusion. Of the four, Strahler order (Strahler) and upstream watershed area (UWArea) were initially chosen because they relate to stream flow and precipitation catchment, and thus seemed more likely to directly impact the effects of climatological variables than elevation or gradient at least in Missouri where the gradient in these metrics is fairly narrow. Regardless, neither variable provided enough information to meaningfully affect model fit (Table 9). However, based on the credible intervals (Bayesian equivalents of confidence intervals), the impact of Strahler order seemed marginally significant, and so we included it in our final model along with the groundwater influence measure (GWInf).

All of the models that include the quadratic seasonal trend are quite similar in terms of RMSPE, meaning that they all are similarly good at predicting water temperatures for unobserved years. Model 1 (no yearly variability of coefficients) with the quadratic seasonal curve is best in terms of RMSPE by a small margin, but it is notably worse than Model 2 with the quadratic seasonal curve in terms of WAIC and DIC. We chose Model 2 with the quadratic seasonal curve as the best overall model because the better WAIC and DIC values suggest a more appropriate model and therefore more reliable credible intervals for estimates and prediction intervals for predictions.

Table 9. Comparison of predictive models for stream temperature. Model 1 assumes no yearly variability in coefficients while Model 2 assumes random yearly variability in coefficients. Climatological variables were air temperature (AT), lag 3 air temperature (ATL3), lag 5 air temperature (ATL5), precipitation (P), precipitation category with cut-off at 3 mm (P>3), and solar radiation (SR). Site characteristics were groundwater influence (GWInf), upstream watershed area (UWArea), and Strahler order (Strahler). DIC and WAIC are Bayesian goodness-of-fit measures similar to AIC. For DIC and WAIC, pDIC and pWAIC are, respectively, the effective number of model parameters. Cross-validation (CV) results leaving whole years of data out for sites with 5 or more years of data are reported in terms of bias or mean prediction error (MPE) and typical magnitude of error or root mean squared prediction error (RMSPE). For DIC, WAIC, MPE, and RMSPE, smaller values indicate a better fit.

Model	Variables	DIC	(pDIC)	WAIC	(pWAIC)	CV By Years	
						MPE	RMSPE
Model 2 + quadratic seasonal curve	AT,ATL3,ATL5,P>3,SR; GWInf, UWArea	69,843	(2613)	70,105	(2631)	-0.015	0.936
	AT,ATL3,ATL5,P>3,SR; GWInf, Strahler	69,842	(2612)	70,104	(2630)	-0.015	0.936
	AT,ATL3,ATL5, P, SR; GWInf, Strahler	75,201	(2472)	75,517	(2544)	-0.020	0.939
	AT, P>3, SR; GWInf, Strahler	72,651	(1949)	72,896	(2019)	-0.007	0.949
Model 2	AT,ATL3,ATL5,P>3,SR; GWInf, UWArea	89,537	(2371)	89,745	(2378)	0.010	1.105
Model 1 + quadratic seasonal curve	AT,ATL3,ATL5,P>3,SR; GWInf, UWArea	80,140	(922)	80,239	(971)	0.012	0.933

Combining best model and climate variables, the overall best model was Model 2 with the quadratic seasonal curve, groundwater influence and Strahler order as the site characteristics, and mean daily air temperature, lag 3 mean daily air temperature, lag 5 daily mean air temperature, upstream total daily precipitation greater than 3 mm (categorical), and total daily incident solar radiation as the climatological predictor variables. We used this model for all sites to assess relationships between the climatological variables and water temperature and the influence of site characteristics on this relationship.

The findings we report here are based on all sites and we highlight the results at four sites that are representative of streams with relatively high or low flow volume and with high or low groundwater influence. Two sites on the Current River, P4A and P7, represent the high flow stream condition (Strahler Order 4 and 5 respectively). Two sites on Mill Creek, P2 and P4, represent the low flow stream condition (Strahler Order 2 and 4 respectively). Current River P7 has relatively high groundwater influence (0.0002 cms/m), while Current River P4A has relatively low groundwater influence (0.00007 cms/m). See maps in

Appendix A to view spatial arrangement of these sites. Groundwater influence in Mill Creek P2 and Mill Creek P4, 0.00003 and 0.00002 cms/m respectively, is similar.

For most sites, the quadratic seasonal trend was similar exhibiting a concave down to relatively flat pattern (Figure 13) with the exception of two sites which were notably concave up: Current River P1 and Roubidoux Creek P1. A third site was slightly concave up but only minimally so we left this out of further discussion. Both sites had data for only 2002 and 2003, and experienced an unusual and pronounced pattern in 2003 in which temperatures began high, were low in August, and high again in the first half of September. We would not expect very reasonable predictions for these sites due to these unusual seasonal trend estimates.

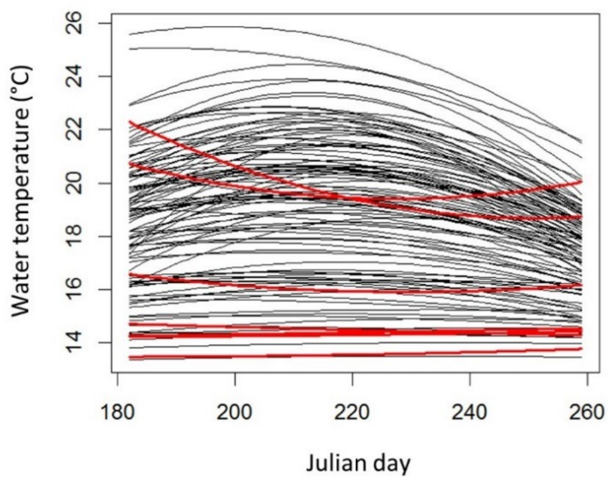


Figure 13. Modeled seasonal trends on water temperature for each site. All curves are concave down with the exception of those shown in thicker, red lines. The two sites which are notably concave up are Current River P1 and Roubidoux Creek P1. Both sites had data for only 2002 and 2003, and experienced an unusual and pronounced pattern in 2003 in which temperatures began high, were low in August, and high again in the first half of September. A third site, was very slightly concave up.

By examining the β coefficients, we can describe the typical relationships between the climatological variables and water temperature at each site, on average over the years (Figure 14). The relationship between the air temperature variables (current day, three days previous, and five days previous) and water temperature is generally positive – for a few sites the estimates are slightly negative but the 95% credible intervals for the estimates all contain 0. Estimates of the average effects of precipitation category and solar radiation were close to 0 in the sense that the 95% credible intervals all contain 0 (Appendix F). However, the precipitation category estimates tended to be negative (so that high precipitation is related to decreases in water temperature) while the solar radiation effect tended to be near zero. In general, the current day's air temperature tended to contribute the most to water temperature prediction. Coefficient estimates at the four highlighted sites are shown in Table 10.

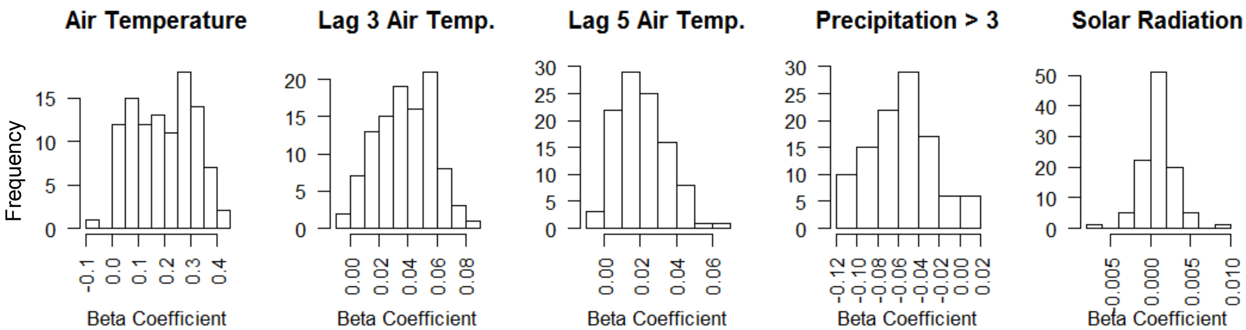


Figure 14. Histograms of coefficient estimates, averaged over years. The coefficient for each of the climatological variables is estimated at each site. The histograms show the distribution of estimates across sites. Lag 3 air temperature means air temperature 3 days previous. Precipitation>3 is a categorical metric for total daily upstream precipitation >3 mm.

Table 10. Typical effect of climatological variables at four sites. For Current River P7, if air temperature increases by 1°C, we expect water temperature to increase by 0.19°C. On days where precipitation is greater than 3mm, we expect water temperature to decrease by 0.0804°C. From this table we can see that the sites with more groundwater influence (Current River P7 and Mill Creek P2) tend to be less affected by changes in climatological variables, while sites on Mill Creek are more variable than sites on the Current River. AT = air temperature.

Site	Ground-water	AT	Lag 3 AT	Lag 5 AT	Precipitation > 3 mm	Solar radiation
Current River P7	0.0056	0.1857	0.0322	0.0173	-0.0804	0.0010
Current River P4A	0.0026	0.1914	0.0330	0.0163	-0.0509	0.0013
Mill Creek P2	0.0012	0.1262	0.0145	0.0062	-0.0289	0.0009
Mill Creek P4	0.0007	0.4039	0.0553	0.0261	-0.0555	0.0033

The model also estimates the variability in the β coefficients, producing yearly coefficient estimates (see Figures 15 and 16 for the yearly coefficient estimates for the four highlighted sites and Appendix G for all sites averaged across years). All sites were missing data for at least one year with the exceptions of Blue Spring Creek P1 and Meramec River P2 and P3, and 11 sites had only a single year of data. For years with no data the model estimates for the yearly coefficients are pulled towards a typical value and the 95% credible intervals for the estimates are notably wider than in years with data. The precipitation coefficients tended to vary a great deal from year to year. Given this variability and the relative flexibility of the model, we would be hesitant in interpreting this coefficient.

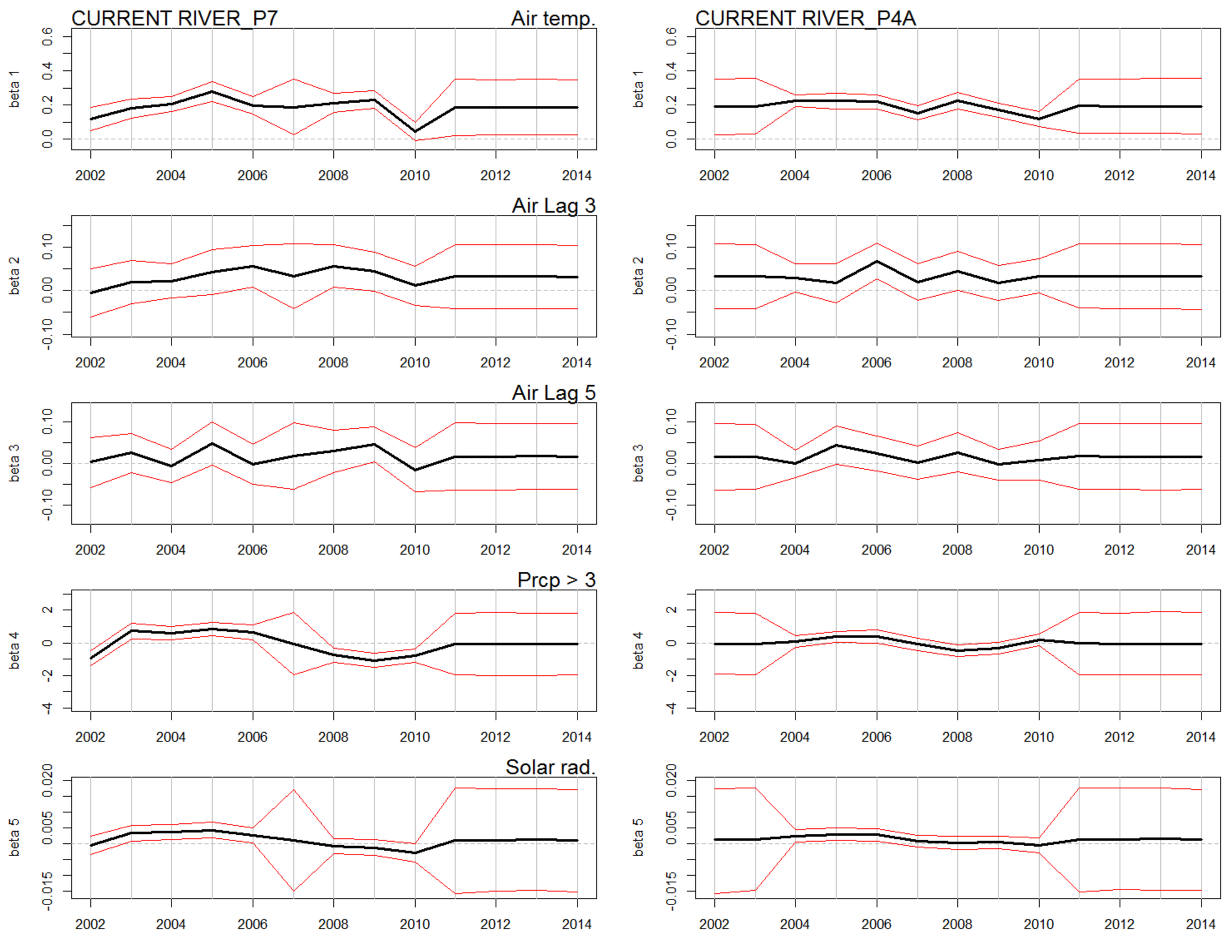


Figure 15. β coefficients describing the linear relationships between the climatological variables and mean daily water temperature at the Current River sites, estimated for each year. The black line is the Bayes' estimate of the parameter for the years 2002 to 2014, and the red lines are the 95% credible interval for the parameter. No data were available for Current River P7 in 2007 and 2011 – 2014. No data were available for Current River P4A in 2002, 2003, and 2011 – 2014. Clear differences between the two sites due to groundwater influence are not readily apparent.

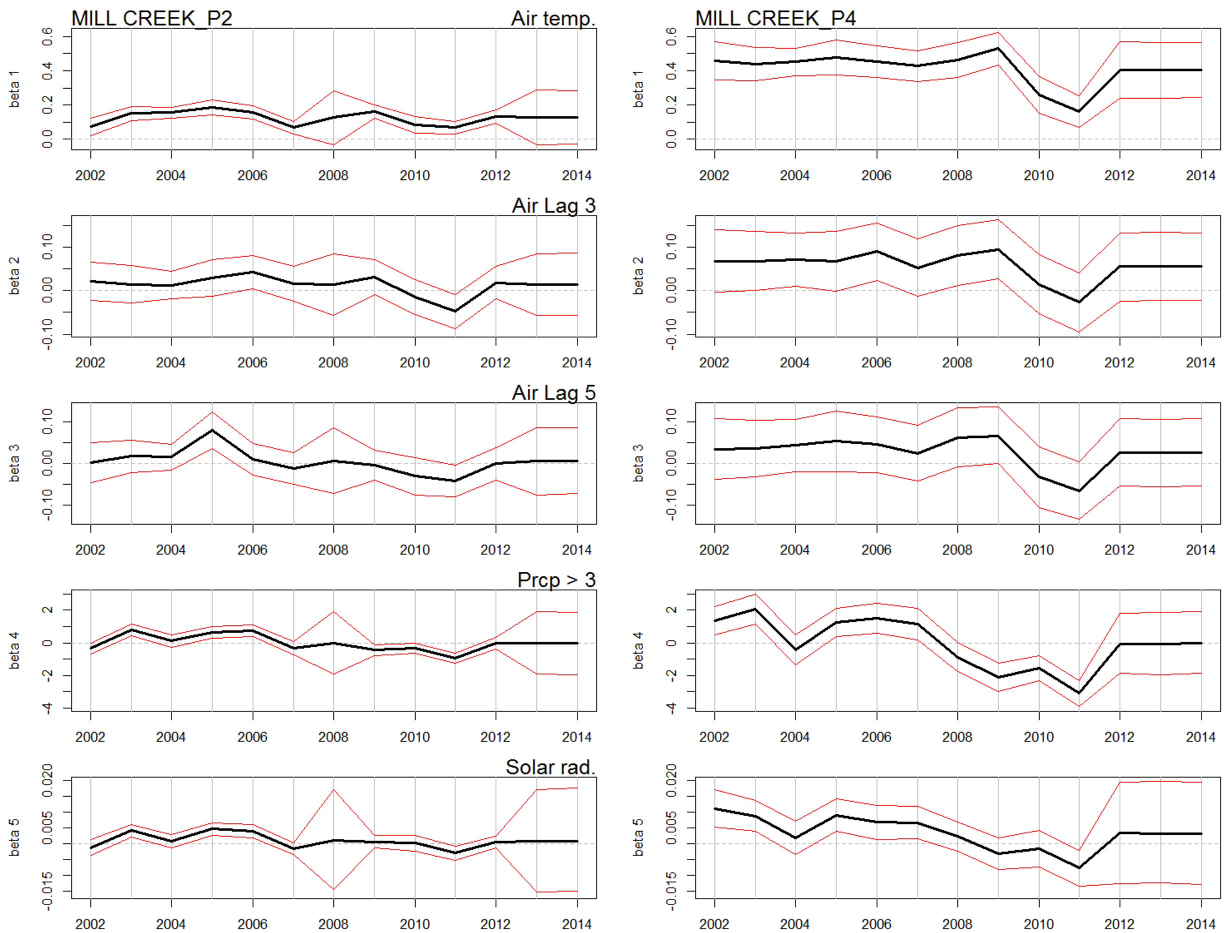


Figure 16. β coefficients describing the linear relationships between the climatological variables and mean daily water temperature at the Mill Creek sites, estimated for each year. The black line is the Bayes' estimate of the parameter for the years 2002 to 2014, and the red lines are the 95% credible interval for the parameter. No data were available for Mill Creek P2 in 2008, 2013, and 2014. No data were available for Mill Creek P4 in 2012 – 2014. At the Mill Creek sites the effect of greater groundwater influence on Mill Creek P2 as compared to Mill Creek P4 is predominantly apparent in the air temperature coefficient which is much lower for Mill Creek P2, though also noticeable in the other coefficients which also tend to be smaller and less variable for Mill Creek P2.

The β coefficients describe the linear relationship between climatological variables and mean daily water temperature at each site, and the site characteristics modify these relationships. We report the impact of the site characteristics in Table 11. For example, for every 1 unit increase in groundwater influence measure, the coefficient for air temperature typically decreases by 0.001. Since the coefficient for air temperature is positive, increasing groundwater influence reduces the impact of air temperature on water temperature. On the other hand, for every 1 unit increase in Strahler order, the coefficient for air temperature typically increases by 0.012. This indicates that, for these sites, air temperature has a greater positive influence on water temperature as stream size increases. Overall, groundwater influence and Strahler order seem to have only a weak impact on the effects of the climatological variables. Better measures of groundwater influence and stream flow would potentially have stronger impacts on the climatological variables.

Table 11. The impact of site characteristics (columns) on β coefficients for climatological variables (rows). The β coefficients describe the linear relationship between climatological variables and mean daily water temperature, and the site characteristics modify these relationships. The top number in each table cell is the posterior mean or Bayes' estimate. The Bayes' estimate can be interpreted as follows: For example, for every 1 unit increase in groundwater influence measure, the coefficient for air temperature typically decreases by 0.001. Since the coefficient for air temperature is positive, increasing groundwater influence reduces the impact of air temperature on water temperature. The numbers in parentheses are the 95% credible interval for the parameter value. If the 95% credible interval does not contain zero, the Bayes' estimate is in boldface. Looking at the 95% credible intervals, one can see that some are more significant than others. For example, the impact of Strahler order on the effect of lag 5 air temperature does not look very meaningful at all because zero is roughly in the middle of the credible interval. On the other hand, there is much more evidence that Strahler order impacts the effect of lag 3 air temperature.

Climate variables	Intercept	Groundwater influence	Strahler order
Air temperature	0.149 (0.062, 0.238)	-0.0010 (-0.0029, 0.0006)	0.0117 (-0.0085, 0.0312)
Lag 3 air temperature	0.015 (-0.009, 0.041)	-0.0002 (-0.0006, 0.0003)	0.0060 (-0.0004, 0.0113)
Lag 5 air temperature	0.018 (-0.006, 0.041)	-0.0002 (-0.0006, 0.0003)	0.0009 (-0.0046, 0.0063)
Precipitation > 3mm	0.041 (-0.222, 0.299)	-0.0002 (-0.0054, 0.0045)	-0.0241 (-0.0854, 0.0378)
Solar radiation	0.000 (-0.010, 0.010)	-0.0000 (-0.0002, 0.0002)	0.0002 (-0.0021, 0.0026)

The model provides predictions for water temperature for each summer from 2002 to 2014 at each site. In Figures 17 and 18, 95% prediction intervals for water temperatures for each summer from 2002 to 2014 are shown as well as the actual observed water temperatures. Across all sites, the 95% prediction intervals contain 95.6% of actual observed water temperatures, confirming that the posterior predictive distribution (PPD) is appropriate. For each site, the standard deviation of the PPD averaged over all the days in the time period of interest can be used to describe prediction uncertainty at each site. Averaged across all sites, the standard deviation of the PPD for 2002 – 2014 is 0.91. In other words, the model estimates that on average the water temperature predictions tend to be off by about 0.91°C. The standard deviation of the PPD for Current River P7, Current River P4A, Mill Creek P2, and Mill Creek P4 are 0.75, 0.66, 0.57, and 1.43°C, respectively. Prediction uncertainty is moderate at the Current River sites, somewhat low at Mill Creek P2 (which has quite a lot of groundwater influence and cool, stable temperatures), and quite high at Mill Creek P4 (which has less groundwater influence and warmer, more variable temperatures). Overall, the predictive ability of the model is reasonably good for the period from 2002 to 2014. However, since the quadratic seasonal trend is fixed (constant) from year to year, if the seasonal trend changes significantly in future time periods, then we should expect the model to produce conservative estimates of water temperature for those time periods.

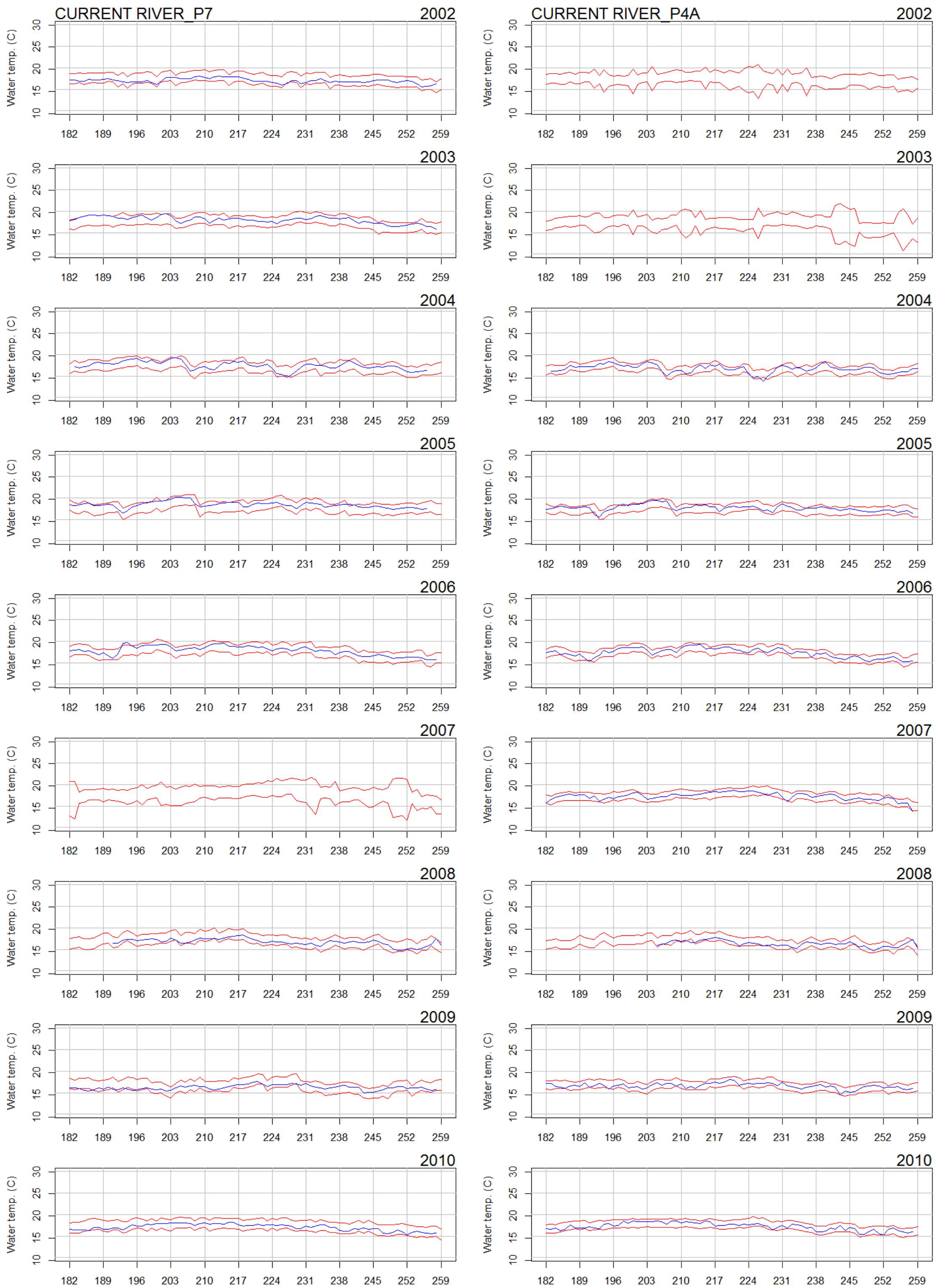


Figure 17. Observed water temperature (blue) and 95% prediction intervals (red) at Current River P7 and Current River P4A. The x-axis is day of year. For years with no observed data, the prediction intervals are wider. At the Current River sites, temperature, temperature variability, and prediction uncertainty are moderate.

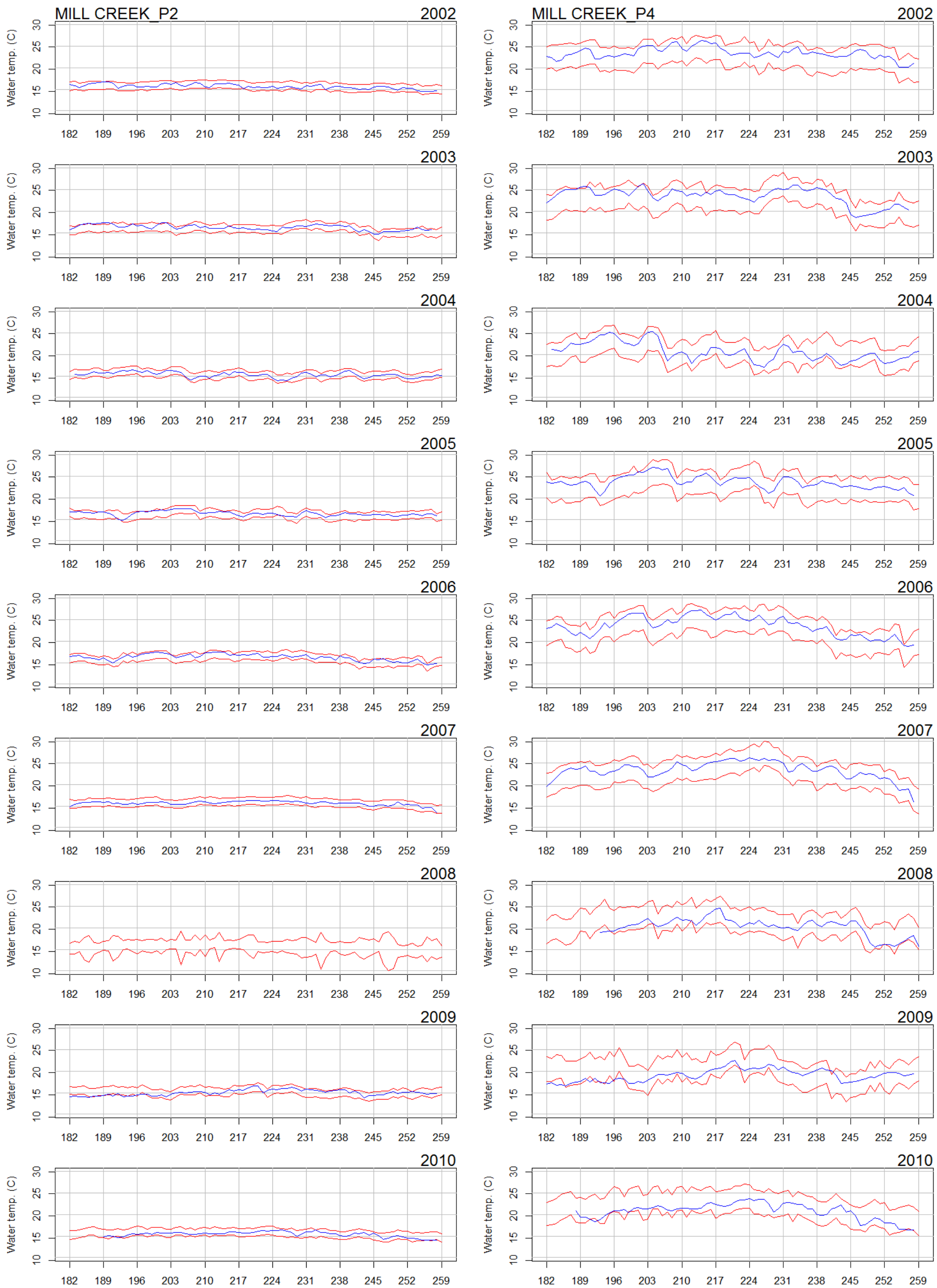


Figure 18. Observed water temperature (blue) and 95% prediction intervals (red) at Milk Creek P2 and Mill Creek P4. The x-axis is day of year. For years with no observed data, the prediction intervals were wider. Temperatures were warmer and there was much greater temperature variability and prediction uncertainty at Mill Creek P4, which had less groundwater influence.

By also fitting a model for minimum daily water temperature, we were able to predict the number of 24 hour periods above 21.1°C (70°F) during each summer ("number of hot days"). One of the advantages of Bayesian models is that it is relatively easy to produce credible intervals for non-standard statistics such as this one. Here we report the observed number of days above 21.1°C as well as the model 95% credible intervals, taking into account changes in the total number of observed days per year. The model performs fairly well: For 78% of the 553 observed site-year pairs, the model estimate of the number of hot days is off by no more than 2 days. At these warmer sites, the model estimates tend to be too moderate, and for 5% of the site-year pairs, the model estimate is off by 10 or more days. The worst sites are Capps Creek P2 and P3, Eleven Point River P1 and P6, and Mill Creek P4 (one of the highlighted sites shown in Figure 19). The 95% credible intervals contain 88% (rather than 95%) of the observed number of hot days, and are thus somewhat optimistic about model certainty. For the highlighted sites shown in Figure 19, only Mill Creek P4 had any hot days (days in which the minimum water temperature was above 21.1°C [70°F]).

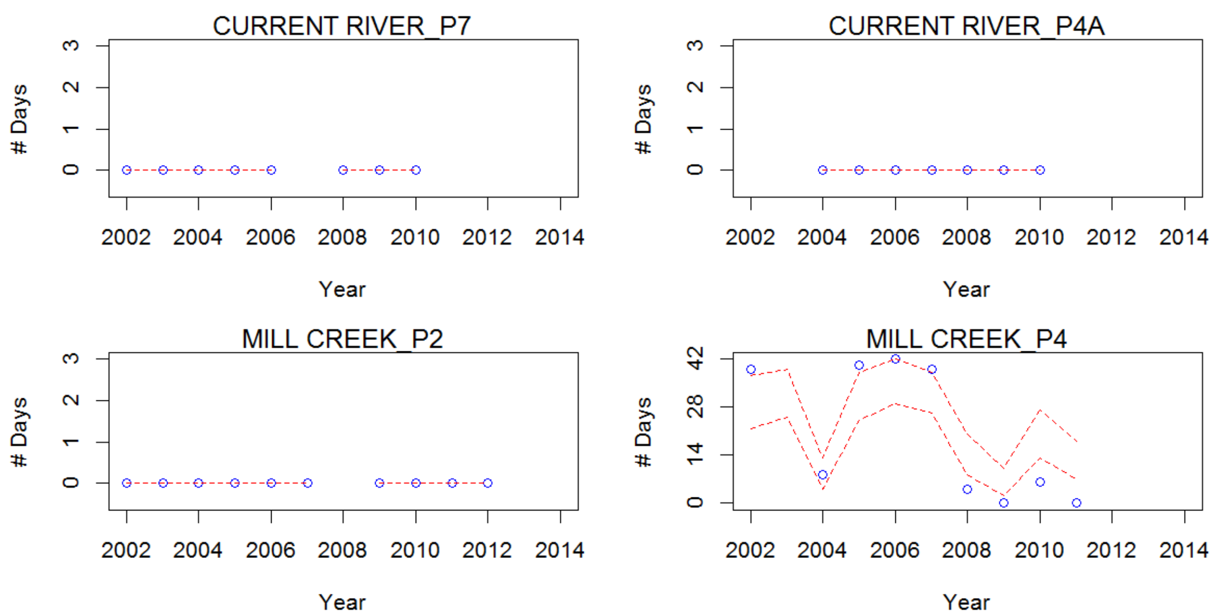


Figure 19. Observed number of hot days – days with minimum water temperature above 21.1°C – (blue dots) and corresponding model 95% credible intervals (dashed red lines), taking into account changes in the total number of observed days per year and excluding years with no data. Only Mill Creek P4 had any hot days. The model tends to overstate certainty in that the 95% credible intervals tend to be too narrow at warm sites such as Mill Creek P4. For the other sites, only one red line is visible because the 95% credible interval contains only 0.

Forecasted stream temperature

We incorporated climate metrics into our stream temperature model partially for the purpose of investigating potential changes in water temperature patterns under future climate scenarios. We compared results based on the three different GCMs for three future time periods: 2040 – 2044, 2060 – 2064, and 2085 – 2089 (for GFDL, climate model predictions are not available for 2085 – 2089).

We used the fitted stream temperature model and the calibrated climate data to produce predictions for 2040 – 2044, 2060 – 2064, and 2085 – 2089. We reported prediction intervals based on the three GCMs combined together. In doing so, the variability between the climate models, and thus uncertainty about climate model predictions, was reflected in the prediction interval width shown in Figures 20 and 21. Predicted changes in mean daily water temperature were very slight, but an increasing trend is apparent from 2040 – 2044 to 2060 – 2064, and again to 2085 – 2089. Sites, like Mill Creek P4 which currently have warmer and more variable temperatures, were likely to show a larger increase in water temperature than sites that are currently cooler and more stable.

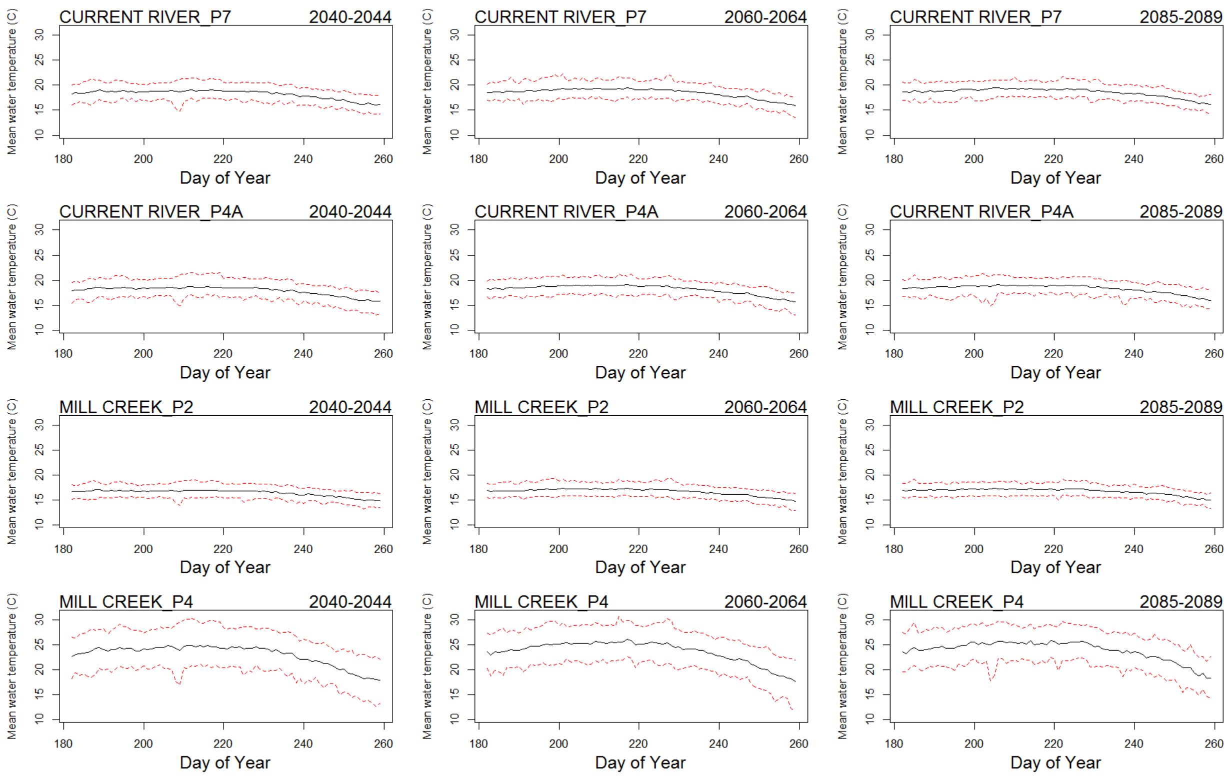


Figure 20. Mean daily water temperature predictions with 95% prediction intervals for three time periods at four sites (Current River P7, Current River P4A, Mill Creek P2, and Mill Creek P4) based on combined downscaled climate model data from three global climate models (ECHAM5, GENMOM, and GFDL). For 2085 – 2089 the estimates are not entirely comparable to the previous time steps because no GFDL data were available. The black line is the mean of the posterior predictive distribution and the dotted red lines are 95% prediction intervals. The predictions for mean daily water temperature do increase over the three time periods, though only very slightly.

Averaged over all sites and summer days, the predicted mean daily water temperature is 18.97°C in 2040 – 2044, 19.23°C in 2060 – 2064, and 19.35°C in 2085 – 2089 for an overall increase of 0.4°C (see Appendix G for mean summer water temperature predictions at each site). Histograms of mean daily water temperature averaged across the summer for each site provide a visual description of the predicted changes at all sites (Figure 22). However, one issue with the model is that the estimated quadratic seasonal trend is fixed instead of being a function of climatological variables. As a result, we expect that the model is overly conservative in terms of the effect of a warmer climate on water temperature. Therefore, the predicted water temperature increases are likely to be biased low.

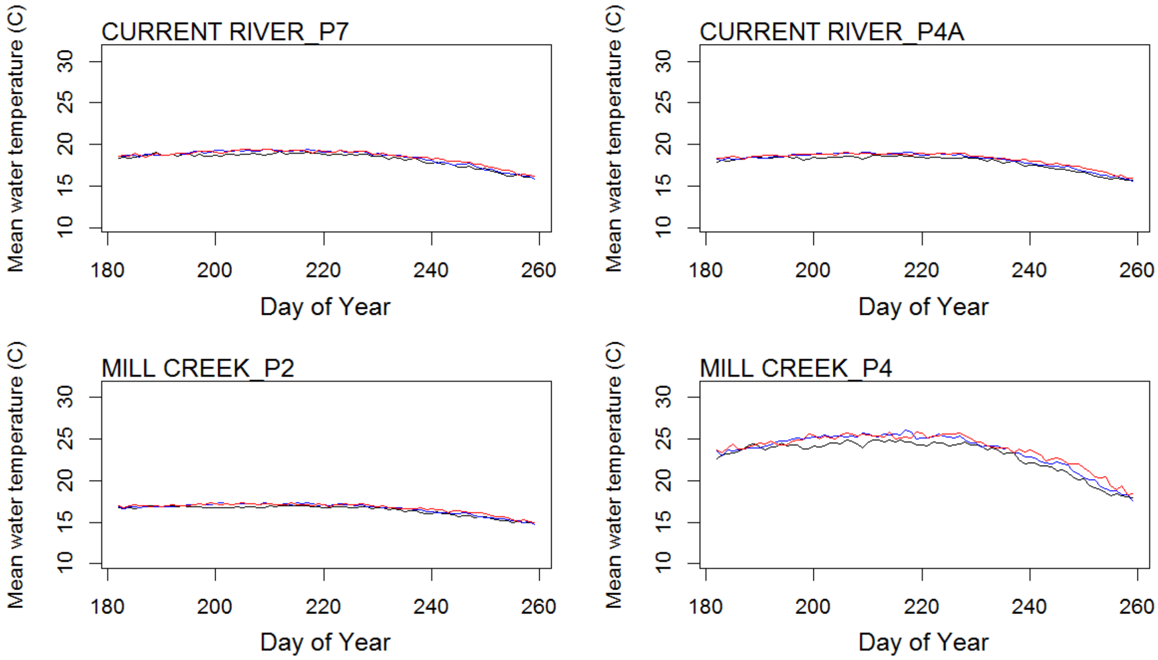


Figure 21. Comparison of mean daily water temperature predictions for three time periods at four sites (Current River P7, Current River P4A, Mill Creek P2, and Mill Creek P4) based on combined downscaled climate model data from three global climate models (ECHAM5, GENMOM, and GFDL). The predictions for 2085 – 2089 are not entirely comparable because no GFDL data were available. The black line is predictions for 2040 – 2044, while the blue and red lines are predictions for 2060 – 2064 and 2085 – 2089, respectively. A slight increase in water temperature over the three time periods is apparent.

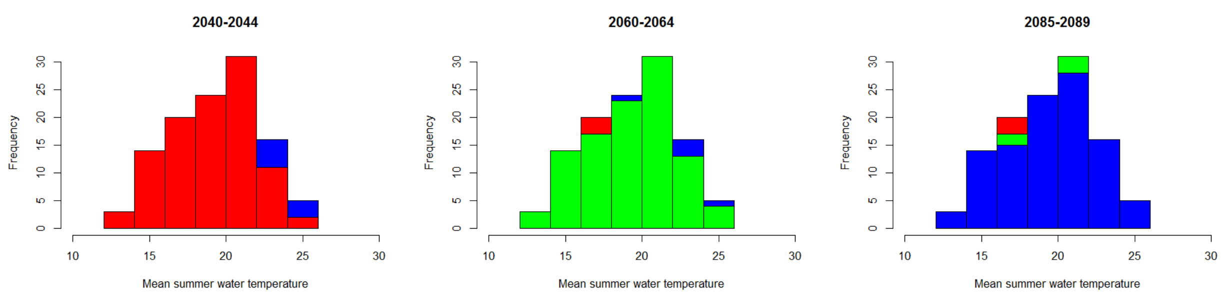


Figure 22. Mean daily water temperature averaged across the summer for all 105 sites for each of three time periods (2040 – 2044 in red, 2060 – 2064 in green, 2085 – 2089 in blue) based on combined downscaled climate model data from three global climate models (ECHAM5, GENMOM, and GFDL). The predictions for 2085 – 2089 are not entirely comparable because no GFDL data were available. Each histogram is overlaid above the histograms for the other two time periods to facilitate comparison. From the histograms one can see that the model predicts a slight increase in mean summer water temperature over the three time periods.

The climate model predictions can also be applied to the fitted model for minimum daily water temperature to produce estimates of the number of hot days – the number of days with minimum water temperature above 21.1°C (70°F) over the summer. The model estimates that many sites will continue

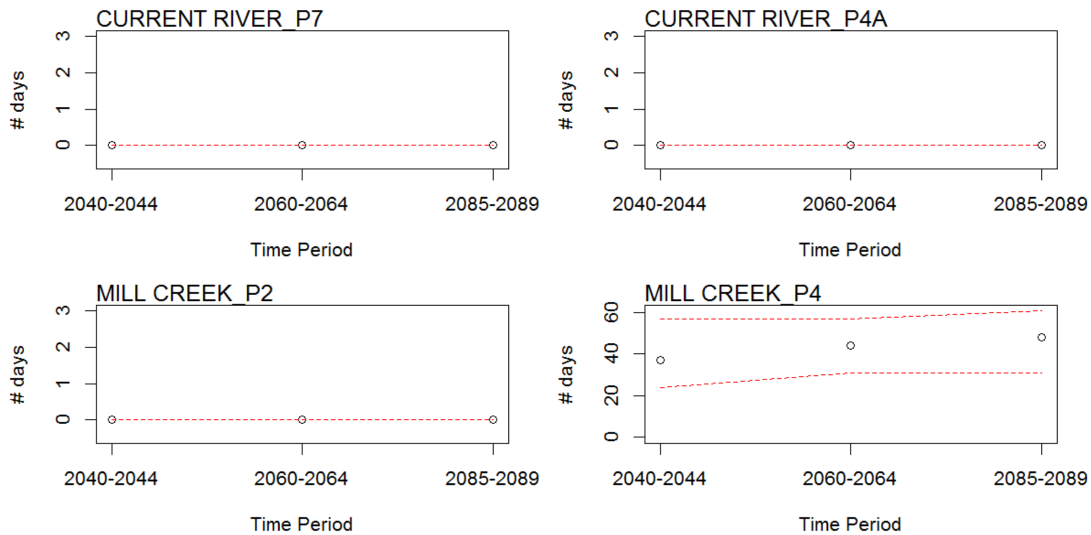


Figure 23. Estimated number of hot days – days with minimum water temperature above 21.1°C (70°F). The estimates for 2085 – 2089 are not entirely comparable to the other time periods because no GFDL data were available. Black dots represent the mean estimates and dashed red lines represent the 95% credible intervals. The model predicts that only Mill Creek P4 will have any hot days. For the other sites, only one red line is visible because the 95% credible interval contains only 0. The estimated number of hot days at Mill Creek P4 are noticeably higher than the mean number of hot days estimated by the model for the 2002 – 2014 time period, suggesting that Mill Creek is at risk of an increasing number of days with minimum water temperature above 21.1°C.

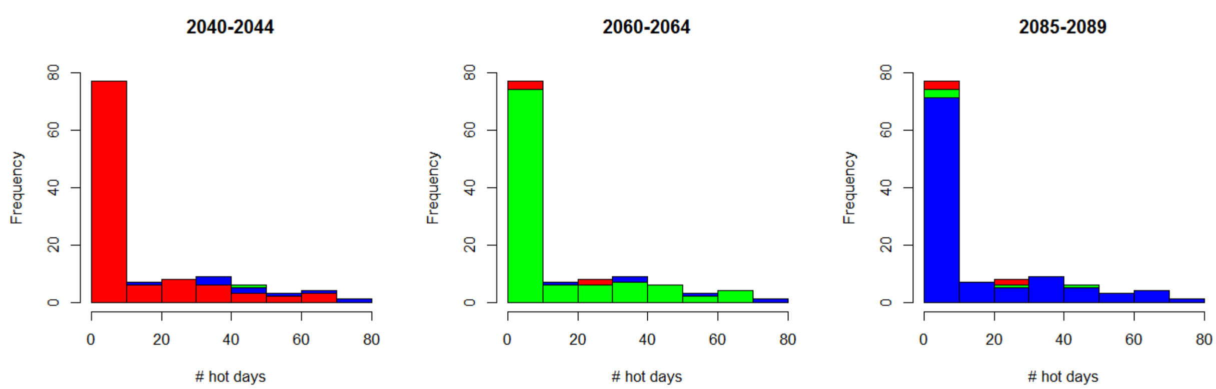


Figure 24. Estimated number of hot days – days with minimum water temperature above 21.1°C (70°F) at all 105 sites (2040 – 2044 in red, 2060 – 2064 in green, 2085 – 2089 in blue). The estimates for 2085 – 2089 are not entirely comparable to the other time periods because no GFDL data were available. Each plot shows a single time period with the histograms for the other two time periods plotted beneath to facilitate comparison. One can see a decrease in the number of sites with 10 hot days or less during the summer, and 2085 – 2089 is the first time period in which a site (Meramec River P1) is estimated to have more than 70 hot days out of the 78 summer days.

to have no hot days. In particular, for 2040 – 2044, it estimates that 51 sites will have less than 1 hot day, for 2060 – 2064, 50 sites, and for 2085 – 2089, 48 sites. In general, the number of hot days increases over the three time periods. Figure 23 shows the estimates with credible intervals for the four highlighted sites, while Figure 24 provides histograms of the estimates across all sites. Although the increases in number of hot days are not dramatic, they are notable. For example, 2085 – 2089 is the first time period in which a site (Meramec River P1) is estimated to have more than 70 hot days out of the 78 summer days. See Appendix H for estimates at each site.

Discussion

Water-climate patterns

Due in part to the temporal breadth of this dataset, we were able to capture significant variation in annual summer water temperatures for this subregion. The years 2003 and 2006 were significantly warmer than all years except 2005, while 2004, 2009, and 2013 were significantly cooler than all other years. The mean values of three climate metrics (solar radiation, air temperature, and precipitation) were able to explain about 50 - 60% of the annual variation in water temperature. Although not capturing all of the annual variation, the general influence of summer water temperatures on aquatic populations at these sites could be assessed in light of these year-specific variations in water temperature. Having this fairly long-term dataset also gave us the opportunity to evaluate whether there was a temporal trend in water temperature in this highly groundwater-influenced system.

We had not expected to find a trend in the Ozark Plateau watersheds because findings of previous research indicated groundwater discharge could buffer stream temperature from climatic changes in air temperature (Burns et al. 2017; Chu et al. 2008). In addition, our snapshot of time might not have corresponded to a detectable change in climate due to interannual and interdecadal variability in atmospheric metrics (Hawkins 2011; Santer et al. 2011; de Elía et al. 2013). However, our analysis provided evidence for a small overall decrease (-0.4°C) in maximum water temperature for the time period from 2002 to 2014 although climate metrics tended to increase slightly (air temperature: 0.2°C, solar radiation: 6.3 W/m^2, precipitation: 0.4 mm) during this period. This drop in water temperature could not be fully explained by metrics of precipitation, solar radiation, or air temperature. Some other or combination of metrics with the capacity to change fairly rapidly (not a geologically stable local variable such as slope) appears to be driving this trend. We have not been able to identify what may have driven water temperatures down over this time period. Further monitoring in these streams could determine whether this downward trend continues.

Thermal similarities of monitoring sites

Given the importance of water temperature on aquatic biota we focused on patterns among thermal summer regimes to group these sites. Groups identified by this analysis were not based solely on one temperature metric, but rather multiple interpretations of temperature. Using only mean July temperature or maximum observed temperature is a viable way to group locations based on temperature, but using only one summary metric eliminates potentially important information when creating biologically relevant groups. For instance, the use of flow metrics has moved past a single summary variable such as average discharge and now dozens of metrics covering magnitude, rate, frequency, duration, and timing are commonly investigated. Our approach borrows from the flow ecology methodology to include temperature metrics in a similar way. The intent for this analysis was to provide resource managers with information on the similarities/dissimilarities among sites as sites that clustered together might be expected to respond similarly to management actions. The overall structure of the clustered sites was well-supported so we visually identified six groups based on apparent breaks in the distance matrix. These groupings are one possible interpretation and could be modified based on management purpose or local knowledge. For example, group 6 (Figure 10) could be further separated into management objectives for Greer and Dewitt-Wilkins spring branches separately from Maramec and Bennett spring branches.

The various frequencies of the stress day metric derived by MDC biologists were useful in differentiating among the groups. Weekly summaries of water temperature have been identified as being linked to growth rates of fish (Eaton and Scheller 1996) so although the metrics associated with 7-day time spans do not appear to strongly characterize differences in the six groups identified here, these may be important in addressing site-specific differences in rates of growth.

We intentionally did not constrain thermally similar groupings by management area or watershed. This provides managers with the opportunity to confer on resource conditions across management and watershed boundaries. Alternatively, if a manager wanted to know more about their system, they could investigate other systems in the same cluster.

Stream temperature model

Our best model for water temperature included a quadratic seasonal trend plus the effect of climatological variables. Separate estimates were produced for each site, and we attempted to account for the annual variations in water temperature using Strahler order and a measure of groundwater influence – spring flow divided by distance to the site summed over all upstream springs. Of the climatological variables we considered, the current day mean air temperature was the strongest predictor of water temperature. In addition we found that information about air temperature from the previous week (mean air temperature for the previous three and five days), as well as precipitation and solar radiation also improved model fit and predictive ability. This finding was expected as it concurs with other research that incorporated air temperature whether groundwater influence was strong or not (DeWeber and Wagner 2014; Troia et al. 2016).

The effect of climatological variables on water temperature varied from site to site. For example, the typical effect of a 1°C increase in current day air temperature was estimated to increase water temperatures between 0 and 0.4°C across the sites. Groundwater influence and Strahler order did not account for most of the site-specific variability. However, based on model estimates, increasing groundwater influence lowered the effect of the current day air temperature. Higher Strahler order was related to larger effects of current day and three days previous mean air temperatures. Because the Daymet data were available daily from 1980 to 2016, this model could be used to make predictions for other years in that range or on days with missing water temperature data (although isolated daily temperatures may not be biologically relevant, this capability could allow for analyses that cannot accommodate missing data).

Forecasted stream temperature

Future management strategies for aquatic biota in the Ozark Plateau streams would benefit from information on whether and if so how, water temperature in these streams might change under future climate conditions. Although water temperature is not the only important metric in developing species or watershed management plans, it has been broadly identified as a primary driver in stream systems (Caissie 2006; Coutant 1999; Wehrly et al. 2003). Based on the Hostetler et al. (2011) climate projections, mean daily water temperature and the number of 24-hour periods above 21.1°C are predicted to increase slightly over the three time periods. Most of the increases were associated with warmer sites that are less influenced by groundwater and are currently near the threshold temperature. However, one issue with the model is that the estimated quadratic seasonal trend is fixed instead of being a function of climatological variables. As a result, we expect that the model likely underestimates the influence of a warmer climate on water temperature. In addition, a critical assumption that we made is that groundwater flow and temperature will remain stable into the future. This is not likely the case. Groundwater temperatures will respond to sustained increases in air temperature albeit slowly. In Sierra Nevada mountain range of western United States, groundwater temperatures are predicted to reflect a response to climatic changes within 20 – 60 years depending primarily on recharge rates with higher elevations responding sooner than lower elevations (Burns et al. 2017). Therefore, future water temperatures could be warmer than predicted.

Future directions

Our findings and the datasets we compiled could be combined with biological datasets to investigate patterns observed in parameters such as distributions, population size, or organism health. For example, did shifts in population size correspond to patterns observed in stream temperature or climatic variables? If riparian forest cover is increased or decreased thereby changing the influence of solar radiation, how might the stream temperature respond? Did growth rates of fingerlings differ among watersheds with differing thermal patterns? The patterns we described for climate and water temperature, the monitoring site groupings, and the temperature model could be used to address these and many other questions.

In addition, there was a consistent seasonal trend where summer water temperatures declined toward the end of the sampling period that we were not able to explain with the site specific or climatic variables we used. Further exploration of this trend and the opposite trend in Current River P1 and Roubidoux Creek P1 could elucidate ecological drivers of stream temperature in this subregion. The strength of our predictive stream temperature model could be improved through including the explanatory variable for the seasonal trend, obtaining more accurate information about spring locations and flows, and accounting for uncertainties in climate metrics since typical MAE for air temperature were relatively large compared to our model's prediction uncertainties, notwithstanding the fact that solar radiation estimate uncertainties are not currently available.

The MDC Ozark Rivers dataset retains potential for addressing additional scientific questions related to management concerns. Previous work in the state of Missouri on the influence of groundwater on stream temperatures was limited to single systems (e.g., Current River, Westhoff and Paukert 2014; Meramec River, Whitledge et al. 2006). The spatial and temporal extent of the Ozark Rivers database would allow further investigation of the relation between groundwater influence and stream temperature. The complicating issue with groundwater influence on stream temperature relates to unique attributes of individual springs and the rivers they join. Westhoff and Paukert (2014) explored this relationship using spring magnitude (% discharge contributed to river by a spring; see Figure 4 in that manuscript). That relationship could be tested using this database if data on spring and river discharge were available. It could also be improved upon by adding a distance factor into the relationship to account for how far from the groundwater source the logger was located. Development of an empirically-based transferable relationship between spring characteristics and stream temperature would allow for more accurate modeling of water temperature. Thus, ecological relationships near springs (e.g., thermal refuge use, fish growth, response to climate change, physiological tolerances) could be used to inform management and conservation.

Modifications from original proposal

We originally intended to incorporate empirical air temperatures associated with each water temperature site; however, air temperature was only collected for more than three years at two sites this assessment component and was dropped from analyses. We had also planned to examine potential changes in stream temperature relative to forecasted changes in land use. However after further consideration, we decided that because the forecast land use data was driven by corn production, this data set was not particularly relevant for the Missouri Ozarks so we developed forecasted stream temperatures based only on climatic projections.

Products

Raw data and summary metrics were imported into a Microsoft Access database and linked to the spatially-referenced collection locations. A geodatabase with duplicate data was created to facilitate use in a geographic information system (GIS). These databases with metadata were submitted to MDC with this report. Our final dataset for all 106 locations contained information on daily minimum, maximum, and mean water temperatures, mean air temperatures, and mean solar radiation at the sample site, and daily total precipitation averaged over the entire upstream watershed for a given site.

Description	File name	File format
Empirical stream temperatures		
Stream temperature records associated with the stream temperature sites	Obj2_stream_temper_data	Text file
Classification data		
StreamThermal calculations for each stream temperature site	Obj2_StreamThermalCalculations	Text file
Cluster metrics and assigned group numbers for subset of stream temperature sites used in cluster analysis	Obj2_HierarchicalClusterAnalysis	Text file
Hierarchical classification of streams based on patterns of stream temperature	Obj2_stream_class	Text file
Projected stream temperatures		
Potential future stream temperatures based on climatic forecasts	Obj5_future_temperature	Text file
Spatial data		
Spatially referenced locations of stream temperature sites.	Obj2_stream_temper_sites	ESRI shapefile
R Code		
R code used to conduct analyses	Multiple files in folder titled Obj2_5 r codes	R file

Stream temperature model for Missouri watersheds

Objectives addressed:
Objective 1: Identify and geo–reference current and past stream temperature data sets in Missouri.
Objective 3: Develop stream water temperature models.
Objective 4: Evaluate whether these differ across subregions.

Our goal was to develop stream water temperature models for Missouri subregions using as many data collection sites as possible to increase the predictive strength of the final products. We reached out to aquatic biologists throughout Missouri and surrounding States with a request to identify and acquire stream temperature datasets. We compiled these data and used a subset to develop stream temperature models and compared differences in measured temperatures between the aquatic subregions and also evaluated the relative increase in model strength as a function of the years of recorded temperatures. These stream temperature models could be used by resource managers to aid in the understanding of species responses (e.g., movement patterns, habitat selection), or for decisions such as where to stock species or to identify watersheds where aquatic biota may be vulnerable to altered hydrology.

Background

There are two general approaches to modeling stream/water temperature: deterministic or physically based, and statistical (stochastic and regression methods) (Beaufort et al. 2016; Caissie 2006). Deterministic models are generally more complex approaches that incorporate heat budget equations to quantify energy exchange between the interface of water with substrate and atmospheric factors to predict water temperature (Benyahya et al. 2007; Herb and Stefan 2011). The complexity of budget equations is variable but can include stream properties such as water depth or heat flux at stream/substrate interface and atmospheric parameters such as wind speed and air temperature. Deterministic models tend to be data intensive and reserved for detailed assessments at the level of individual streams or small watersheds (Beaufort et al. 2016).

Statistical models are a less data intensive approach typically utilizing the strong relationship between atmosphere and water. These models are more appropriate for larger spatial scales (Caissie 2006). Statistical modelling approaches can be grouped as regression or stochastic. Regression relies on data that is not autocorrelated so performs better for longer time steps (i.e. weekly to annual periods). Deterministic and stochastic approaches are commonly used for modeling daily streams temperatures and can result in similarly robust models. However, stochastic models do not require the extensive empirical data necessary to calculate heat budgets (Caissie 2006). We used the stochastic approach to develop stream temperature models due to the lack of consistent datasets required for deterministic models.

To address objectives 1, 3 and 4 we: 1) contacted aquatic biologists throughout the state to locate available stream temperature datasets that had been collected for a continuous period of time, and 2) used the compiled datasets to develop water temperature models for Missouri streams and assess whether separate models should be developed for each aquatic subregion.

Methods

Stream temperature datasets

We documented locations where continuous stream temperature data had been or were being collected in Missouri. We contacted local and regional agency and university biologists to learn whether they had or knew of individuals who had temperature data from Missouri streams. For a dataset to be included in this data documentation effort, temperature records must have been obtained at regular intervals for a period spanning multiple months. We located water temperature datasets for 349 unique sites throughout the CP and OP (Figure 25) that had been collected over the last two decades (Table 12). We were unable to locate any continuous water temperature data for the Mississippi Alluvial Plains subregion therefore, we did not build an associated temperature model. It was questionable whether we could have produced a reliable model for this subregion due to the numerous water control measures and highly modified channel networks.

Additional resources

Additional information on water temperature research in Missouri can be found through the online resources and select publications listed here.

<u>Online lists</u>
USGS publications: https://mo.water.usgs.gov/publications/bibliography/#v
University of Missouri Extension: http://extension.missouri.edu/publications/
University of Missouri, Water Research Center: http://engineering.missouri.edu/water/

<u>Selected grey-literature references</u>

Bowie, J. E. 1971. Temperature of Missouri streams: U.S. Geological Survey, 350 p.
Vineyard, J. D., and G. L. Feder. 1974. Springs of Missouri: Rolla, Missouri Division of Geology and Land Survey Water Resources Report 29, 266 p. (reprinted 1982).

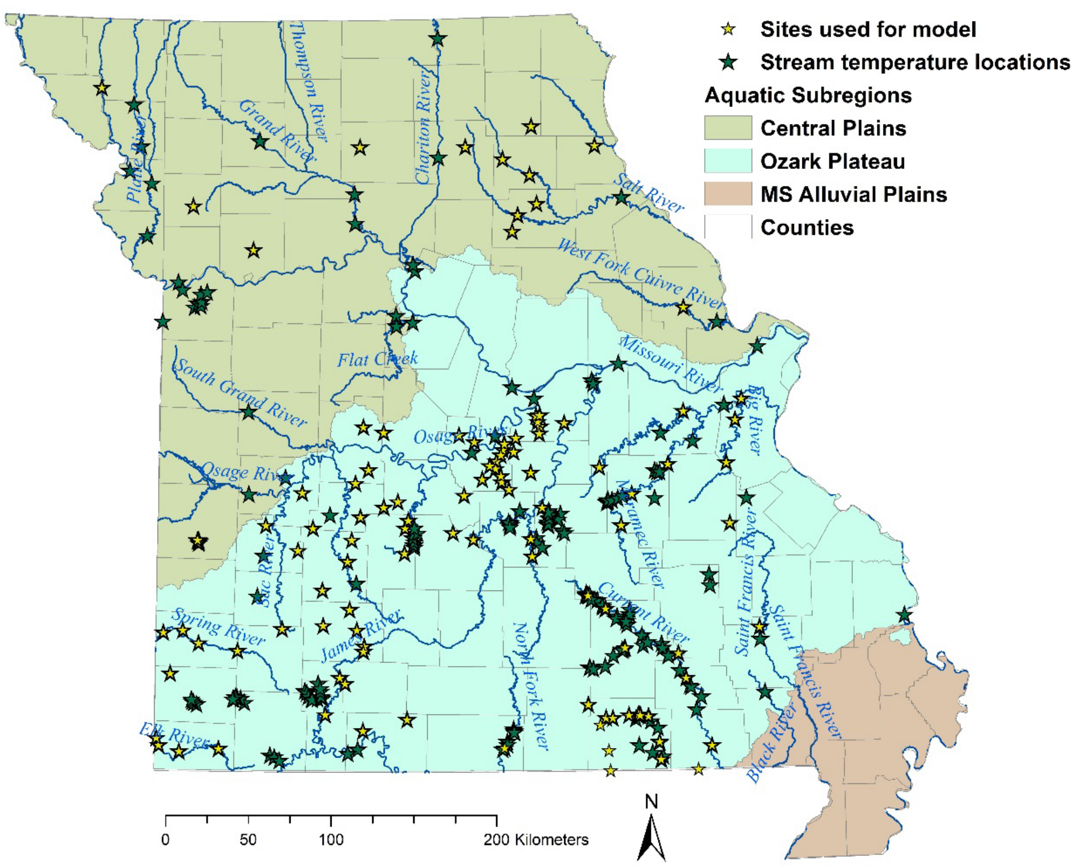


Figure 25. Map depicting the distribution of locations where water temperature had been continuously recorded for at least one season in Missouri relative to political and ecological boundaries. Sites used to develop stream temperature models are colored yellow.

Table 12. Organizations that provided stream temperature datasets or summary information about the data. Temporal period applies to the entire dataset not each site.

Agency/Organization	Temporal coverage	Duration/period	Interval	# of sites
MO Department of Conservation	1995-ongoing	continuous/seasonal	hourly	120
National Forest Service	2014-ongoing	continuous/annual	hourly	21
National Park Service	2013-ongoing	continuous/annual	4 hours	4*
University of Missouri	2010-ongoing	continuous/annual	15 min – hourly	172
US Geological Survey, gage sites	2006-ongoing	continuous/annual	15 min – hourly	26
Southern Illinois University	2009-2012	continuous/seasonal	hourly	6

* National Park Service (NPS) has continued monitoring at 9 sites initially established by Univ of Missouri; for the purpose of reporting site information, these 9 sites are not included in the NPS count of sites throughout this report.

Stream temperature model

From the stream temperature datasets, we selected sites with records that spanned at least one 365-day period and excluded sites that were specifically monitoring springs or USGS gages (as the associated monitoring probes tend to be in deeper, slower moving water). These sites spanned a fairly short temporal period from 2009 – 2015. To develop the stream temperature models, we selected data between 2010 and 2015 for a relatively consistent temporal coverage and to maximize the number and spatial distribution of sites used (Figure 26). The mean duration of records per site was 2.2 years. Water temperature records were plotted against date to visually screen for erroneous values and anomalies in temperature measurements that could indicate a temperature logger was buried, frozen in ice, or no longer in water (Appendix I). Erroneous values and anomalies accounted for approximately 1% of the recorded data and were flagged in the stream temperature database which has been provided as a product.

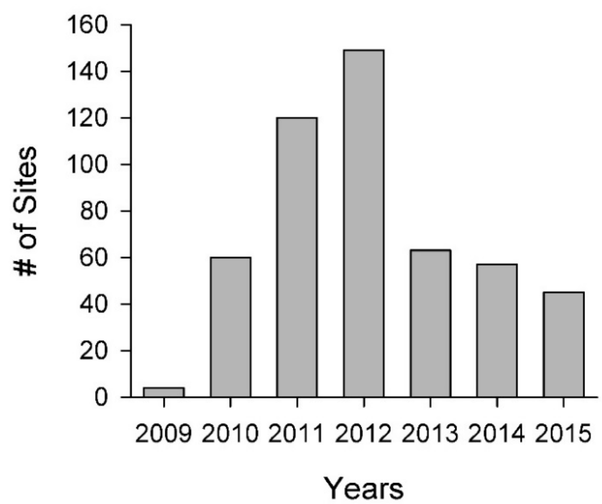


Figure 26. Number of stream temperature sites with records during a given year.

Stream temperature records varying from 15-minute to hourly intervals were summarized as daily means for the associated stream segment (n=143). Ninety percent of qualifying sites were located on unique stream segments. We had hoped to acquire a sufficient number and distribution of sites to incorporate spatial dependencies (Isaak et al. 2010; Peterson and Ver Hoef 2010) but based on discussion with Drs. Daniel Isaak, USFS, and Jay Ver Hoef, NOAA, the density and distribution of our sites was insufficient to adequately refine predictions based on spatial connectivity influences.

Predictor metrics

Predictor variables comprised 20 climatic, landscape, and local metrics shown to be associated with stream temperature (Table 13; Caissie 2006; Herb et al. 2008; Isaak and Hubert 2001; Troia and Gido 2014; Ward 1985; Webb et al. 2003; Webb et al. 2008). Climate data were obtained as daily netcdf4 files from the Oakridge National Laboratory Daymet V3 dataset for 2010 - 2015 (http://dayment.ornl.gov; (Thornton et al. 2016). This dataset provided daily means for precipitation (mm), air temperature (°C), and solar radiation (W/m^2). Daily solar radiation and air temperature were associated with the mid-point of each stream segment using *R* with the packages: raster V2.5-8, ncdf4 V1.15, and rgdal V1.1-10. The same *R* packages and RivEx 10.19 (Hornby 2015) were used to calculate an area-weighted total daily precipitation for the upstream watershed (including the focal catchment) of each stream segment. In addition to daily air temperature, we used lag day residuals for days 1 through 5 and day 7. We selected these particular lag days based on examination of subregion cross-correlations between air and water temperature records.

Landscape metrics (Table 13) were derived primarily with ArcGIS 10.3 and the RivEx toolset 10.19 using the 2011 National Landcover Dataset (https://www.mrlc.gov/nlcd2011.php; (Homer et al. 2015), a 10-meter digital elevation model (ftp://msdis.missouri.edu/pub/Elevation/10mDEM/; (Center for Agricultural 2003), and Missouri stream and catchment datasets (Missouri Resource Assessment Partnership 2006). Land cover classes were summarized as percent cover within watersheds (watershed is defined here as the total land area contributing to the downstream end of a stream segment). Slope and maximum catchment elevation were derived from a 10-meter digital elevation model. Shreve link was included in the Missouri streams dataset (Missouri Resource Assessment Partnership 2006). Latitude was based on the mid-point of stream segments. Spring influence was based on mean flow (cms) divided by the distance from the midpoint of a stream segment to each upstream spring. For springs without an unknown flow rate, we used 0.0003 cms which corresponds to the lowest measured spring flows in Missouri. The watershed influence of spring flow was calculated as the sum total of all upstream spring influences.

Model development

We followed the approaches of Cassie et al. (1998), Jeong et al. (2013), and Troia et al. (2016) to develop models for Missouri streams that predicted daily mean water temperature (Figure 27). This stochastic approach assumes that for a given time period, there is an annual component of temperature which would be the same across sites and the remaining variation (residuals) would be explained by the site-specific characteristics (elevation, slope, latitude, etc.). In addition, this approach incorporated nonlinear responses which were anticipated since we were utilizing more than a single year of temperature records (Caissie 2006). Models were developed separately for the OP and CP aquatic subregions due to differences in factors that influence stream temperature such as geomorphology and land use. We developed and tested the model using water temperature records from sites that met the criteria described above in the datasets section. These datasets were spatially linked to 143 stream segments across Missouri.

We first separated the annual and daily residual components using a generalized additive model (GAM) for air (AT annual, AT residual) and water temperatures (WT annual, WT residual; e.g. mean daily water temperature =Julian day). A sine function was fitted using daily temperatures for a 365-day year and was not limited to positive values for either the water or air temperature annual components. The GAM models were fit using the R program and mgcv library. Initial assessments of model fit were evaluated using generalized cross-validation and deviance scores. With the annual components for air and water temperature removed, a random forest model was built for daily WT residuals as a function of AT residuals plus the other climatic and physical site-specific metrics listed in Table 13. The random forest models were built in R using the randomForest V4.6-12 library. Random forest models are very flexible ensemble learning approach that can fit nonlinear relationships, model interactions, and do not require assumptions of data distribution found in other parametric approaches (Breiman 2001; Elith et al. 2008). Random forest is a robust method for making predictions (Cutler et al. 2007). The random forest approach also is able to handle numerous variables while limiting issues of over-fitting.

Table 13. List of metrics used to develop stream temperature models for Missouri. CARES = Center for Agricultural, Resource and Environmental Systems, University of Missouri; MoRAP = Missouri Resource Assessment Program; NLCD = National Landcover Dataset; RivEx = add on package to ArcGIS.

Variable type	Scale	Landscape and Environmental metrics	Data source
Climate	Stream segment	Same day AT residual	Daymet data V3
	Stream segment	1-day lag AT residual	Daymet data V3
	Stream segment	2-day lag AT residual	Daymet data V3
	Stream segment	3-day lag AT residual	Daymet data V3
	Stream segment	4-day lag AT residual	Daymet data V3
	Stream segment	5-day lag AT residual	Daymet data V3
	Stream segment	7-day lag AT residual	Daymet data V3
	Stream segment	Mean daily solar radiation (W/m^2)	Daymet data V3
Landscape	Stream segment	Slope (degrees)	CARES 10-meter DEM; ArcGIS
	Stream segment	Shreve link	MoRAP
	Stream segment	Latitude (dd)	ArcGIS
	Catchment	Percent urban cover	NLCD 2011
	Catchment	Percent agricultural cover	NLCD 2011
	Catchment	Percent forest land cover	NLCD 2011
	Catchment	Percent grassland/prairie cover	NLCD 2011
	Catchment	Percent shrubland cover	NLCD 2011
	Catchment	Maximum elevation (meters)	CARES 10-meter DEM
	Watershed	Spring influence	Derived using RivEx
	Watershed	Total daily precipitation (mm)	Daymet data V3
	Watershed	Watershed area (km^2)	RivEx

Models were trained and initial testing was conducted for subregion models using a five-fold cross-validation (leave-one-out) approach with performance assessed using mean root mean square error (RMSE) and mean coefficient of determination (R^2). With this approach the data are divided into five groups and one group is left out iteratively to be used for testing the model. This is repeated five times so that all data serve to train and test the model. We opted not to use separate calibration and validation temporal periods because the total temporal period of this study was likely too brief for this technique (Benyahya et al. 2007). Because our primary intent was to predict water temperature at unsampled sites rather than unsampled years, the sampled stream segments were divided into five nearly equally-sized groups for each subregion. Once adequate models (based on $R^2 > 0.7$) were obtained, the final models were built using all data to predict daily WT residuals for the corresponding geographic regions. The resulting WT residuals were added to the annual WT fitted values to calculate daily mean WT for unsampled stream segments.

General steps followed to develop stream temperature models

Step 1. Generalized Additive Model: model annual components

a) $WT_{(t)}$ = Julian day + $WTresidual_{(t)}$
b) $AT_{(t)}$ = Julian day + $ATresidual_{(t)}$
- WT: mean daily water temperature
- AT: mean daily air temperature
- WTresidual: residual WT not captured in annual component
- ATresidual: residual AT not captured in annual component
- *t:* time; in this case, Julian day (Jan 1 = 1 and Dec 31 = 365)

Step 2. Random Forest: develop predictive model for $WTresidual_{(t)}$ using site specific characteristics and air temperature residuals

c) $WTresidual_{(t)}$ = $ATresidual_{(t)}$ + ATresidual lag $days_{(t)}$ + site specific characteristics

Step 3. Random Forest: predict daily $WTresidual_{(t)}$ for sites without water temperature measurements

d) $WTresidual_{(nt)}$ = $ATresidual_{(nt)}$ + ATresidual lag $days_{(nt)}$ + site specific $characteristics_{(n)}$
- *n:* unsampled streams

Step 4. Generalized Additive Model: predict mean daily water temperature

e) $WT_{(nt)} = f(\text{JulianDay}) + WTresidual_{(nt)}$
- $WT_{(nt)}$: predicted daily mean water temperature

Figure 27. General steps followed to develop water temperature models for Missouri streams.

Model strength relative to number of years with data

To evaluate the strength of temperature models relative to the number of years of data used to develop the models, we identified sites that had four years of nearly continuous records (< 10 days missing) between July 2011 and June 2015. Thirteen sites met this criterion. Temperature records for each sampled site were divided into years (1 July through 30 June of subsequent year) - Year 1 corresponded to the period from July 2011 – June 2012; Year 2: July 2012 – June 2013; Year 3: July 2013 – June 2014; Year 4: July 2014 – June 2015. These were then combined into all cross-wise groups of 1, 2, and 3 years. Each combination was then used to predict stream temperature of individual years. For example, the model developed using Year 1 data was used to predict stream temperature separately for Years 2, 3, and 4, while a model developed with data from Year 1, 3, and 4 was used to predict stream temperature for Year 2.

Results

Stream temperature datasets

All sites with coordinates (n=328) were geo-referenced and associated with static environmental metrics (e.g., slope, elevation, stream size) known to influence or correlate to water temperature. See Appendix I for site specific information on duration of record collection, data source, location, and stream and watershed size. We error checked locations for inaccuracies by cross-referencing the georeferenced site with ancillary information from the collection records such as county, stream name, or watershed. Record intervals varied from every 15 minutes to 4 hours for a period of least three months with very few extending more than 10 years (Table 12, Figure 28). The majority of sites occurred within moderate-sized streams (Strahler order 3 – 6), and watersheds <25 km^2 or between 100 – 5000 km^2 (Figure 28).

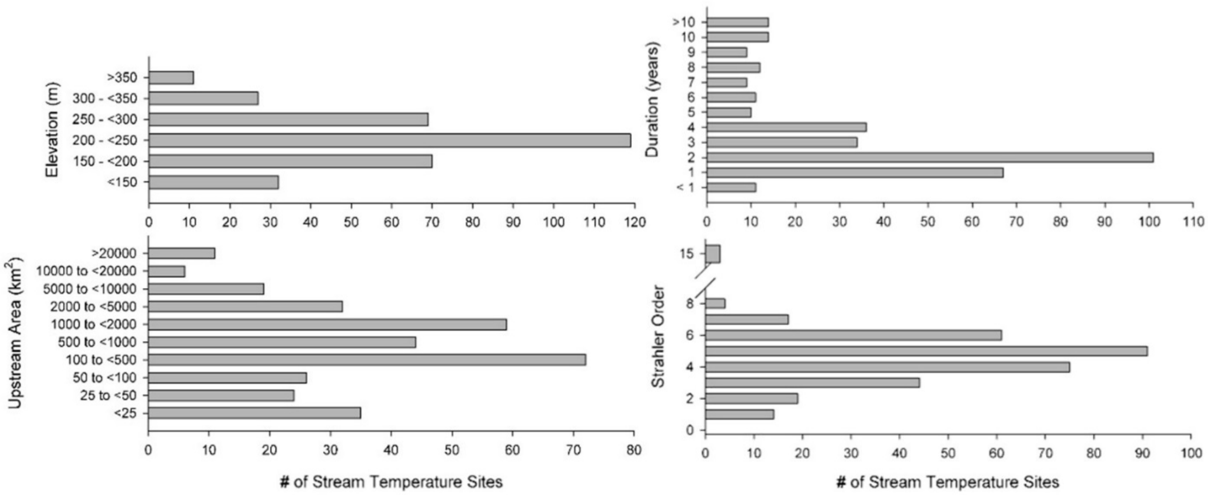


Figure 28. Summary information depicting the distribution of sites with stream temperature records across physical and temporal parameters. Note: the scale on the X axis changes across graphs.

These sites provided representation in approximately two-thirds of Missouri's HUC8 watersheds (44 of 66 HUC8) and 84 % of Missouri's Ecological Drainage Units (16 of 19 EDU) although more than two-thirds of these datasets fell within the Ozark Plateau aquatic subregion and no data were located for the Mississippi Alluvial Plains (Figure 29). This bias was due in part to the large dataset in Ozark streams provided by MDC to address Objective 2. However, we never located stream temperature monitoring data for the Central Plains subregion except for the sites we established to address Objectives 6 and 7, 26 sites recently added by MU and MDC for a study on mid-sized rivers, and 10 USGS gage stations. As of July 1, 2017, 3 of these 10 gage stations were no longer funded to collect data.

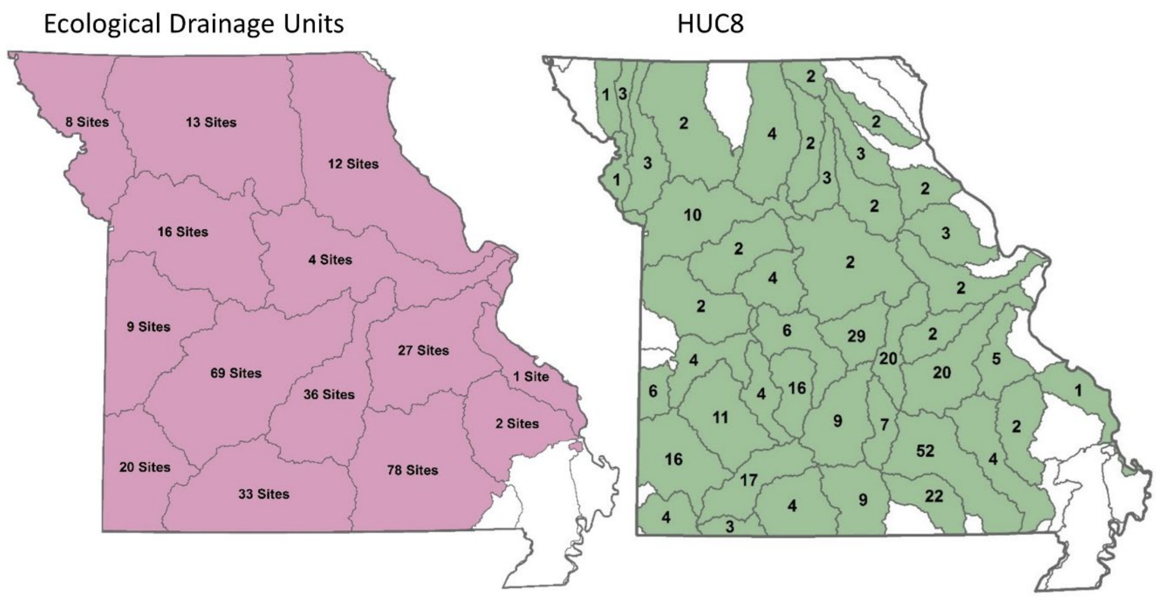


Figure 29. Summary of the number of stream temperature sites per ecological drainage unit and HUC8 watershed boundaries.

Stream temperature model

The range of water temperatures recorded in both regions was similar with mean temperature being cooler in the more northern CP (Table 14). The Daymet air temperatures followed a similar pattern. For a subset of streams adjacent to USGS gage sites where air temperature was recorded (n=37), we calculated the correlation with Daymet air temperature daily means and found that the Daymet data had the same fairly strong correlation with the USGS air temperature records regardless of the subregion (Pearson's correlation, r=0.89, OP and CP).

Table 14. Water and air temperature summary metrics for aquatic subregions recorded between 2010 and 2015. Water temperature is based on records from sampled streams while air temperature is based on the Daymet dataset (Thornton et al. 2016).

Aquatic Subregion	Water Temperature (°C)			Air Temperature (°C)		
	Minimum	maximum	mean	minimum	maximum	mean
Central Plains	0.0	32.65	13.34	-21.25	34.25	12.16
Ozarks	0.0	32.59	15.47	-19.25	34.75	13.87

Physical and climatic characteristics of streams in the CP and OP aquatic subregions are provided in Tables 15 and 16. The 2011 – 2012 time period was the warmest year sampled for both subregions and driest year for the OP (Table 15). For the CP the driest year was 2013 – 2014 (although only marginally drier than 2011 – 2012) which corresponded to the coolest year for this subregion. The 2014 – 2015 period marginally had the wettest daily average precipitation but also had the most extreme maximum daily precipitation. The coldest temperatures occurred during 2013 – 2014. Sampled watersheds in the CP were smaller than those in the OP (Table 16) but this also reflected inherent differences in watershed size across all streams in these regions (Table 17). Although the OP has the highest elevations in Missouri, it also had the lowest elevations both for sampled and unsampled stream segments. As expected, values for spring influence were higher in the OP (Figure 1, Table 16).

Table 15. Daymet air temperature (AT) and precipitation (Prcp) mean, minimum, and maximum by annual periods (e.g. June 1, 2010 – July 1, 2011) for sampled streams.

Year	Subregion	AT mean	AT min	AT max	Prcp mean	Prcp min	Prcp max
2010 - 2011	CP	11.94	-17.00	31.00	3.26	0.00	88.45
	OP	13.95	-16.50	32.50	3.77	0.00	126.90
2011 - 2012	CP	14.24	-10.75	34.25	2.35	0.00	97.80
	OP	15.57	-8.00	34.75	2.86	0.00	100.52
2012 - 2013	CP	12.00	-14.00	33.25	3.16	0.00	104.60
	OP	13.72	-8.50	34.00	3.34	0.00	102.43
2013 - 2014	CP	10.76	-21.25	31.00	2.25	0.00	100.62
	OP	12.51	-19.25	30.50	3.24	0.00	133.46
2014 - 2015	CP	11.43	-16.25	30.50	3.58	0.00	161.58
	OP	13.18	-13.25	30.75	3.48	0.00	112.28

Table 17 provides a characterization of the spatial and temporal distribution of water temperature records used to develop the stream temperature models. Data were most limited in number and spatial distribution for 2010 with only 2 stream segments within a single Ecological Drainage Unit (EDU) in the CP. For the OP, streams sampled in 2010 only represented 2 EDUs however, these were spread across the north-south breadth of this region (Figure 1) which is the geographic gradient where we would expect to capture the most thermal variation. Excluding 2010, the number of streams was similar across years and EDUs in the CP. Except for EDU 28, the OP had better spatial and temporal representation across all EDUs and years.

Table 16. Landscape metrics summarized by aquatic subregion. Land use was based on the National Land Cover Dataset 2011.

	Aquatic Subregion					
	Central Plains			Ozark Plateau		
Landscape metrics	**min**	**max**	**mean**	**min**	**max**	**mean**
Sampled streams						
Shreve link	1	1,065	699	1	2,715	307
Slope (deg)	0.4	8.3	3.0	0.0	18.2	3.8
Latitude	37.7	40.2	40.0	36.2	38.5	37.5
% Urban	2.2	18.4	13.7	0.0	51.7	10.2
% Forest	0.5	48.0	7.5	0.0	96.9	52.9
% Shrub	0.0	4.3	0.2	0.0	20.0	0.4
% Agriculture	0.1	68.2	56.4	0.0	73.9	5.0
% Grassland/pasture	0.3	56.2	11.9	0.0	89.3	26.1
Elevation – minimum (m)	150.2	287.6	253.1	86.1	387.9	236.7
Elevation – maximum (m)	190.4	305.2	274.7	109.5	418.6	285.6
Catchment area (km^2)	0.7	13.5	3.3	<0.1	17.5	3.1
Watershed area (km^2)	6.5	3,928.6	2650.0	2.2	9,809.7	1,177.3
Spring influence	0.0	$3.9e^{-06}$	$9.1e^{-08}$	0.0	$7.5e^{-03}$	$1.6e^{-04}$
All Missouri streams						
Shreve link	1	13,254	96.3	1	44,784	210.7
Slope (deg)	0.0	23.5	3.3	0.0	40.1	4.7
Latitude	37.5	42.0	39.7	35.7	39.4	37.5
% Urban	0.0	100.0	6.3	0.0	100.0	6.1
% Forest	0.0	100.0	16.0	0.0	100.0	55.2
% Shrub	0.0	68.1	0.5	0.0	100.0	0.5
% Agriculture	0.0	100.0	34.9	0.0	100.0	4.0
% Grassland/pasture	0.0	100.0	34.9	0.0	100.0	29.1
Elevation – minimum (m)	123.0	458.3	274.3	72.6	684.3	276.9
Elevation – maximum (m)	123.0	488.6	292.7	73.1	759.7	312.1
Catchment area (km^2)	0.0	125.6	1.9	0.0	107.6	1.7
Watershed area (km^2)	0.0	35,355.7	294.5	<0.1	55,058.1	481.7
Spring influence	0.0	$8.00e^{-04}$	$4.35e^{-08}$	0.0	1.02	$4.73e^{-05}$

Table 17. Number of stream segments with empirical water temperature records for a specified year and geographic region.

Subregion	EDU ID	2010	2011	2012	2013	2014	2015
Central Plains	11		1	1	1	1	
	12		1	2	2	2	1
	14		1	2	2	2	2
	15	2	2				
	16		8	8	8	8	4
Total		***2***	***13***	***13***	***13***	***13***	***7***
Ozarks	21	22	28	51	6	5	2
	22		6	7	9	8	8
	23		1	5	5	5	4
	25		9	9	9	9	9
	27	27	41	30	8	8	7
	28		1	1	1	1	1
	29			8	8	8	7
Total		***49***	***86***	***111***	***46***	***44***	***38***

Model development

We tested our assumption that more accurate model inputs would be obtained at the aquatic subregion scale versus statewide by conducting the initial GAM step (Figure 27, Step 1) for streams across Missouri and then separately for the OP and CP regions. We had predicted that the initial GAM model for water temperature created using all data would be less robust than those for each aquatic subregion due to regional differences in climate, topography, landcover, and other influences on water temperature. We also predicted that the OP model would be less robust than that for the CP due to the moderating influence of groundwater from numerous springs throughout the OP and the lack of detailed information on the groundwater inputs. For air temperature models (a component for the stream temperature model), we hypothesized that GAM models developed by subregion also would perform better than a model for the entire state although we did not expect to see a difference in model strength between subregions. Our results partially supported these hypotheses (Table 18). Based on combined information for adjusted R^2 and generalized cross-validation (GCV) measures, the water temperature (WT) models for subregions performed better than the state-wide model with the CP being the strongest model. However, based on adjusted R^2 for the air temperature (AT) models, the subregion models did not differ from the state model while the GCV indicated a slight improvement for the OP and a decreased strength for the CP model.

Table 18. Measures of initial GAM performance using all sites throughout the State of Missouri and then with sites separated by aquatic subregions. WT = water temperature; AT = air temperature; GCV = generalized cross-validation.

		WT(*t*)		**AT(*t*)**	
Subunit	**Boundary (# samples)**	**Adj r^2‡**	**GCV‡**	**Adj r^2**	**GCV**
State	MO sites (N = 143)	0.85	10.61	0.80	21.56
Aquatic Subregion	Central Plains (N = 15)	0.91	7.82	0.80	24.81
	Ozark Plateau (N = 128)	0.85	8.44	0.80	20.78

‡ higher values for adjusted R^2 and lower values for GCV indicate better models

Model assessment

Based on the sine curve for each aquatic subregion, between the years 2010 – 2015 the maximum air temperatures were reached on adjacent days in the aquatic subregions (CP = 25.9°C on July 18; OP = 26.5°C on July 17) while minimum air temperature (-6.2 and -2.2°C respectively for CP and OP) occurred on January 1 in both subregions. Water temperature peaked (26.5°C) on the same day as air temperature (July 18) in the CP. In the OP, water temperature peaked (25.3°C) two days later than the respective peak air temperature implying a measurable lag day influence. Minimum water temperature (-0.8 and 4.1°C respectively for the CP and OP) occurred on Jan 1, the same day as the minimum air temperature. Although the summer air temperatures (Figure 30a) are similar and winter air temperatures drop below 0°C in both regions, maximum and minimum water temperatures in the OP are correspondingly lower and higher than those in the CP (Figure 30b). A simple linear regression of water temperature as a function of air temperature results in a slope of 0.7 with an intercept of 5.6°C for the OP while the CP had a slightly higher slope (0.8) and lower intercept (4.0°C). This was expected because as discussed in Cassie (2006) groundwater-fed streams tend to have higher intercepts (less likely to freeze) with lower slopes (less variance in extremes) than non-groundwater systems. In addition, differences in elevation and minimum air temperature likely contributed to the differences observed in water temperatures between these subregions.

The root mean squared error (RMSE) for predicting stream temperature across all years was 0.52°C for the CP and 0.58°C for the OP indicating an approximately 0.5°C inaccuracy. Based on the Nash-Sutcliffe coefficient of efficiency (NSE) the predicted water temperatures for both regions were nearly a match to the observed values (NSE values: CP = 0.997, OP = 0.994). A NSE of 1 corresponds to a perfect match between observed and predicted values. Both models were well within standards suggested for good model performance (<10% bias; (Moriasi et al. 2007) although the models slightly over-predicted stream temperature (% bias values: CP = 0.390, OP = 0.242). The RMSE for the 5-fold cross-validations of the intermediate random forest step (RMSE: CP = 1.22°C; OP = 1.64°C) were only somewhat higher than what Troia et al. (2016) reported (1.14°C) for a smaller region in Kansas. We calculated RMSE by month for each subregion to evaluate whether model performance varied seasonally (Figure 31). The CP model varied less than the OP model across months with the lowest RMSE values occuring between September to November although the highest RMSE was only 0.59°C (July). There was a distinct seasonal pattern in the OP model where RMSE values were highest for the summer and winter months. As with the CP model, July had the highest RMSE of 0.77°C. The strong seasonal deviation between predicted and empirical values in the OP was expected due to the prevalence of groundwater influx in that karst system. As air temperatures increase in the summer, the corresponding response of water temperature is lower than would be expected and conversely as air temperatures drop toward 0°C in the winter, the thermally stable inputs from groundwater maintain fluvial temperatures at warmer levels.

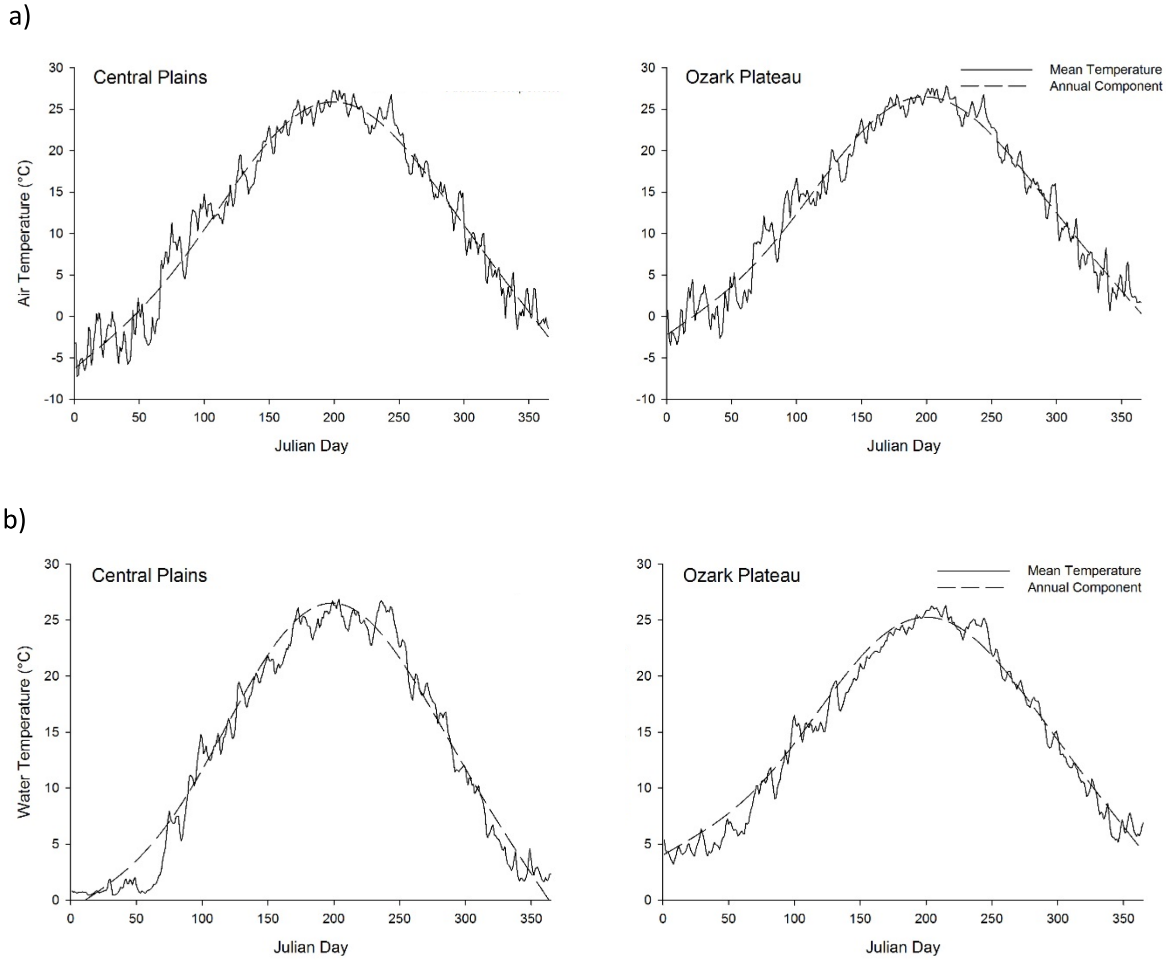


Figure 30. Using Daymet climate data from 2010 to 2015, depicted are a) the spline plots of annual component of air temperature relative to mean daily air temperature for all stream segments by aquatic subregions – Central Plains and Ozark Plateau and b) the corresponding plots for the annual water temperature component relative to recorded mean daily water temperatures.

We also examined model performance (RMSE) across two measures of stream size: Strahler order and Pflieger's size classes (Pflieger 1989). We only report RMSE for those categories with a minimum sample size of 3 stream segments (Table 19). Based on Pflieger stream size class for the OP, there was a trend toward decreasing RMSE with increasing stream size which did not correspond to increasing sample size. Model strength relative to Strahler Order was variable. One possible explanation for the less accurate models of smaller streams may relate to pool isolation during low- or no-flow conditions.

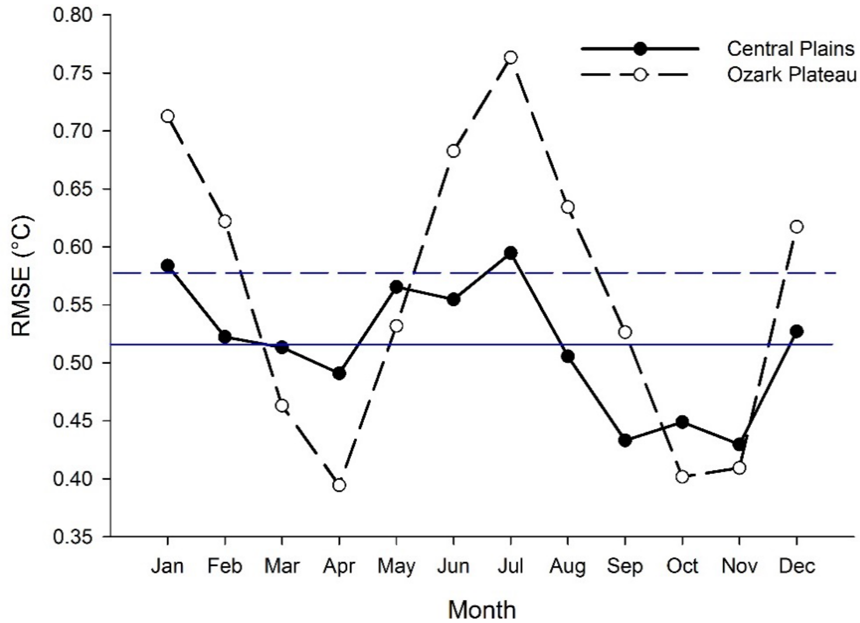


Figure 31. Root mean square error (RMSE; °C) values for predicted daily water temperature by aquatic subregion and month. The blue lines represent the annual mean RMSE for each subregion (dashed line: Ozark Plateau; solid line: Central Plains).

Table 19. Model performance measurements for stream temperature models relative to aquatic subregion and two metrics of stream size. Root mean square error (RMSE) values for two classes of stream size – Strahler order and a Missouri specific classification developed by Pflieger (1989). Numbers in parentheses are the number of sampled stream segments. RMSE (°C) values are not provided for sample sizes under 3.

	Strahler order						Pflieger size class			
Subregion	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**
Central Plains				0.47 (4)	0.49 (6)				0.51 (11)	
Ozark Plateau	0.91 (9)	0.48 (9)	0.56 (21)	0.65 (27)	0.52 (38)	0.45 (22)	0.75 (15)	0.65 (31)	0.52 (56)	0.49 (26)

The relative strength for predictive metrics was evaluated using the percent increase in mean square error (MSE) for each subregion (Table 20). This assessment method is a measure of the relative importance for each predictive metric. It can be thought of as how much the MSE increases (indicating a decrease in model strength) if that metric was left out. Solar radiation and the same day AT residual were the strongest predictor metrics for WT residuals in both the CP and OP random forest models although within the OP the relative strength was substantially higher for the other metrics. The CP model was driven primarily by climate metrics with stream size and watershed area being the strongest of the landscape metrics and spring influence the weakest predictor. For the OP, precipitation, spring influence, and latitude were stronger drivers than the lag-day AT residuals. As with the CP model, stream size and watershed area ranked high in the OP.

Table 20. Predictor metrics ordered by relative prediction strength (top to down, strongest to weakest) for the Central Plains and Ozark Plateau.

Central Plains		Ozark Plateau	
Metric	**% increase in MSE**	**Metric**	**% increase in MSE**
Solar radiation	125.22	Solar radiation	222.07
AT residual, same day	121.44	AT residual, same day	151.55
AT residual, 7-day lag	91.18	Watershed precipitation	124.35
Watershed precipitation	89.89	Watershed spring Influence	114.82
AT residual, 5-day lag	72.36	Latitude	107.01
AT residual, 1-day lag	59.23	AT residual, 7-day lag	97.91
AT residual, 4-day lag	57.72	Watershed area	93.30
AT residual, 2-day lag	56.55	Shreve link	87.49
AT residual, 3-day lag	55.85	Slope	83.67
Shreve link	43.64	AT residual, 5-day lag	80.50
Watershed area	41.76	% urban	77.10
Latitude	32.02	Maximum elevation	71.57
% agriculture	23.10	% forest	67.09
Maximum elevation	21.69	AT residual, 4-day lag	66.85
Slope	21.55	% grassland/pasture	66.77
% shrub	20.42	AT residual, 3-day lag	64.51
% forest	19.57	AT residual, 1-day lag	63.50
% grassland/pasture	15.49	AT residual, 2-day lag	61.35
% urban	13.38	% agriculture	59.37
Watershed spring Influence	8.58	% shrub	38.43

Predicted temperatures followed expected patterns for the respective subregions (Figure 32). Water temperature increased with stream size and generally along a north to south gradient. The highly spring-fed streams in the central OP produced an exception to the latitudinal gradient with water temperatures being cooler despite being farther south. The more uniform gradient of water temperature in the CP creates a visually clearer depiction of stream networks within watersheds. Stream networks in the OP, particularly in the central area, appear more diffuse due to the higher level of within stream variation in water temperatures (Figures 32 and 33).

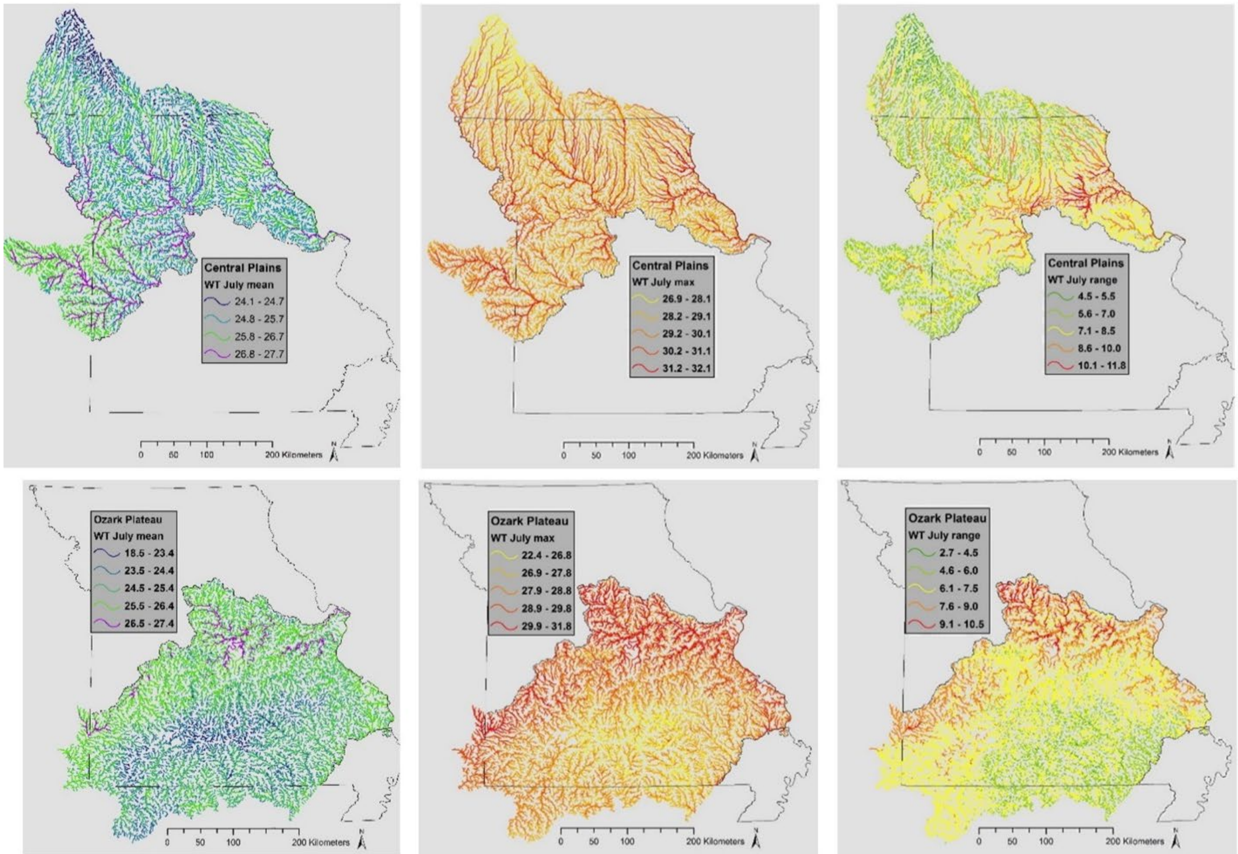


Figure 32. Depiction of July mean, maximum, and range (maximum – minimum) based on predicted daily water temperatures for the Central Plains and Ozark Plateau aquatic subregions. Note: temperatures are scaled to highlight the within subregion and metric gradient. Larger versions of these maps are in Appendix J.

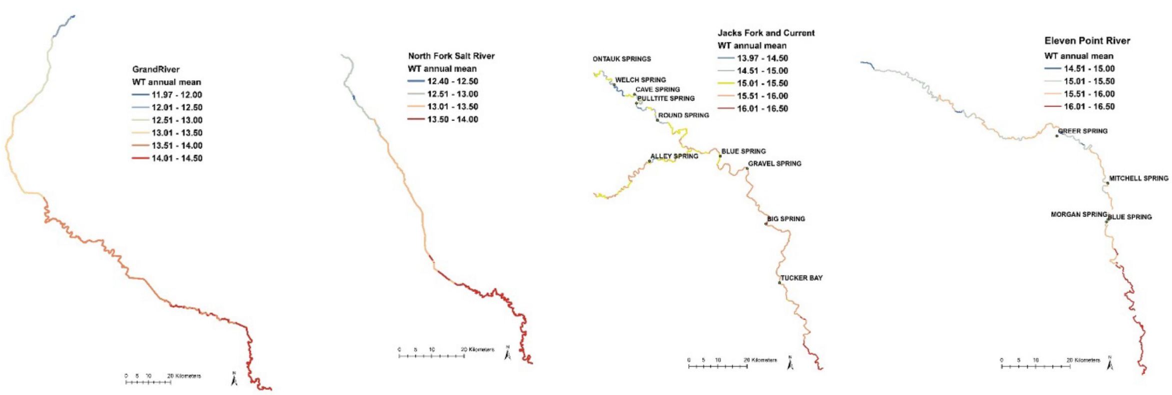


Figure 33. Depiction of longitudinal variation in predicted annual mean water temperatures for two Central Plains rivers (Grand and North Fork Salt) and two Ozark Plateau rivers influenced by cold water springs (Jack's Fork and Current, and Eleven Point). Larger versions of these maps are in Appendix K.

Model strength relative to number of years of data

Because our intent was to compare the relative model strength and our sample size was relatively small (n=13) for this subset of the stream temperature data, we ran these models using the entire dataset (as opposed to a 5-fold cross-validation approach) and did not conduct separate models for the aquatic subregions. The predictions made using the greatest number of years tended to have the lowest RMSE values (Table 21). Year 1 was individually the worst predictor for any years (RMSE >2.7°C) and was the poorest predicted even using multiple year models. Year 1 was the warmest year of our study period (Figure 34) for both water and air temperature. The mean RMSE values for predictions based on 1, 2, and 3 years of data were 2.31°C, 2.09°C, and 2.00°C respectively.

Table 21. Relative ability of stream temperature models to predict alternate years based on the use of single to multiple years of recorded water temperature. Table contains the pairwise root mean square errors (RMSE). Sample sites with four continuous years of data records were used to examine how much influence multiple years of data had on the strength of the resulting temperature models. Shaded cells indicate years that were not predicted using the associated model. For example, a predictive model developed with data from year 2 was not used to predict year 2.

	RMSE (°C) for Predicted Years			
Years used in prediction models	**Year 1**	**Year 2**	**Year 3**	**Year 4**
Year 1		2.93	2.92	2.72
Year 2	2.97		2.06	1.74
Year 3	2.94	2.02		1.53
Year 4	2.64	1.73	1.54	
Years 1 & 2			2.12	1.78
Years 1 & 3		2.14		1.71
Years 1 & 4		2.09	1.96	
Years 2 & 3	2.87			1.40
Years 2 & 4	2.73		1.71	
Years 3 & 4	2.76	1.81		
Years 1, 2 & 3				1.48
Years 1, 2 & 4			1.82	
Years 1, 3 & 4		1.92		
Years 2, 3 & 4	2.77			

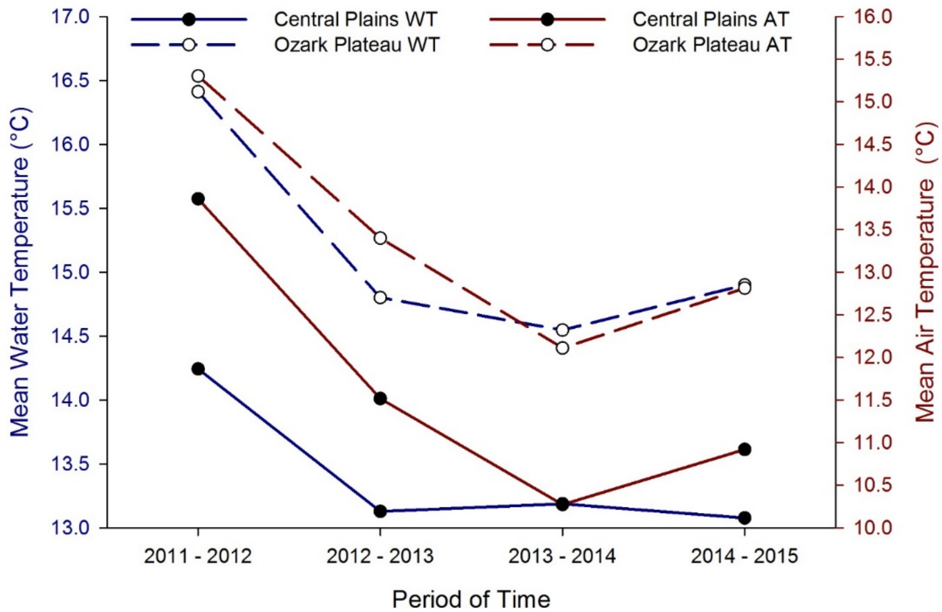


Figure 34. Comparison of mean recorded water and Daymet air temperature by aquatic subregion for annual time periods (1 July – 30 June; Year 1: 2011 – 2012, Year 2: 2012 – 2013, Year 3: 2013 – 2014, Year 4: 2014 - 2015).

Discussion

Stream temperature model

Previous research suggested stream temperature models developed at regional scales with landscape level data may be limited to coarse time scale predictions (e.g. monthly mean) with the best RMSE values tending to be in the 2°C range (Wehrly et al. 2009). Our results suggest that accurate stream temperature predictions can be obtained for daily time steps at the stream segment scale across large geographical regions. Using a stochastic approach that accounted for annual components of air and water and modeled the residuals with site-specific metrics (Caissie et al. 1998; Jeong et al. 2013; Troia et al. 2016), we obtained robust (RMSE< 0.6°C) daily water temperature predictions for stream segments throughout two aquatic subregions (each ~170,000 km^2). Based primarily on research in smaller watersheds, RMSE values under 2°C are considered good results for daily stream temperature models (Caissie 2006). As anticipated, we observed improvements in model strength when we separated the samples by ecologically different aquatic subregions versus treating as a single region. Although we expected groundwater influence to confound model development for the OP, model strength was similar for both regions. The overall variation was under 1°C even in the Ozark Plateau headwaters.

Stream temperature predictions across broad spatial scales are more commonly conducted for coarse temporal scales (e.g. weekly, seasonal, annual; Hill et al. 2013; Isaak et al. 2010; Mohensi et al. 1998; Wehrly 2009). A few studies have published results for daily water temperature models across broad regions. One such was DeWeber and Wagner (2014) where they obtained RMSE values of 1.8 – 1.9°C for predictions of mean daily stream temperature across the native range of Brook Trout (*Salvelinus fontinalis*). DeWeber and Wagner (2014) noted that van Vliet et al. (2012) developed a less robust (RMSE = 2.8°C) global river model that used information at a substantially coarser resolution and was therefore not comparable. Our study was conducted at the same spatial resolution (stream segment) as

DeWeber and Wagner (2014), although based on a shorter temporal span (5 years as opposed to their 30 years). An additional difference is that our model encompassed the annual cycle while DeWeber and Wagner (2014) focused on the spring to summer period. Because we only had five years of data available, our model likely does not incorporate the breadth of annual variation which would be captured with a 30-year dataset. This, in addition to a smaller geographic range, could partially explain why we obtained better predictive performance. In a smaller scale study using the statistical approach that we followed, Troia et al. (2016) reported the cross-validation RMSE for an intermediate step that was approximately 0.1°C lower than our comparable RMSE. Given that their study was for a single watershed (~8,000 stream segments) while our study covered two aquatic subregions with each containing over 58,000 stream segments, we had expected our RMSE values would be larger than theirs. However, based on the cross-validation assessment, our daily temperature model still performed well when predicting to other streams.

As expected the strength of model predictions was closely tied with the number of years of data. Temperature predictions improved on average by 0.2°C between using one versus two years of records and by an additional ~0.1°C with three years of records. We would expect to observe continued improvements in model strength with additional years as well as spatial coverage.

Given the seasonal influence of groundwater on fluvial temperatures, we were not surprised to find that the stream temperature model for the OP performed better in the spring and fall when groundwater has less of a moderating impact on the influence of air temperature. The worst performing month for both models was July which is a critical period when stream temperatures can exceed thermal tolerances of aquatic organisms. This limitation should be considered when using these July predictions; however, the deviation in predicted temperature was only slightly over 0.5°C in the CP and around 0.8°C in the OP.

The predictor metrics used for the stream temperature model were similar in relative importance to those used by others (Troia et al. 2016) and as expected, the relative importance of metrics differed slightly among aquatic subregions. Stream temperatures in the CP were driven far more by climate (solar temperature, air temperature, and precipitation) than those of the OP. Although climatic influences were important in the OP, other geographic attributes tied with stream size and latitude were also influential predictors.

Spatially and temporally explicit stream temperature predictions can be used to inform current and future management decisions for thermally sensitive species and to assess water quality. Although individual organisms often live in thermal microclimates (Brewer 2013; Dobos et al. 2016; Ebersole et al. 2001; Peterson and Rabeni 1996; Westhoff et al. 2016) these microclimates are influenced by the thermal profile in the associated water matrix. Maximum daily temperatures have been commonly associated with occurrence of aquatic species (Dunham et al. 2003; Ebersole et al. 2001) although thermal tolerances of organisms typically depend on the period of exposure which is often reported as the number of days over or under a specified temperature (Cox and Beauchampe 1982; Ganser et al. 2013, 2015; Wehrly et al. 2007). Temperature is also linked with metabolism of aquatic organisms. Under projected climate change scenarios, for every 1 °C rise in stream temperature Smallmouth Bass (*Micropterus dolomieu*) are expected to increase growth by over 5% with a corresponding increase in consumption of over 25% (Pease and Paukert 2014) although exceeding 27 °C may reduce growth potential (Whitledge et al. 2006). Westhoff and Paukert (2014) predicted that under future climate scenarios, optimal growth days for largemouth bass (*Micropterus salmoides*) would increase although decrease for the Ozark hellbender (*Cryptobranchus alleganiensis*) even where spring influence was high. The temporal and spatial resolution of our predictions provide measures of the longitudinal dynamics of stream temperature which are known to be important to aquatic organisms, and for identifying shifts related to anthropogenic alterations within a watershed as well as broader changes in climate.

Temperature models also have utility for identifying when small changes in temperature may have detrimental impacts or alter population demographics. Lethal responses have been documented even when water temperatures change by as little as 1°C (Cox and Beauchamp 1982; Fields et al. 1987). Slight changes in water temperature also have been shown to impact survival, growth, consumption, and reproduction. For example, Brook Trout delayed spawning and constructed fewer redds when the summer mean of maximum daily air temperature increased by 1°C (Warren et al. 2012). Crayfish mortality increased 2 to 4-fold when water temperature increased by 0.3 to 1.2°C in streams affected by acidic discharges from mines (Hartman et al. 2010). Also, as mentioned in the previous paragraph, Pease and Paukert (2014) noted expected changes in growth and consumption for smallmouth bass.

An important difference between our model and other efforts is that we have provided a tool to assess annual response or variation while the more typical approach has focused on the warmest period of the year. Although elevated water temperatures can heavily influence survival and health of aquatic organisms, describing thermal patterns during other periods can provide critical information for watershed management as shown by the smallmouth bass use of springs as thermal refugia (Westhoff et al. 2016). Most of the year smallmouth bass stay within stream channels but have been shown to congregate in or near springs during the summer and winter. Presumably these fish are sheltering from excessively warm or cold waters depending on the season. This temperature model provides an opportunity to elucidate year-round patterns.

The OP and CP models can be used for quantifying general patterns and ranges of stream temperatures both spatially and temporally within these aquatic subregions of Missouri. The modeling approach we have described is a robust method for predicting stream temperatures in Midwestern streams and within the differing aquatic subregions of Missouri. This approach could be applied to other stream temperature datasets or based on a user's interests and information needs, could be applied to different subsets of the Missouri stream temperature data we compiled. For the purpose of presenting this approach and discussing general patterns, we subdivided the compiled dataset by aquatic subregion. Another user might subdivide this same dataset to revise these temperature models for 3rd order streams of the OP or for a specific seasonal period to link predicted temperature with records of aquatic species collected during the same season. In addition, the models provided can be further developed by incorporating additional stream temperature records that add to the spatial or temporal coverage.

Future directions

Stream temperature models could be improved with the implementation of monitoring networks with more spatially intensive sampling that would provide the opportunity to include spatial dependencies (Braun et al. 2015; Isaak et al. 2014; Jackson et al. 2016; Ver Hoef and Peterson 2010). Such a network would consist of monitoring of tributaries as well as main stem channels. There were a few watersheds with more intensive sampling efforts that might be suitable for incorporating spatial dependencies, particularly if sampling continues at those sites (Figure 25).

Caveats to use

Users should keep in mind the scale at which these models were developed and not attempt to apply the results to small spatial scales such as microhabitats or to expect a predicted stream temperature to exactly match an empirical measurement taken at one location. These models are best applied to streams with similar ecological characteristics as those where the samples were collected. For instance, only a small percentage of headwater and second order streams were included in this dataset (Figure 28) therefore users should expect predictions for these stream sizes to be less robust.

Products

The list of sites with stream temperature records was provided in Appendix A and was made available as a GIS shapefile and Excel spreadsheet. In addition, stream temperature records were provided as a comma delimited text file. All products included an associated metadata file in FGDC format. Raw data and summary metrics are provided as a Microsoft Access database linked to the spatially-referenced locations. A geodatabase with duplicate data also was created to facilitate use in a geographic information system (GIS).

Description	File name	File format
Stream temperature data		
Stream temperature records obtained for all monitoring sites in Missouri	Obj1_doc_stream_temper_data.csv	Text file
Stream temperature model for Missouri streams		
Empirical hourly water temperatures used in model	Obj3_WaterTemperatures	Text file
Predictor metrics associated with sampled sites	Obj3_Predictors	Text file
Predicted daily water temperatures	Obj3_PredictedWaterTemperatures	Text file
Spatial data		
Missouri stream layer	MO_streams	ESRI shapefile
Missouri catchment layer	MO_catchments	ESRI shapefile
Stream temperature monitoring sites in Missouri	Obj1_AllWaterTempSites	ESRI shapefile
R code		
R code for running temperature model	Multiple files in folder titled Obj2_5 r codes	R file

Influence of stream flow on water temperature in Missouri streams

Objectives addressed:
Objective 6: Develop stream temperature models incorporating flow rate.
Objective 7: Evaluate whether these differ by Missouri stream type or subregion.

Our objectives for this section were to determine the relationship between stream temperature and flow across aquatic subregions and stream classifications. The results of this section provide a statistical basis for predicting how stream temperature could change under scenarios of water withdrawal from a stream system.

Background

Stream temperature is tightly linked with stream discharge primarily as a function of energy exchange, volume, and source. The volume of water within a water body influences the overall heating capacity of water while mixing of water sources can moderate those temperatures (e.g., spring water inputs, hyporheic exchange; Caissie 2006). Higher discharge levels have been shown to lower stream temperature regardless of watershed size or temporal scale and tend to be more influential over shorter time-frames and in larger watersheds (Webb et al. 2003). Although stream temperature generally is not directly correlated with discharge, the moderating effects of discharge have a substantial influence (see General Introduction section for more details).

Changes to natural flow patterns alters stream habitat, physical structure, and function and ultimately the biodiversity within these systems (Bunn and Arthington 2002; Poff and Ward 1989). A common source of alteration is withdrawal of stream water for agricultural or commercial purposes that results in lower than normal flows. Low flows have been linked to increases in water temperature maximum and range that can result in reduced recruitment and diversity of sensitive aquatic biota (Rolls et al. 2012).

Research to describe the influence of discharge on stream water temperature is typically done within small watersheds to incorporate fine details such as hypolimnetic flows, residence time, and detailed heat exchange equations (e.g., Hockey et al. 1982; Sinokrot and Stefan 1993; Constanz 1998; Sinokrot and Gulliver 2000). However, water management plans are usually developed for multiple watersheds necessitating the development of coarser approaches. Recent efforts along this line have produced physically based models for large river basins at a global scale (van Vliet et al. 2012; van Vliet et al. 2013).

We describe our approach to capture the general relationship between discharge and water temperature as a means of obtaining a scientific basis for estimating the change in water temperature under scenarios of water withdrawals.

Methods

Study area

The study sites for this section fell within two ecoregions in Missouri: Central Plains (CP) and Ozark Plateau (OP) aquatic subregions (Figure35; Pflieger 1989; Sowa et al. 2005). These subregions have geologically and ecologically distinct histories that have resulted in important differences relative to what drives stream temperatures. The majority of the plateau is underlain by highly permeable limestone and dolomite bedrock. Topographic relief is higher in the OP with forest habitat being the dominant habitat and streams are typically confined to narrow channels in steep valleys. Soils in the OP typically are shallow with low nutrient levels and fall dominantly in the NRCS B and C hydrologic soil groups (approximately 55% and 40% respectively). These hydrologic groups are characterized by unimpeded to only somewhat restricted water transmission with moderately low to high runoff potential. In the CP, the thick layers of glacial till and loess are dominated by agriculture and grassland vegetation. Streams in the plains tend to consist of wide, braided meanders sloping gradually through wide valleys. Bedrock consists of shale, limestone, and sandstone. Soils in this region fall predominantly into the NRCS C hydrologic soil group followed by B and D (C: 50%, B: 28%, D: 22%). Hydrologic soil group D are generally high in clay content with restricted water transmission characteristics and high runoff potential (NRCS 2007).

Climatically these two regions are fairly similar based on annual air temperature (Sowa et al. 2005). Mean annual air temperature and precipitation increase along a gradient from the northwest to the southeast corners of the state. Stream temperatures in both regions are generally considered warm except where influenced by groundwater inputs (Annis et al. 2010). The numerous springs in the Ozark Plateau (OP) contribute to suitable habitat conditions for several species that benefit from moderated water temperatures. See General Introduction for more details on the climate and geophysical characteristics of these aquatic subregions.

Data sets

Stream temperature data

We selected study sites from a list of USGS gages in Missouri that had been identified previously as least impacted by anthropogenic alterations that could influence this relationship (Kennen et al. 2009). Kennen et al. (2009) had classified many of these gage sites into one of five streamflow classes (Intermittent, Perennial/Flashy, Perennial/Moderate, Perennial/Stable, Perennial/Super Stable) based on the seasonality and stability of surface flow (Table 22). We obtained a probable classification for unclassified gage sites by rerunning Kennen et al's. (2009) Missouri Stream Classification tool with looser restrictions on the number of consecutive years with records. Once all sites were classified we filtered the list to obtain a distribution across aquatic subregion, streamflow classes, watershed sizes, and those near or within MDC priority watersheds with sensitive aquatic species (e.g., Ozark hellbenders, sheepnose) which are important to the Missouri Department of Conservation (MDC). Our final list was composed of 62 sites (Table 22; Figure 35). Only one of these USGS gage sites recorded stream temperature.

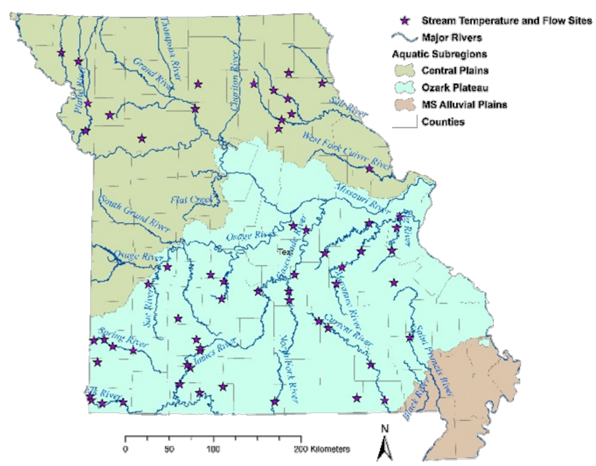


Figure 35. Map depicting the location of USGS gage sites used for this analysis relative to aquatic subregions.

In 2011, stream temperature was monitored at 38 of the selected USGS gage sites. An additional 24 gage sites were monitored in 2012. Near each gage site, two loggers (a mix of Onset Computer Corporation (HOBO Water Temp Pro V1 and V2) and Solinst Canada Ltd (Levelogger Model 3001 Mini LT)) were deployed which recorded temperature at hourly intervals corresponding with the timing of USGS gage flow records. After 2012 only the Pro V2 loggers were used as the project transitioned to MU. Loggers were placed along the stream thalweg within the nearest downstream run or riffle habitat that had an adequate attachment location. As exposure to solar radiation can increase the temperature being recorded by over 1.5°C (Johnson and Wilby 2013) loggers were located in shaded areas. Loggers were attached to either a metal stake pounded into the substrate, to imbedded large woody debris, or the trunk or root wad of living trees (Figure 36). Each site was given a unique sequential number identifier and each logger location was assigned a letter.

Table 22. List of USGS gage sites where stream temperature loggers were placed nearby for the purpose of linking water temperature with flow rates. Classification codes: PRF – perennial, runoff, flashy; PGS – perennial, groundwater, stable; PGSS – perennial, groundwater, super-stable; PRMB – perennial, moderate baseflow; INT – intermittent (Kennen et al. 2009). We used the Missouri Stream Classification Tool to provide the probable classification for streams not classified by Kennen et al. (2009); USGS gage stations on these streams had less than 20 years of consecutive flow data.

Aquatic Subregion	Site Name	Kennen et al. (2009) Classification	Probable Classification
Central Plains			
	Crooked Creek near Paris	PRF	
	Crooked River near Richmond	PRF	
	Cuivre River near Troy‡	PRF	
	Elk Fork Salt River near Madison	PRF	
	Grand River near Sumner‡	PRF	
	Little Platte River near Plattsburg		PRF
	Locust Creek near Linneus	PRF	
	Long Branch Creek near Atlanta	PRF	
	Middle Fork Salt River near Holliday		PRF
	Nodaway River near Graham	PRMB	
	North Fork Salt River at Hagers Grove		PRF
	North Fork Salt River near Shelbina		PRF
	One Hundred Two River near Bolckow‡		PGS
	Platte River at Sharps Station‡		PRF
	Platte River near Agency‡	PRF	
	South Fabius River above Newark		PRF
	South Fabius River near Taylor	PRF	
Ozark Plateau			
	Beaver Creek at Bradleyville	PGS	
	Big Creek at Sam A Baker State Park		PGS
	Big Piney below Fort Leonard Wood		PGS
	Big Piney River near Big Piney	PGS	
	Big River at Byrnesville	PGS	
	Big River at Irondale	PGS	
	Big River near Richwoods	PGS	
	Big Sugar Creek near Powell		PGS
	Bourbeuse River at Union	PGS	
	Bourbeuse River near High Gate	PRF	
	Buffalo Creek at Tiff City		PRF
	Bull Creek near Walnut Shade		PGS

Aquatic Subregion	Site Name	Kennen et al. (2009) Classification	Probable Classification
Ozark Plateau (cont)			
	Cedar Creek near Pleasant View	PRF	
	Current River above Akers		PGSS
	Current River at Doniphan	PGSS	
	Current River at Montauk State Park		PGSS
	Current River at Van Buren	PGSS	
	Eleven Point River near Bardley	PGSS	
	Elk River near Tiff City	PGS	
	Finley Creek below Riverdale		PGS
	Gasconade River at Jerome	PGS	
	Gasconade River near Hazelgreen	PGS	
	Gasconade River near Rich Fountain		PGS
	Indian Creek near Lanagan		PGS
	James River at Galena	PGS	
	James River near Boaz		PGS
	James River near Springfield		PGS
	Little Niangua River near Macks Creek		PRF
	Little Sac River near Morrisville	PGS	
	Maries River at Westphalia	PRF	
	Meramec River at Cook Station	PGSS	
	Meramec River near Eureka	PGS	
	Meramec River near Steelville	PGS	
	Meramec River near Sullivan	PGS	
	Niangua River above Lake Niangua near Macks Creek		PGS
	Niangua River at Windyville		PGS
	North Fork River near Tecumseh	PGSS	
	North Fork Spring River near Purcell		PGS
	Pearson Creek near Springfield		PGS
	Shoal Creek above Joplin	PGS	
	South Fork Dry Sac River near Springfield		PGS
	Spring River at Carthage		PGS
	Spring River at La Russell		PGS
	Spring River near Waco	PGS	
	Weaubleau Creek near Weaubleau		PRF

‡ These gage sites were not used in the final analysis because loggers were continually washed away at these sites.

In 2015 several loggers were incorrectly launched and recorded hourly within the hour (e.g. 14:22 instead of 14:00). For these temperature data, we rounded the time of temperature record to the nearest corresponding gage observation. In some cases, this meant temperature records were linked with flows recorded on the half hour or 15 minute interval. Loggers were swapped out approximately every year and replaced with a new logger. When a logger could not be relocated or its location was no longer in a suitable site (e.g. habitat had become a pool, was no longer shaded, or was dry), we relocated them to a new location and assigned a new unique location identifier.

After data were downloaded from retrieved loggers, each logger was re-evaluated for precision by placing it in a water bath with other loggers (see Appendix L for details). Temperature records from the study sites were error-checked to identify erroneous outliers and periods of time where the data loggers may have been either out of the water or buried in substrate (Figs. 37 and 38). No records were used for subsequent analyses where the water temperature was below 1°C to avoid periods when the water was not flowing.

Figure 36. Photos showing a typical logger attachment and placement.

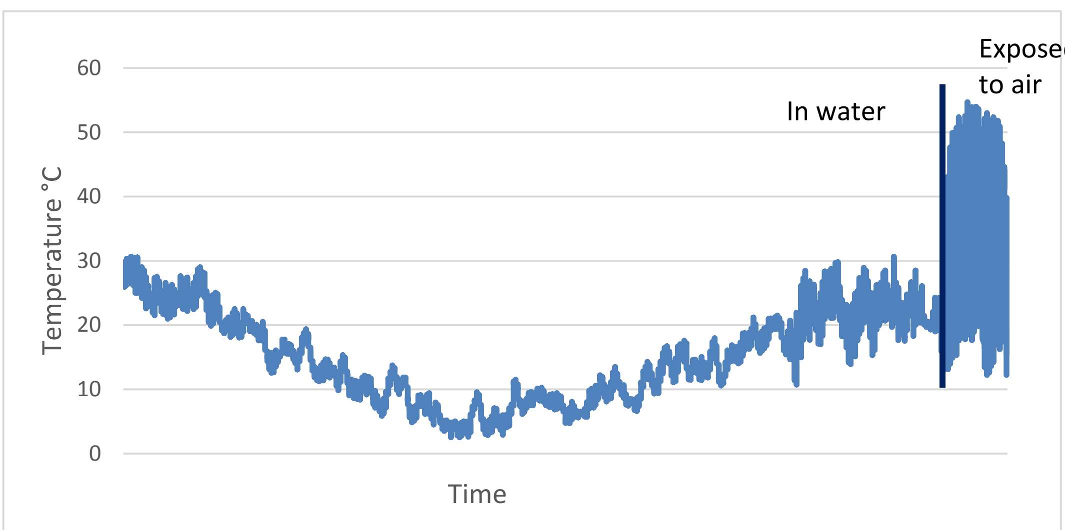


Figure 37. Example of stream temperature records showing a typical pattern observed when a temperature logger was no longer submerged. Temperature records show low variation and maximum measurements remain below 35°C while the logger was inundated followed by increased daily variability and temperatures above 45°C when the logger became exposed to the air in the late summer.

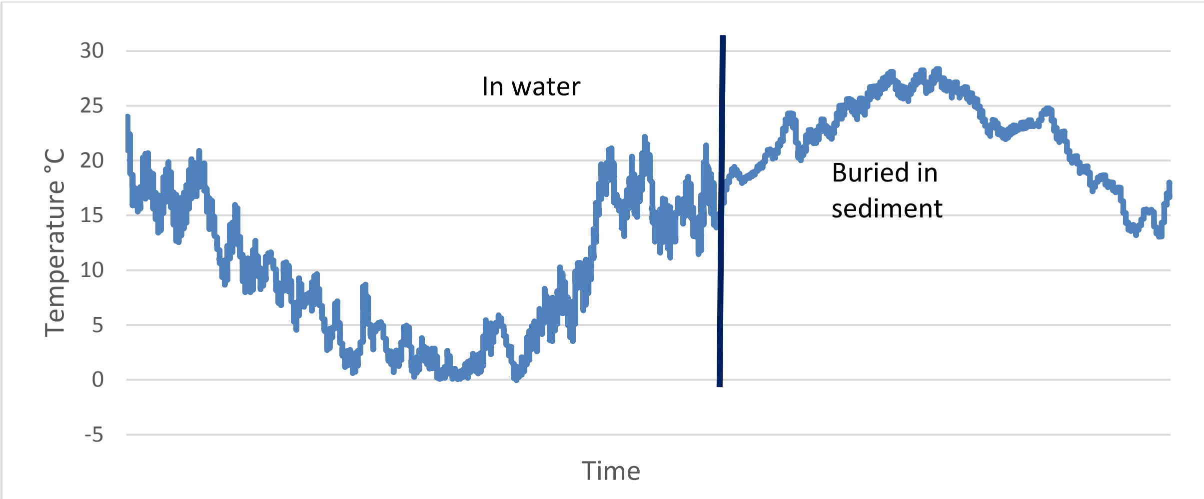


Figure 38. Example of temperature records showing a typical pattern observed when a temperature logger became buried by sediment. Daily variation decreased substantially in early May which likely indicated that the logger was buried.

Stream discharge data

Stream discharge records were obtained from the USGS gage sites for the period between June 2011 and Aug 2015 using the dataRetrieval 2.5.13 package in program R. Only records that had been approved as correct by USGS were used in subsequent analyses. The 80th percentiles for each site were calculated based on measurements during this time span (Table 23). Percentiles were calculated with the zero flow measurements excluded. Records taken during discharge events exceeding the 80th percentile per gage site were excluded from analyses to reduce the spurious influence of surface runoff and extreme flow rates.

Table 23. Summary metrics (mean, minimum, maximum, and 80th percentile) for the discharge records of each study site.

Subregion		Discharge (cms)			
Gage name	Gage ID	mean	min	max	80th
Central Plains					
Crooked Creek near Paris	5503800	0.16	0.00	1.11	1.13
Crooked River near Richmond	6895000	0.46	0.00	3.40	3.40
Cuivre River near Troy	5514500	3.12	0.02	22.51	22.51
Elk Fork Salt River near Madison	5506800	0.58	0.01	3.26	3.26
Little Platte River near Plattsburg	6821080	0.11	0.00	1.05	1.05
Locust Creek near Linneus	6901500	1.44	0.02	9.20	9.20
Long Branch Creek near Atlanta	6906150	0.06	0.00	0.31	0.31
Middle Fork Salt River near Holliday	5506350	1.21	0.01	7.31	7.33
Nodaway River near Graham	6817700	13.69	0.91	50.40	50.69
North Fork Salt River at Hagers Grove	5502300	0.87	0.01	4.96	4.96
North Fork Salt River near Shelbina	5502500	1.23	0.02	9.57	9.57
South Fabius River above Newark	5498700	0.59	0.00	3.00	3.03
South Fabius River near Taylor	5500000	1.75	0.00	12.26	12.26

Subregion		Discharge (cms)			
Gage name	Gage ID	mean	min	max	80th
Ozark Plateau					
Beaver Creek at Bradleyville	7054080	3.52	0.45	9.88	9.88
Big Creek at Sam A Baker State Park	7037300	2.74	0.06	6.91	6.91
Big Piney below Fort Leonard Wood	6930060	9.48	3.85	21.38	21.38
Big Piney River near Big Piney	6930000	7.76	3.03	17.64	17.64
Big River at Byrnesville	7018500	9.44	1.44	25.71	25.71
Big River at Irondale	7017200	1.30	0.04	5.27	5.27
Big River near Richwoods	7018100	7.45	1.06	20.10	20.10
Big Sugar Creek near Powell	7188653	1.43	0.04	4.30	4.30
Bourbeuse River at Union	7016500	5.34	0.62	20.78	20.78
Bourbeuse River near High Gate	7015720	0.49	0.00	2.63	2.63
Buffalo Creek at Tiff City	7189100	0.77	0.11	2.15	2.15
Bull Creek near Walnut Shade	7053810	1.77	0.07	6.65	6.65
Cedar Creek near Pleasant View	6919500	2.08	0.00	9.88	9.88
Current River above Akers	7064533	7.74	4.22	14.64	14.64
Current River at Doniphan	7068000	61.05	35.68	104.49	104.49
Current River at Montauk State Park	7064440	2.42	1.46	4.08	4.08
Current River at Van Buren	7067000	43.96	25.43	67.96	67.96
Eleven Point River near Bardley	7071500	18.65	7.56	30.58	30.58
Elk River near Tiff City	7189000	10.04	1.56	24.47	24.47
Finley Creek below Riverdale	7052345	3.30	0.31	9.34	9.34
Gasconade River at Jerome	6933500	34.88	11.69	94.58	94.58
Gasconade River near Hazelgreen	6928000	11.81	1.39	38.23	38.23
Gasconade River near Rich Fountain	6934000	39.96	13.28	110.44	110.44
Indian Creek near Lanagan	7188885	2.98	0.77	7.76	7.76
James River at Galena	7052500	14.42	1.71	41.91	41.91
James River near Boaz	7052250	7.33	0.89	19.77	19.77
James River near Springfield	7050700	2.43	0.03	8.35	8.35
Little Niangua River near Macks Creek	6925250	0.40	0.00	2.52	2.52
Little Sac River near Morrisville	6918740	2.22	0.10	6.80	6.80
Maries River at Westphalia	6927000	1.08	0.01	6.12	6.12
Meramec River at Cook Station	7010350	1.27	0.22	3.68	3.68
Meramec River near Eureka	7019000	37.19	7.22	111.57	111.57
Meramec River near Steelville	7013000	7.94	3.14	19.65	19.65
Meramec River near Sullivan	7014500	16.45	5.21	44.74	44.74
Niangua River ab Lake Niangua nr Macks Creek	6923940	8.55	3.71	20.81	20.81
Niangua River at Windyville	6923250	2.69	0.45	9.63	9.63
North Fork River near Tecumseh	7057500	15.20	8.44	26.14	26.14
North Fork Spring River near Purcell	7185910	1.37	0.00	8.13	8.13
Pearson Creek near Springfield	7050690	0.42	0.06	1.12	1.12
Shoal Creek above Joplin	7187000	6.78	1.24	16.88	16.88

Subregion		Discharge (cms)			
Gage name	Gage ID	mean	min	max	80th
Ozark Plateau (cont)					
South Fork Dry Sac River near Springfield	6918493	0.21	0.03	0.54	0.54
Spring River at Carthage	7185765	4.53	0.55	14.64	14.64
Spring River at La Russell	7185700	3.52	0.42	10.22	10.22
Spring River near Waco	7186000	6.88	0.70	26.59	26.59
Weaubleau Creek near Weaubleau	6920520	0.09	0.00	0.62	0.62

Water temperature – discharge model

We used generalized additive models (GAM) to identify the relationships between predictor metrics and hourly water temperature because non-linear relationships have been demonstrated between hourly measures of water and air temperatures (Webb et al. 2003). This statistical approach allows for nonlinear relationships between predictors and the dependent variable, assumes no interaction between predictors, and provides a regression model that can be used to evaluate the relationship between individual predictors and the response. These models consist of a response, an additive predictor, and a smooth function that relates each predictor to the response;

$$y = s_0 + s_1(X_1) + \dots + s_p(X_p),$$

where p = the number of predictor variables and s is a smooth function.

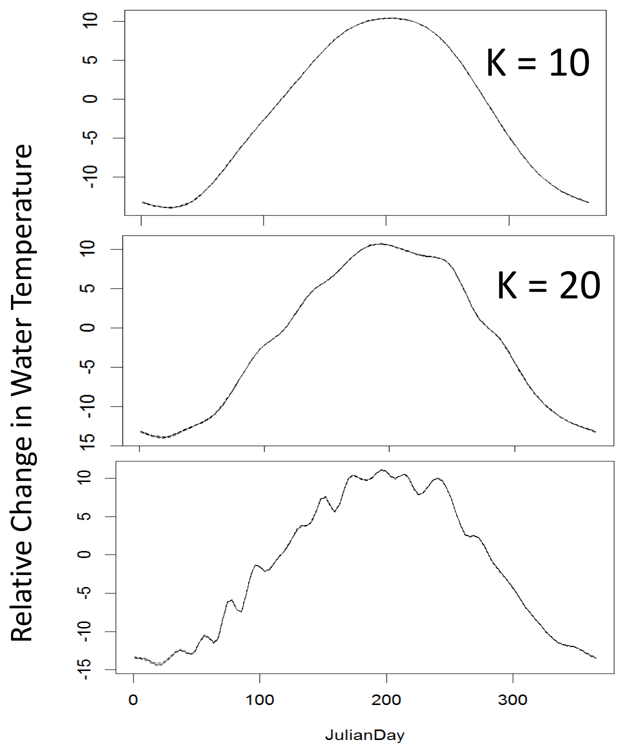
For each aquatic subregion (Ozark Plateau and Central Plains), we selected a subset of predictor metrics that had provided high prediction strength for water temperature (Table 20) and added hourly discharge from the nearby USGS gage. The initial list of additional predictors included solar radiation, watershed precipitation, watershed spring influence, latitude, watershed area, and air temperature. We dropped watershed precipitation because its inclusion in previous models was as a surrogate for discharge. Because same day air temperature had a substantially stronger influence than the other air temperature metrics, we retained the same day air temperature and eliminated all of the lag day air temperature variables. Although we did not expect spring influence would have much predictive strength for the CP model, we included the entire suite of metrics in all models to facilitate comparisons between subregions. We incorporated Julian day as a parameter to account for the temporal component of water temperature.

We conducted model evaluation using generalized cross validation (GCV), Akaike information criterion (AIC), and adjusted r^2. The GCV is an approach to model evaluation that reduces computational costs relative to the leave-one-out cross validation approach while providing an estimate of model performance (Wahba 1990). It checks how well a particular model can predict data that were not included in the original model development. The lower the GCV value, the better the model performance, although alone this value does not mean much. This metric is better used as a relative measure to compare models. Similar to AIC, GCV penalizes models with larger numbers of predictors.

Selection of spline functions

Selection of smooth functions for each predictor metric was based primarily on the type of dataset and model fit. For the temporal component, we used cubic cyclical regression spline that treats the first and last Julian Day as being similar (Wood 2004). For the remainder of the predictors excluding discharge, we used thin plate regression splines. For discharge, we used a cubic regression spline because this resulted in a slightly better model fit. All of these spline types require specifying another function called the basis term (K) which stipulates the number of basis functions (also known as knots) that will be used

(Wood 2004). An appropriate basis term was determined for each predictor by examining the resulting model evaluation values (GCV, AIC, and adjusted r^2) for points of stabilization and visually evaluating the plotted relationship of each predictor to water temperature. In addition, we looked at the expected degrees of freedom (EDF) which should remain below the smoothing parameter (Wood 2004). The purpose of visual evaluation was to look for where the general relationship between predictors and water temperature began to be lost (Figure 39). Figure 39 depicts several panels showing the relative change in water temperature across Julian Days with an increasing number of knots. As the number of knots are increased, the model begins to capture variations that exist within the temporal period of our dataset. Although capturing those variations improves the ability to model within the years 2011 – 2015, we lose the more general relationship between a predictor metric and water temperature. Therefore, we opted to use basis functions which captured the general relationship so that this model could predict to other years.



K	EDF	GCV	AIC	Adj. r^2
10	7.99	8.24	1286359	0.89
20	18.0	8.06	1280631	0.89
40	38.0	7.51	1262177	0.90

Figure 39. Plots depicting the modeled relationship between Julian Day and relative change in hourly water temperature from the mean with increasing smoothing values. In the table are the corresponding model evaluation metrics. Top to bottom each plot shows the increasing ability of the model to explain variability in the data points as opposed to the pattern we might observe if we had more years of data. At K = 40 is an example of overfitting the data.

Prediction dataset

To provide estimates of water temperature response to changes in flow by aquatic subregion and stream type, we created a dataset for each sampled site with the fixed site characteristics (spring influence, latitude, upstream watershed area), Julian Days for a year (1 – 365), and mean air temperature and solar radiation per Julian Day that were documented for each sample site.

Results

Data collection and summary

Retention rates for the temperature loggers varied between the aquatic subregions with higher rates of non-retrieval in the CP primarily due to flooding events that completely altered stream channels and washed away the objects where loggers had been attached. Four CP sites were removed from analysis because of the difficulties we had in maintaining loggers at those sites and subsequent lack of consistent data (Table 22). We obtained an average of 3 years of stream temperature records per sample site (CP:

2.8 years; OP 3.1 years). The USGS gage data were consistent across our sampling period with only a few temporal gaps (92% correspondence to hourly stream temperature records).

Stream temperatures and climate metrics were similar across the two aquatic subregions with the more southerly OP having slightly warmer air and water temperatures (Table 24). We sampled a larger range of watershed sizes in the OP than in the CP. Overall the discharge rates in the OP were substantially higher than in the CP despite a greater range of precipitation in the CP. This apparent disconnect between discharge and precipitation is likely a function of the larger watersheds sampled in the OP. As expected, the estimates of spring influence were very low in the CP.

Table 24. Summary metrics for the sample sites used to develop water temperature models that incorporated stream discharge.

Aquatic Subregion / Metric	Mean	Minimum	Maximum	Standard Deviation
Central Plains (13 sites)				
Water temperature, hourly (^oC)	14.09	0.00	36.41	9.33
Discharge, hourly (cms)	7.73	0.00	1186.48	37.25
Solar radiation, mean daily (W/m^2)	327.29	38.40	550.40	106.39
Upstream precipitation, total daily (mm)	2.79	0.00	161.58	8.00
Air temperature, mean daily (^oC)	12.56	-21.00	33.00	10.54
Upstream spring influence (cms/stream distance [km])	0.000000	0.000000	0.000004	0.000001
Watershed area (km^2)	998.77	59.72	3928.62	992.18
Latitude (decimal degrees)	39.67	39.01	40.19	0.30
Ozark Plateau (45 sites)				
Water temperature, hourly (^oC)	15.84	0.00	35.79	7.86
Discharge, hourly (cms)	17.29	0.00	3907.73	59.20
Solar radiation, mean daily (W/m^2)	336.21	38.40	566.40	103.03
Upstream precipitation, total daily (mm)	3.35	0.00	115.54	8.25
Air temperature, mean daily (^oC)	14.33	-19.25	34.00	10.26
Upstream spring influence (cms/stream distance [km])	0.0001	0.0000	0.0008	0.0002
Watershed area (km^2)	1682.84	5.14	9809.73	2062.57
Latitude (decimal degrees)	37.52	36.59	38.51	0.57

Water temperature – discharge model

We developed water temperature with discharge models for both the annual and late summer relationships in each aquatic subregion. These were done to assess relative change in water temperature annually and for late summer, which is when we would anticipate that water temperatures could exceed thermal maximums for some species. We also created models for stream flow classes (Table 22) that characterized at least three sites within an aquatic subregion. We hypothesized that models based on flow class would be stronger than models based on subregion due to the influence of flow on water temperature. We selected these scenarios to provide examples of how this model could be used to assess a relative change in water temperature across a gradient of discharge rates.

Parameter specification

Spline type used for each predictor metric is shown in Table 25 and the justification was provided in the methods section. These regressive spline types require setting the number of bases or knots for each predictor. Knots can be thought of as the number of inflection points allowed in the regression line. To determine an appropriate starting number for each predictor we created individual GAM models of water temperature with each predictor (e.g. water temperature = s(Julian Day)). We then evaluated the model fit across a range of potential number of knots going from 5 to 40. The number of knots selected for each predictor was the same across the aquatic subregions with the exception of spring influence (Table 25). In the CP, the relationship between spring influence and water temperature was linear and did not require setting a smoothing spline. The full models were developed using these initial selections and the relationships between predictors and water temperature were reevaluated to determine whether individual relationships had changed when combined with the other predictors. None of the relationships had changed. If we had observed any changes in relationships, we would have further refined the number of knots used for those predictors.

Table 25. Predictors used in the base prediction model including the basis type and number of knots.

Predictor	Spline Type	# of Knots
Discharge	Cubic regression	5
Solar radiation	Thin plate regression	8
Air temperature	Thin plate regression	10
Spring influence	Thin plate regression	3*
Watershed area	Thin plate regression	5
latitude	Thin plate regression	5
Julian Day	Cyclic cubic regression	10

*applies only to the OP.

Base model

Prior to model development, records with water temperature below 1˚C were excluded to eliminate confounding effects of frozen water. We used the base models to create predictive models for aquatic subregions and stream classes within subregions. Models were refined slightly between the aquatic subregions to account for the weaker influence of springs in the CP.

The final base models for each aquatic subregion were:

<u>Central Plains</u>

Water temperature = s(Julian Day) + s(discharge) + s(solar radiation) + s(air temperature) + s(watershed area) + *spring influence* + s(latitude)

<u>Ozark Plateau</u>

Water temperature = s(Julian Day) + s(discharge) + s(solar radiation) + s(air temperature) + s(watershed area) + *s(spring influence)* + s(latitude)

Annual models

We were able to develop robust models for each subregion with the stronger model being for the CP (Table 26). We had anticipated obtaining a weaker model for the OP region because of the general lack of information for groundwater in this region where springs are abundant. The lower model strength for the OP could also be a function of the greater breadth of landscape parameters, such as watershed size, that we sampled in this subregion (Table 24).

Table 26. Model evaluation statistics for annual water temperatures within each aquatic subregion. GCV = generalized cross-validation.

Aquatic subregion	Adjusted r^2	GCV
Central Plains	0.96	3.34
Ozark Plateau	0.93	4.57

Figures 40 and 41 contain plots of the relationships between individual predictors and water temperature for models developed by aquatic subregion. These graphs depict the relative change from mean water temperature as a function of each predictor with the other predictors held at their mean values. It should be noted that these relationships tend to be less reliable at the extremes of each predictor, although sample size can be a contributing factor. This tendency is best observed in the plots of solar radiation levels. The standard deviation increases at the lowest and highest levels of solar radiation.

The relationships between predictors and water temperature were fairly similar across aquatic subregions. There are a few relationships (e.g. latitude in the CP and solar radiation in the OP) where the response changes trajectory in the middle ranges of the predictor. In most cases, the relative influence on water temperature is fairly minimal (±0.5˚C). However the watershed area relationship in the CP shifts substantially from a warming trend as watershed size increases to a cooling trend at the largest watershed size. This goes counter to the general relationship of larger streams (with the corresponding larger watershed area) being warmer than smaller streams (Caissie 2006; Vannote et al. 1980). However, this apparent incongruency is likely because the CP site with the largest watershed is the only perennial stream with a moderate base flow that we sampled. All other CP sites were perennial, flashy streams with smaller watersheds and lower discharge levels (Table 22). The stability of flow for this single site could explain why the relationship changed from a warming trend to cooling.

The relationship of water temperature with discharge varied between the aquatic subregions (Figures 40 – 42). The relationship in the OP was consistent with expectations of higher discharges leading to cooler temperatures. However, in the CP there was a tendency to return to the mean water temperature at higher discharges which may be a confounding influence of the site with the largest watershed and highest flows being in a different flow class than the other CP sites. At the extreme low discharges water temperature also tended to return to the mean rather than continuing to increase. The unexpected downtick at the lowest flows could be due to an unmeasured influence. The subregion relationships remained similar across the late summer and stream flow classes so we did not repeat Figures 40 and 41 for the other scenarios.

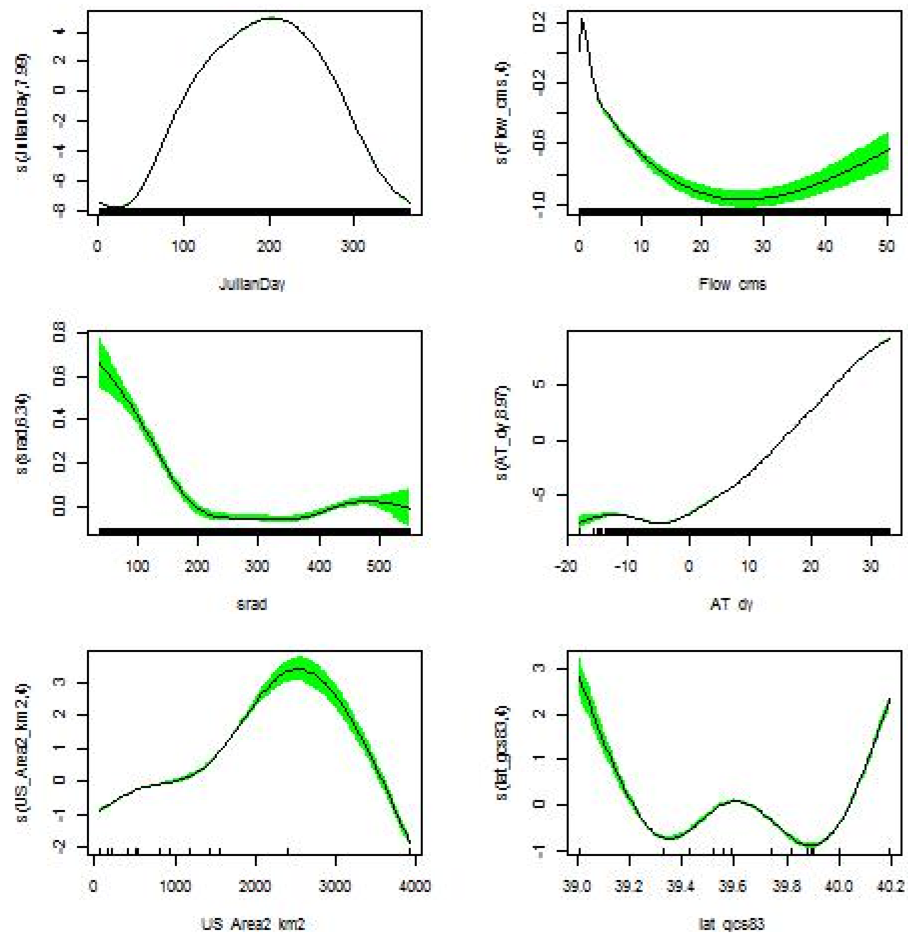


Figure 40. Plots of the relative change from mean water temperature in the ***CP streams*** *for each of the predictor metrics including a rug plot of data records. Upstream spring influence is not included here due to this not being an informative metric for this subregion. The y-axis for all metrics indicates the spline relationship of water temperature to each metric. This can be thought of as the change in water temperature relative to the corresponding level of each metric.*

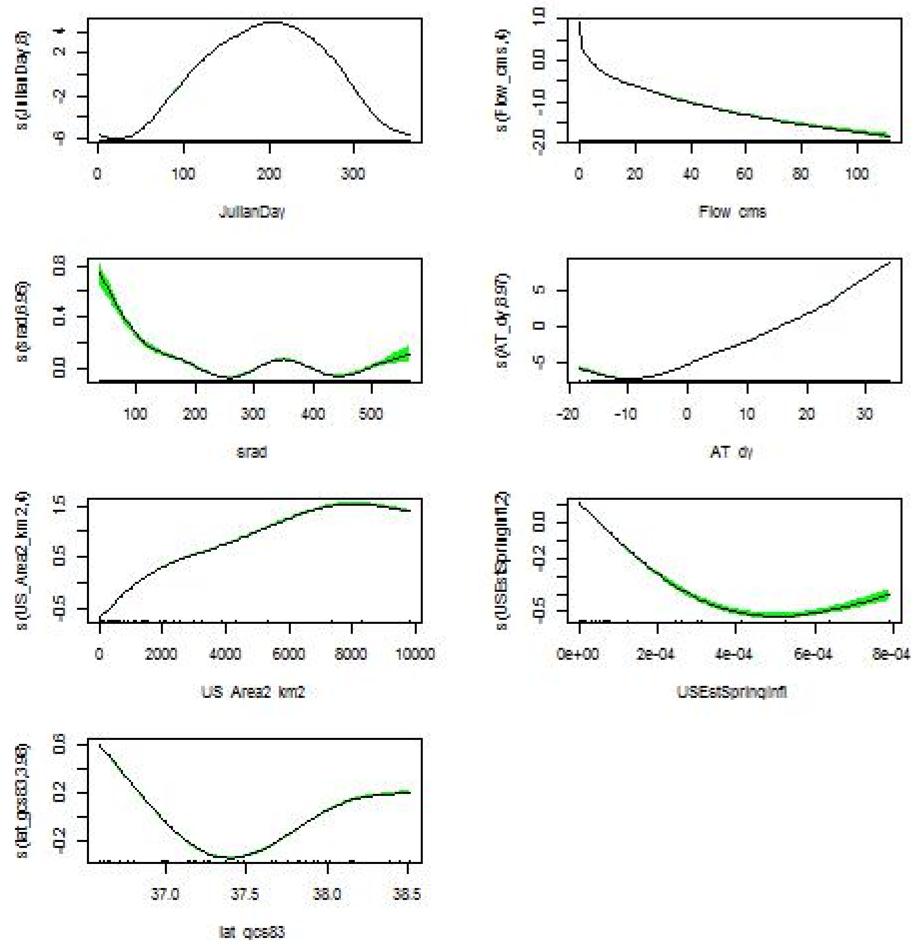


Figure 41. Plots of the relative change from mean water temperature in the ***OP streams*** *for each of the predictor metrics including a rug plot of data points. The y-axis for all metrics indicates the spline relationship. This can be thought of as the change in water temperature relative to the corresponding level of each metric.*

In the CP subregion, low discharge alone only contributed to a 0.2°C increase in water temperature over the mean (Figure 42). However, in the OP, low discharge accounted for a nearly 1°C rise over the mean water temperature. In the CP model, there was a downtick in water temperature at the lowest discharge levels despite a large number of measurements. We are not sure why this downturn occurred for the CP streams. The OP model followed an expected trend with water temperature and did not have a similar downtick.

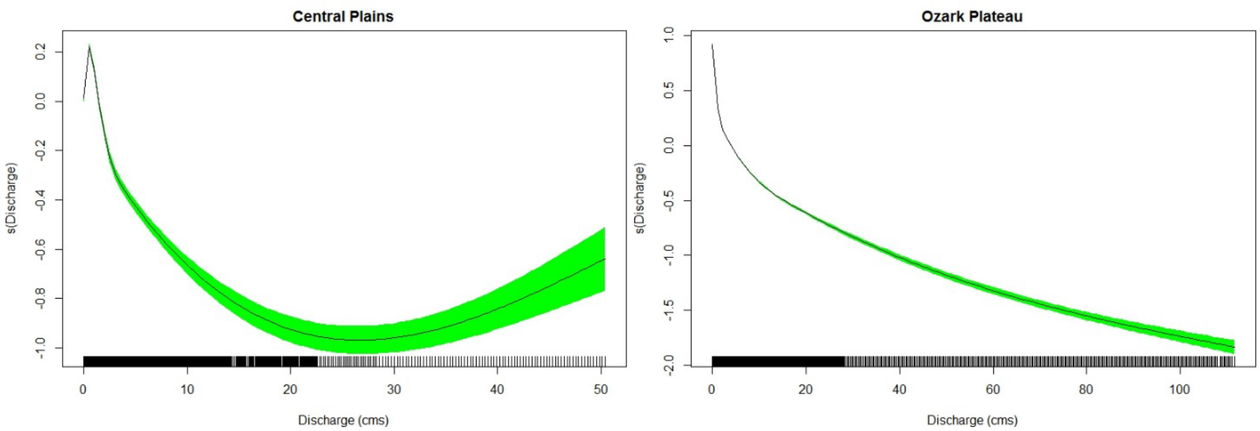


Figure 42. Relative change from mean water temperature (y-axis) across the range of discharge (cms) used in the water temperature – discharge models for the Central Plains and Ozark Plateau aquatic subregions. These are for discharge alone, without taking into account other climate and environmental modifiers of water temperature.

When discharge was combined with the other climate and physical habitat modifiers of stream temperature, the CP model predicted an expected increase in water temperature within riffle habitat at 1.1˚C at the lowest flow measurement (Figure 43). The OP model predicted a larger increase of 2.7˚C.

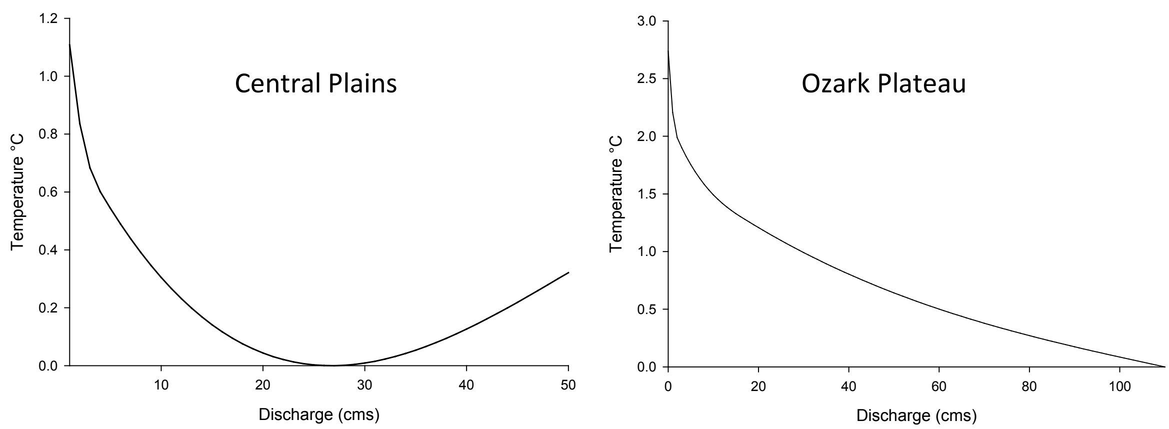


Figure 43. Predicted change in water temperature in riffle/run habitat relative to discharge rates based on an annual model that incorporated the other climate and physical modifiers of water temperature.

Late summer models

For this scenario, we developed models for each aquatic subregion using only the records for the months of July and August. Model strength did not change substantially when we used this narrower time period. The OP model improved slightly while the CP model weakened marginally (Table 27). For both subregions, the relative change of water temperature with discharge alone remained the same as in the annual model (top panel in Figure 44). We also observed the same downtick in water temperature at the lowest discharge rate in the CP. When the climate and physical modifiers were included, the CP model predicted an expected increase of 1.2 ˚C at the lowest discharge within riffle habitat while the OP model predicted a 2.7 ˚C increase (bottom panel in Figure 44).

Table 27. Model evaluation statistics for the July through August period within each aquatic subregion. GCV = generalized cross-validation.

Aquatic subregion	Adjusted r^2	GCV
Central Plains	0.95	3.43
Ozark Plateau	0.93	4.51

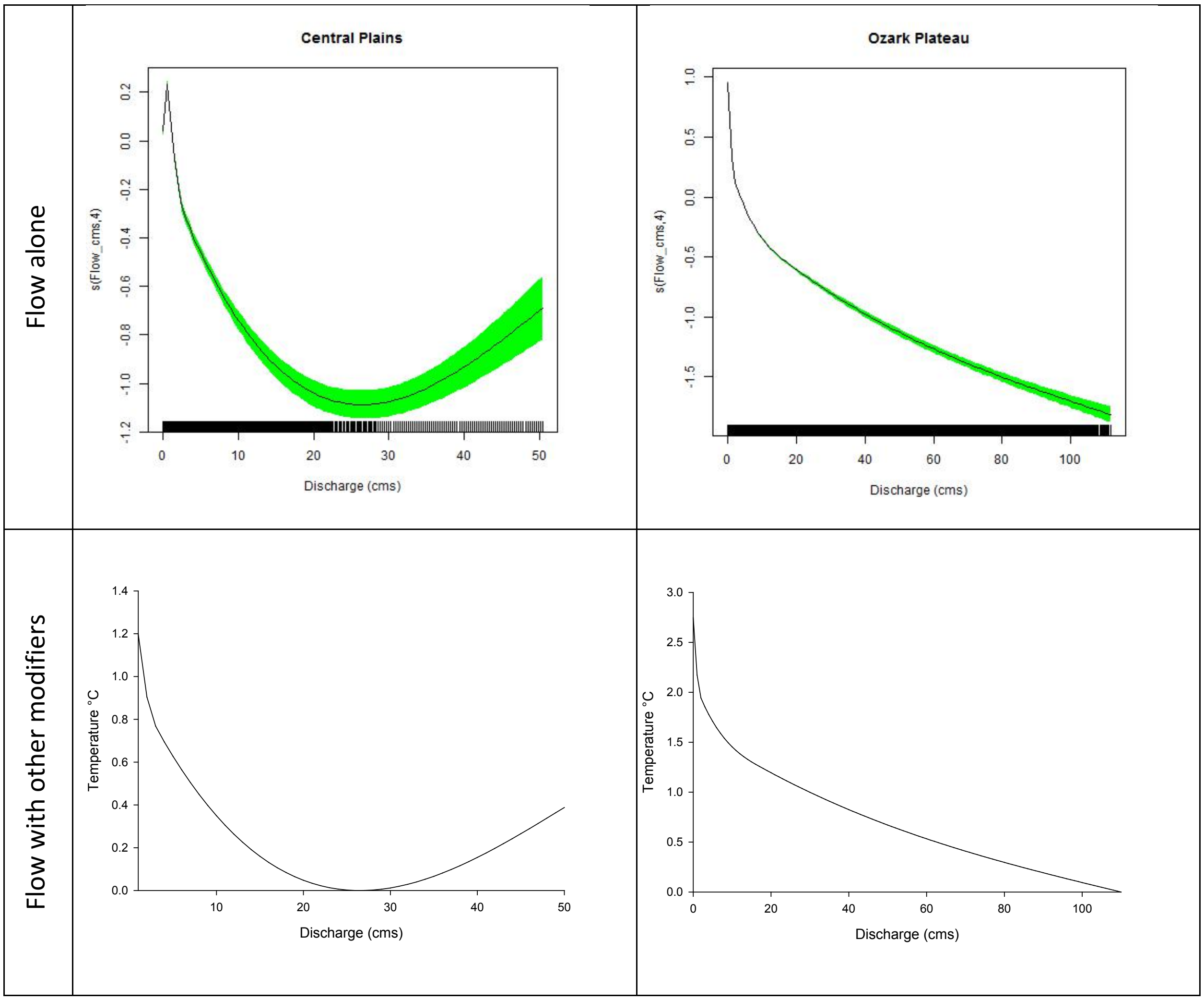


Figure 44. Relative change from mean water temperature (y-axis) across the range of discharge (cms) used in the water temperature – discharge models for July through August in the Central Plains and Ozark Plateau aquatic subregions. The top panels depict the relationship between discharge and water temperature without accounting for other modifiers. The bottom panels depict the predicted relationship with the other climate and environmental metrics influences.

Stream class models

For this scenario we developed models based on stream flow class for the annual period within the aquatic subregions. Only one stream class in the CP was represented by at least three sites while there were three classes that met this criteria in the OP. Breaking the subregion data into stream classes only improved model strength slightly in the CP which is not surprising because only one site fell into a different flow class (Table 28). Model strength improved for two of the OP flow class models while decreased for the perennial groundwater super stable class. Sample size alone does not appear to explain which class models improved over the annual model.

Table 28. Number of sampled sites by aquatic subregion and stream flow class with the corresponding model evaluation statistics. We developed models only for those categories with at least three sites. GCV = generalized cross-validation; AIC = Akaike information criterion.

			Model evaluation		
Aquatic Subregion	**Flow class**	**Count of Sites**	**Adjusted r^2**	**GCV**	**AIC**
Central Plains	Perennial runoff flashy	12	0.96	3.29	987540
	Perennial runoff moderate baseflow	1	----	----	----
Ozarks	Perennial groundwater stable	32	0.95	3.40	3417134
	Perennial groundwater super stable	7	0.86	4.90	145141
	Perennial runoff flashy	6	0.96	3.20	499272

The general relationship of discharge alone to water temperature remained similar to that observed in the annual model with the exception of the PRF class in the OP. As depicted in the upper right panel of Figure 45, the relationship for this flow class in the OP is sigmoidal. A possible explanation is the high level of variability between watershed size and water temperature for this particular model as shown in the inset figure. The relative change in water temperature was also similar to those observed in the annual model with the exception of the OP – PGSS where a nearly 4 ˚C increase above the mean temperature was documented at the lowest discharge levels (Figure 45).

With all modifying metrics incorporated, the models for the flow classes projected increases at lowest discharges of CP-PRF: 1.9 ˚C, OP – PGS: 2.0 ˚C, OP – PRF: 2.0 ˚C, and OP – PGSS: 8.7 ˚C. The OP-PGSS model projected the highest relative temperature change of all the scenario models we developed. We had anticipated that this flow class would change the least due to the stability of groundwater flow however the empirical data demonstrated a large increase in water temperature at low flows. It may be worth revisiting the PGSS classification of these sites and exploring this reason for this response in more detail.

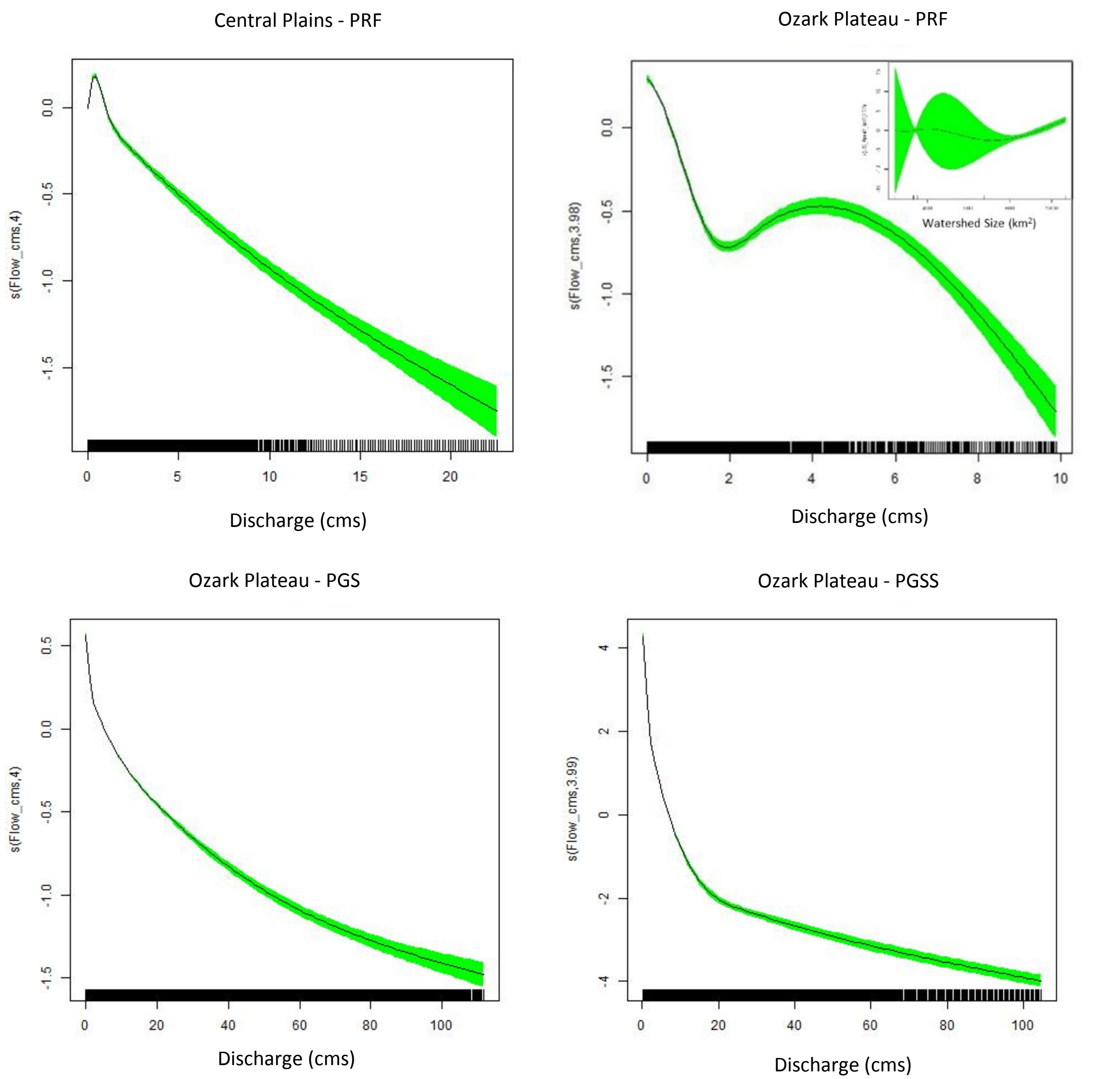
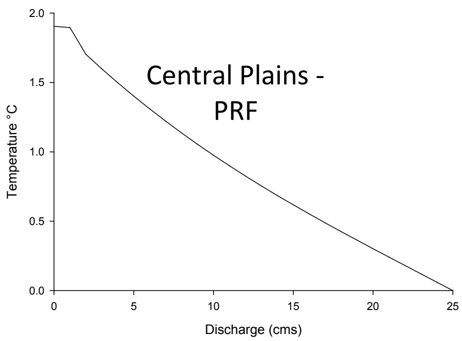


Figure 45. Relative change from mean water temperature (y-axis) across the range of discharge (cms) used in the water temperature – discharge models stream flow classes in the Central Plains and Ozark Plateau aquatic subregions. These are for discharge alone, without taking into account other climate and environmental modifiers of water temperature. The inset in the upper right panel depicts the relationship between watershed size and water temperature which may provide an explanation for the sigmoidal relationship observed between discharge and water temperature in the OP-PRF model. PRF = perennial runoff flashy, PGS = perennial groundwater stable, PGSS = perennial groundwater super stable.



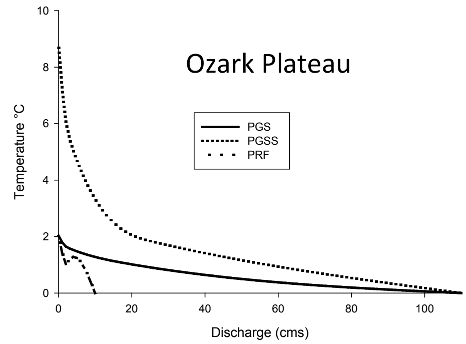


Figure 46. Predicted change in water temperature relative to discharge rates based on stream flow class models that incorporated the other climate and environmental modifiers of water temperature. PRF = perennial runoff flashy, PGS = perennial groundwater stable, PGSS = perennial groundwater super stable. Note: we did not extrapolate beyond the discharge levels used in developing each model therefore the plot for the OP PRF model does not extend beyond 10 cms and the CP PRF plot ends at 25 cms (see Figure 45).

Discussion

Our findings indicate that the relative response of water temperature varies across Missouri's aquatic subregions and stream flow classes with some slight seasonal differences. We provided a few scenario assessments to demonstrate how this approach could be used depending on the region, season, or stream class of interest. Additional scenarios such as stream size, a different regional grouping, or changes in climate could be assessed using the provided dataset with the caution to consider whether there are sufficient data available. Another possibility would be to examine the relationship between water temperature and discharge for individual streams that were sampled. This would potentially provide a better estimate for the individual stream however be less applicable to other streams.

These robust stream temperature - discharge models provide a scientific basis for land managers and decision makers to evaluate how management actions and other activities that modify stream discharge may lead to alterations in stream temperature and thus aquatic biota. The approach we used for this project provides a conservative estimate for change in water temperature if discharge levels were to increase or decrease. The estimates are conservative due to the coarse-scale nature of the data used in these models and that we are summarizing patterns across individual streams. A primary benefit of this approach is having the ability to make these estimates without needing the extensive habitat and water transport data (e.g., infiltration times, channel width and depth for the reach of interest, hypolimnetic flow rate), required for more standard approaches such as energy balance models.

The models we provided could be used to identify stream reaches where thermal conditions for sport fish or native species may become unsuitable or thermal barriers may develop that would fragment stream habitat and impair native fish restoration efforts. Once identified, these areas could be targeted for management options to ameliorate the projected changes or to focus collection of datasets that would be needed for energy balance models. As an outreach tool, these models could facilitate education of staff, legislators, landowners, and citizens about the positive and negative consequences of water uses on aquatic resources and the benefits they provide to Missourians.

Future directions

The stream temperature – flow relationships described through this modeling approach were based on a three to five year snapshot. A longer period of sampling would increase the breadth of natural variation experienced in these watersheds to improve the rigor of the models.

The results of the predicting change in water temperature in PGSS streams warrant further investigation because the relative change in temperature was four-times higher than that predicted for other stream classes which was counter to what we anticipated. Potentially a site or sites have been misclassified. Another possibility is that the relative change from the mean temperature is greater because at some measure of low discharge, the influence of cold groundwater is overcome by the influence of other factors such as air temperature. These streams tend to be colder in the summer than streams in other classes but if there is a tipping point at which discharge is so low that warming can occur more rapidly, then the deviation from mean temperature could be high.

Modifications from original proposal

After inspection of flow data from gage stations and recommendations from MDC, three of the sites originally proposed for establishing temperature gages were eliminated from the study due to strong anthropogenic influences.

Caveats to use

The model results presented in this section are intended to describe general relationships within aquatic subregions temporally (i.e., annual and late summer) and by stream classification. Specific models for Individual streams would better describe local relationships between discharge and stream temperature. Such models could be developed using the approach we have described if sufficient data records are available.

Products

Raw data and summary metrics were imported into a Microsoft Access database and linked to the spatially-referenced collection locations. A geodatabase with duplicate data also was created to facilitate use in a geographic information system (GIS). These databases will be distributed to MDC.

Description	File name	File format
Stream temperature data sets		
Stream temperature records obtained from sampled sites	Obj6_doc_stream_temper_data.csv	Text file
Stream temperature –discharge model for Missouri streams		
Empirical hourly water temperatures and discharge used in modeling	Obj6_WaterTemperatures	Text file
Predictor metrics associated with sampled sites	Obj6_Predictors	Text file
Predicted daily water temperatures	Obj6_PredictedWaterTemperatures	Text file
Spatial data		
Missouri stream layer	MO_streams	ESRI shapefile
Missouri catchment layer	MO_catchments	ESRI shapefile
USGS gage sites where stream temperature monitoring sites were established	Obj6_Gage_WaterTempSites	ESRI shapefile
R code		
R code for running temperature model	Obj6_WT_discharge_code	R file

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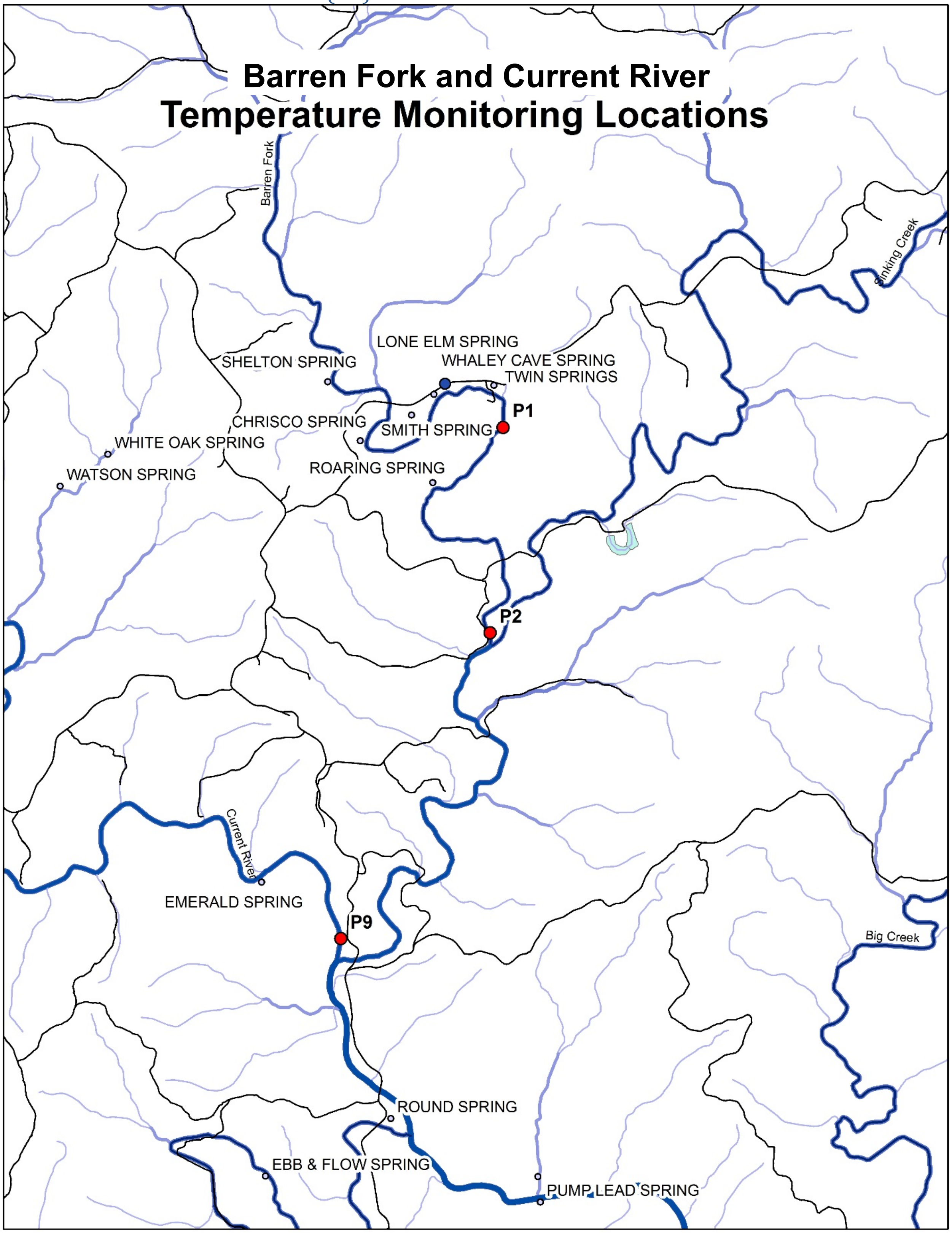
Appendix A: List of latitude and longitude of monitoring sites in the Ozark Plateau. In addition, maps depicting location and site ID for Ozark Plateau sampling sites. P_Num is the unique site identifier within a stream that was assigned by Missouri Department of Conservation.

Site number	River	P_Num	Latitude	Longitude
1	BARREN FORK	P1	37.36955	-91.3879
2	BARREN FORK	P2	37.34366	-91.3905
3	BENNETT SPRING BRANCH	P1	37.71704	-92.8576
4	BENNETT SPRING BRANCH	P2	37.73102	-92.8572
5	BLUE SPRING CREEK	P1	38.12446	-91.201
6	BLUE SPRING CREEK	P1A	38.1163	-91.185
7	BLUE SPRING CREEK	P2	38.11634	-91.1667
8	CAPPS CREEK	P1	36.86839	-94.0107
9	CAPPS CREEK	P2	36.8901	-94.0365
10	CAPPS CREEK	P3	36.8971	-94.0609
11	CAPPS CREEK	P4	36.89882	-94.0689
12	CAPPS CREEK	P5	36.89723	-94.0718
13	CAPPS CREEK	P5A	36.88723	-94.0831
14	CAPPS CREEK	P6	36.88633	-94.0894
15	CRANE CREEK	P1	36.93464	-93.601
16	CRANE CREEK	P2	36.92415	-93.5882
17	CRANE CREEK	P3	36.90445	-93.5766
18	CRANE CREEK	P4	36.89338	-93.5146
19	CRANE CREEK	P5	36.89556	-93.4808
20	CRANE CREEK	P6	36.89043	-93.5553
21	CRANE CREEK	P7	36.88856	-93.5516
22	CURRENT RIVER	P1	37.46034	-91.6842
23	CURRENT RIVER	P2	37.46049	-91.6833
24	CURRENT RIVER	P2A	37.44994	-91.6834
25	CURRENT RIVER	P2B	37.44955	-91.6869
26	CURRENT RIVER	P2C	37.4506	-91.6818
27	CURRENT RIVER	P3	37.45326	-91.6794
28	CURRENT RIVER	P4	37.45002	-91.6602
29	CURRENT RIVER	P4A	37.42177	-91.6093
30	CURRENT RIVER	P4B	37.42632	-91.6506
31	CURRENT RIVER	P5	37.37382	-91.5553
32	CURRENT RIVER	P6	37.39447	-91.5744
33	CURRENT RIVER	P7	37.37381	-91.5555
34	CURRENT RIVER	P8	37.42762	-91.6502

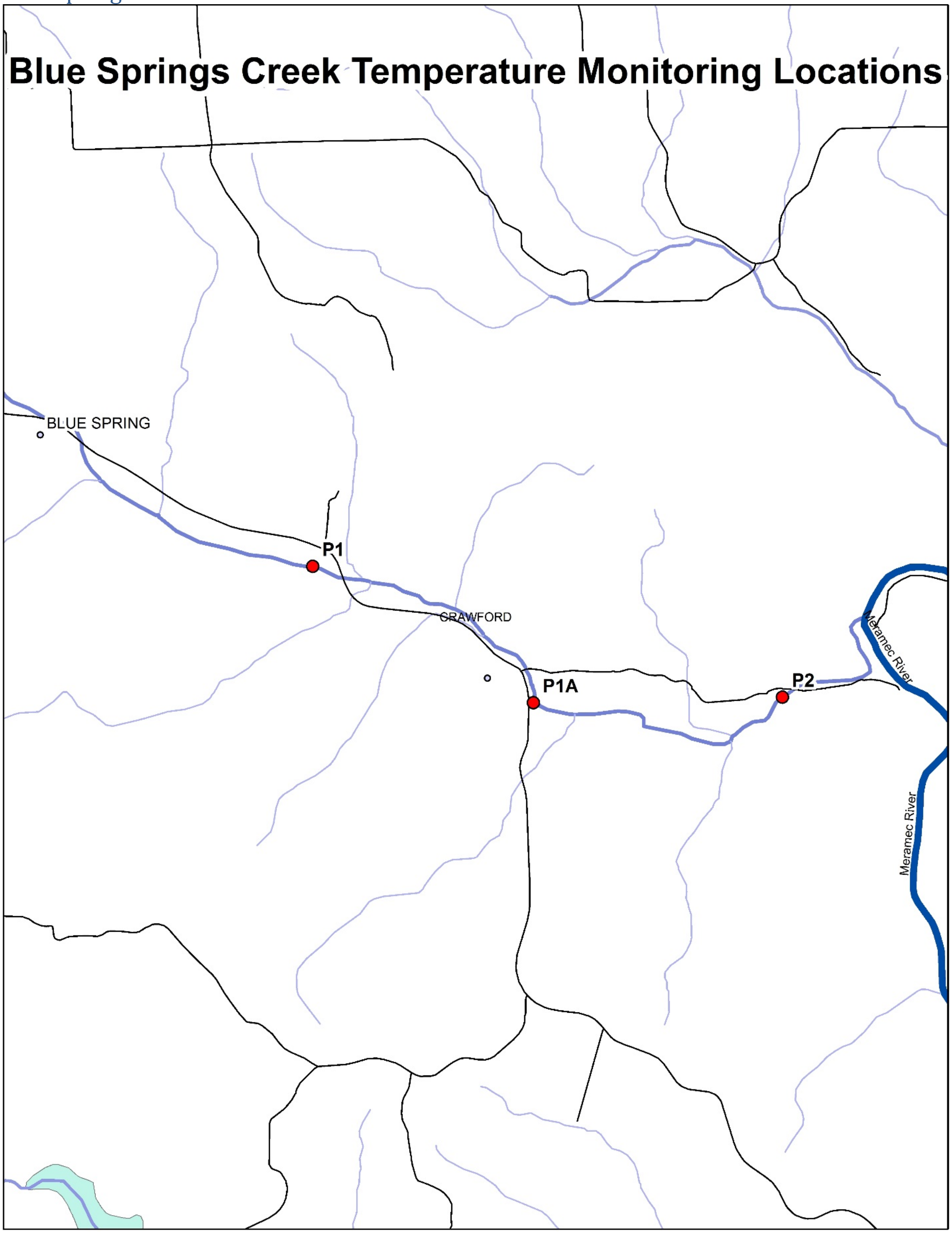
Site number	River	P_Num	Latitude	Longitude
35	CURRENT RIVER	P9	37.30539	-91.4149
36	DEWITT-WILKINS SPRING	P1	37.83582	-91.9374
37	DEWITT-WILKINS SPRING	P2	37.83724	-91.9383
38	DEWITT-WILKINS SPRING	P3	37.83941	-91.938
39	ELEVEN POINT RIVER	P1	36.79716	-91.338
40	ELEVEN POINT RIVER	P2	36.79026	-91.3263
41	ELEVEN POINT RIVER	P3	36.7606	-91.2586
42	ELEVEN POINT RIVER	P4	36.7243	-91.2107
43	ELEVEN POINT RIVER	P5	36.64421	-91.2011
44	ELEVEN POINT RIVER	P6	36.5688	-91.1782
45	ELEVEN POINT RIVER	P7	36.54937	-91.1913
46	GREER SPRING BRANCH	P1	36.77486	-91.3603
47	GREER SPRING BRANCH	P2	36.79233	-91.3444
48	HICKORY CREEK	P1	36.85709	-94.3353
49	HICKORY CREEK	P1A	36.86565	-94.3541
50	HICKORY CREEK	P3	36.87406	-94.3642
51	HICKORY CREEK	P4	36.88401	-94.3705
52	LITTLE PINEY CREEK	P1	37.91237	-91.9319
53	LITTLE PINEY CREEK	P2	37.89579	-91.8536
54	LITTLE PINEY CREEK	P3	37.86488	-91.8704
55	LITTLE PINEY CREEK	P4	37.8042	-91.8425
56	LITTLE PINEY CREEK	P5	37.78982	-91.828
57	MARAMEC SPRING BRANCH	P1	37.9535	-91.5327
58	MARAMEC SPRING BRANCH	P2	37.95927	-91.5324
59	MERAMEC RIVER	P1	37.95658	-91.5248
60	MERAMEC RIVER	P2	37.96458	-91.5243
61	MERAMEC RIVER	P3	37.96709	-91.524
62	MERAMEC RIVER	P3AA	37.96676	-91.4973
63	MERAMEC RIVER	P3AAA	37.96676	-91.4973
64	MERAMEC RIVER	P4	37.97656	-91.4583
65	MERAMEC RIVER	P5	37.98902	-91.4249
66	MILL CREEK	P1	37.83465	-91.9394
67	MILL CREEK	P10	37.85211	-91.9437
68	MILL CREEK	P1A	37.83941	-91.9386
69	MILL CREEK	P2	37.87431	-91.9279
70	MILL CREEK	P2A	37.8743	-91.9279
71	MILL CREEK	P3	37.86879	-91.932
72	MILL CREEK	P3A	37.88956	-91.9263
73	MILL CREEK	P4	37.90446	-91.9372
74	N FORK WHITE RIVER	P1	37.73212	-92.8645
75	N FORK WHITE RIVER	P2	37.74715	-92.8582

Site number	River	P_Num	Latitude	Longitude
76	N FORK WHITE RIVER	P3	37.76771	-92.8675
77	N FORK WHITE RIVER	P4	37.78987	-92.8629
78	N FORK WHITE RIVER	P5	37.79449	-92.8351
79	N FORK WHITE RIVER	P6	37.82172	-92.8568
80	N FORK WHITE RIVER	P7	36.72497	-92.1874
81	N FORK WHITE RIVER	P8	36.71508	-92.183
82	NIANGUA RIVER	P1	36.70743	-92.1822
83	NIANGUA RIVER	P2	36.70752	-92.183
84	NIANGUA RIVER	P3	36.65786	-92.2297
85	NIANGUA RIVER	P3A	36.64143	-92.23
86	NIANGUA RIVER	P4	36.64169	-92.2299
87	NIANGUA RIVER	P5	36.61544	-92.2607
88	ROARING RIVER	P1	36.58292	-93.8352
89	ROARING RIVER	P2	36.57267	-93.8054
90	ROARING RIVER	P3	36.55471	-93.7704
91	ROUBIDOUX CREEK	P1	37.82485	-92.2017
92	ROUBIDOUX CREEK	P2	37.83521	-92.2028
93	ROUBIDOUX CREEK	P4	37.83694	-92.1959
94	ROUBIDOUX CREEK	P5	37.8458	-92.2008
95	ROUBIDOUX CREEK	P6	37.85096	-92.2105
96	ROUBIDOUX SPRING BRANCH	P1	37.82531	-92.2017
97	SPRING CREEK PHELPS	P1	37.71304	-91.9773
98	SPRING CREEK PHELPS	P2	38.32793	-91.1547
99	SPRING CREEK PHELPS	P3	37.76557	-92.0199
100	SPRING CREEK PHELPS	P8	37.73765	-92.0193
101	SPRING CREEK PHELPS	P9	37.71405	-91.9805
102	SPRING CREEK-STONE	P1	36.97516	-93.5118
103	SPRING CREEK-STONE	P2	36.9015	-93.4902
104	SPRING CREEK-STONE	P2A	36.90409	-93.4909
105	SPRING CREEK-STONE	P3	36.93008	-93.4973
106	SPRING CREEK-STONE	P4	36.94703	-93.4968

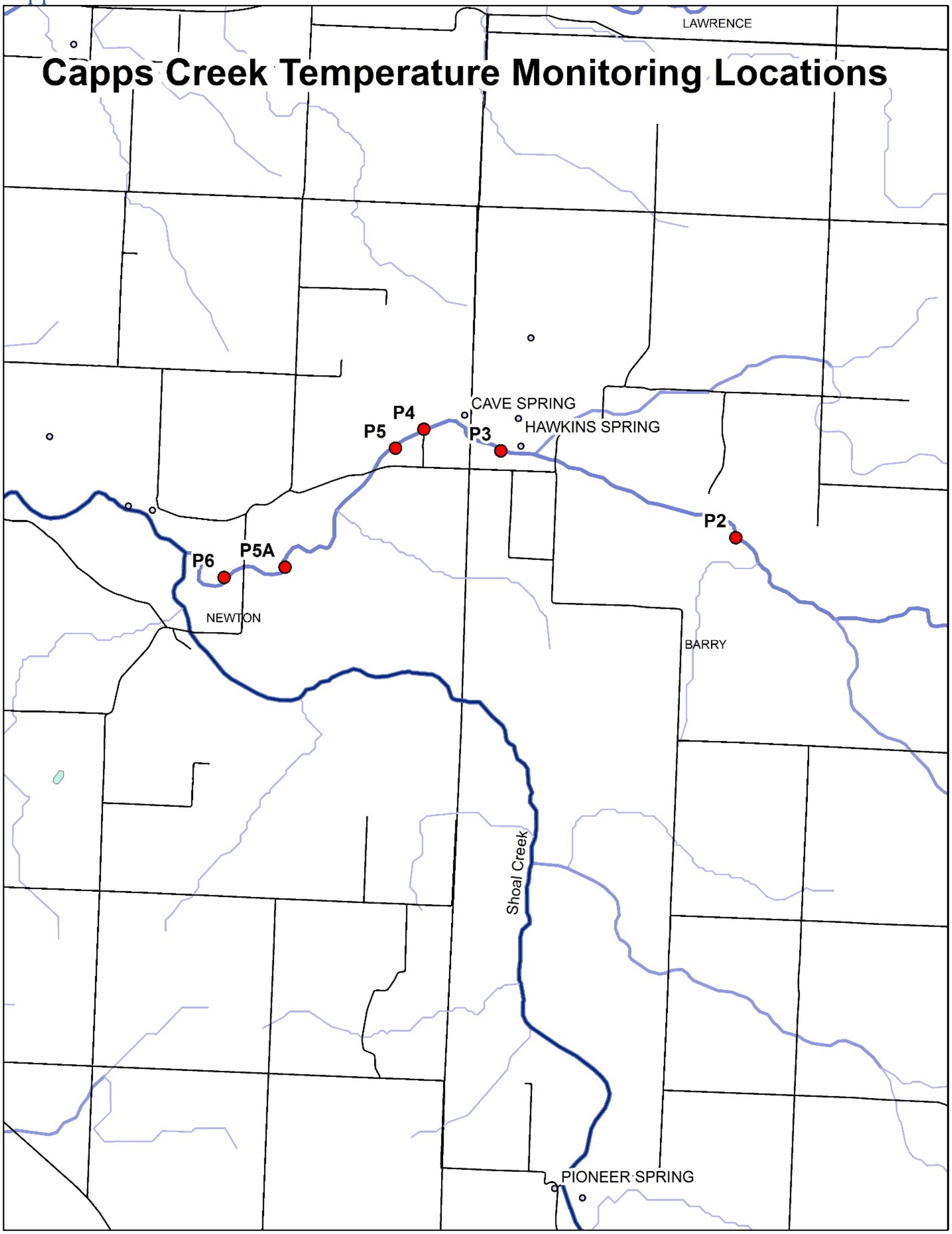
Barren Fork and Current River (P9)



Blue Spring Creek

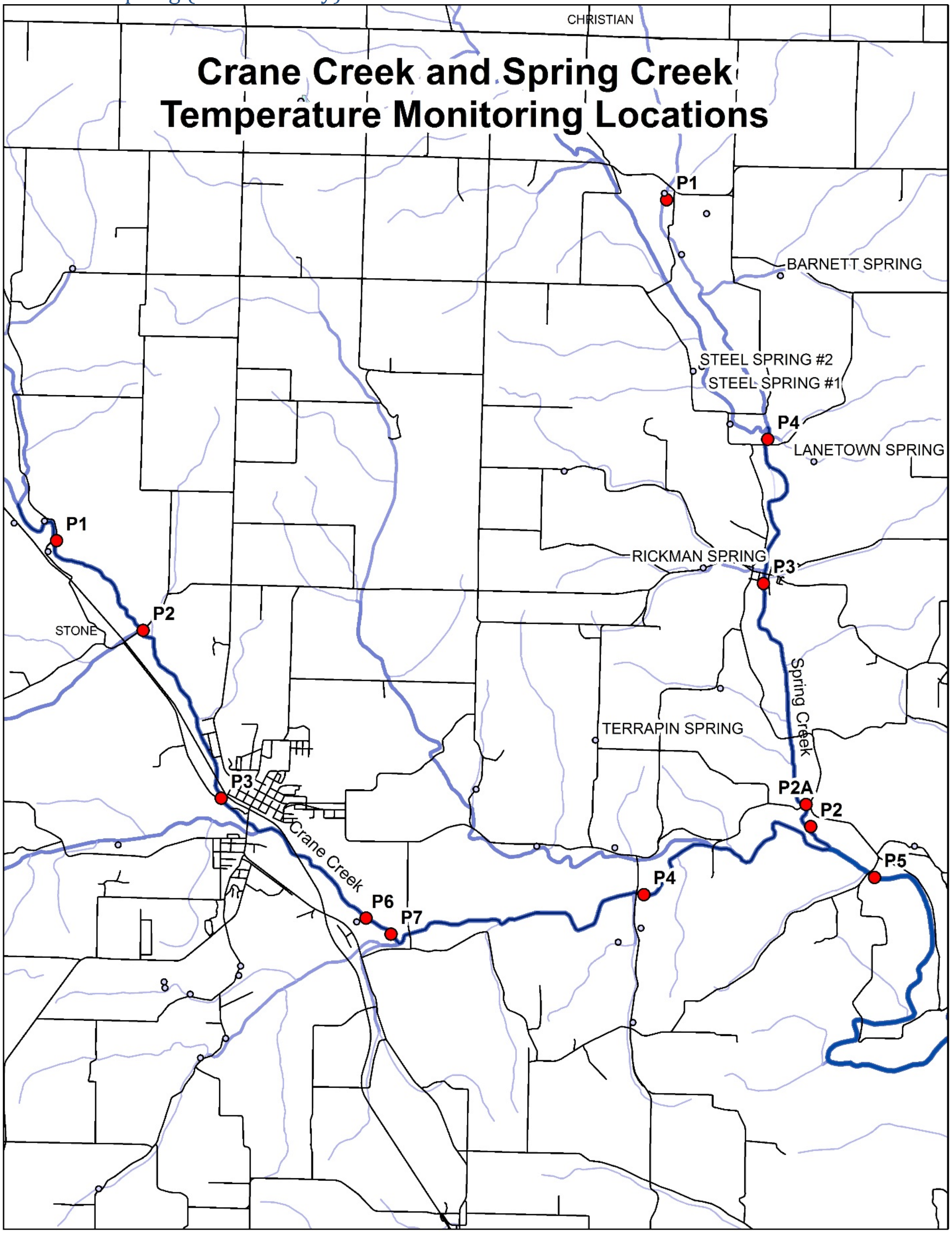


Capps Creek

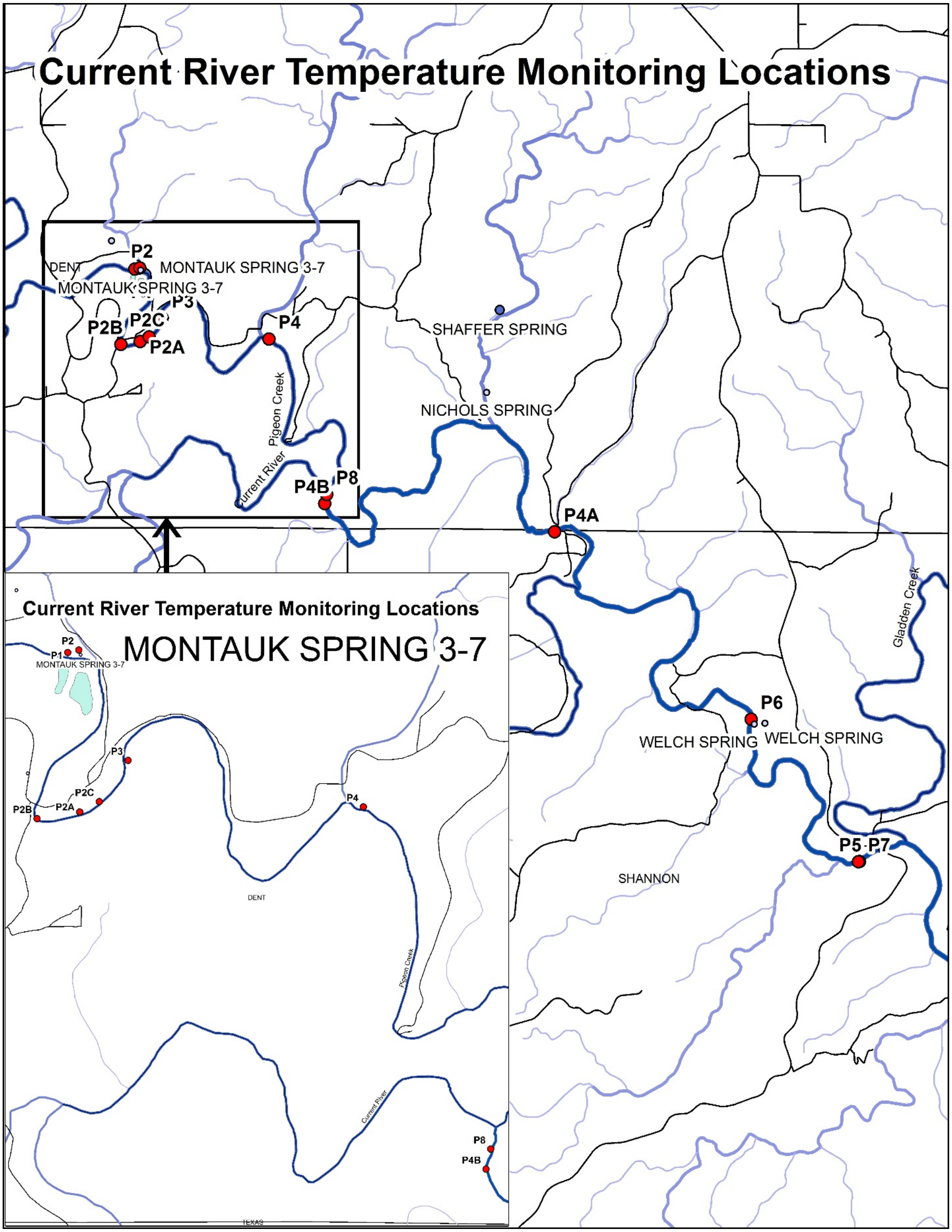


LAWRENCE
Capps Creek Temperature Monitoring Locations
CAVE SPRING
HAWKINS SPRING
P4
P5
P3
P2
P6
P5A
NEWTON
BARRY
Shoal Creek
PIONEER SPRING

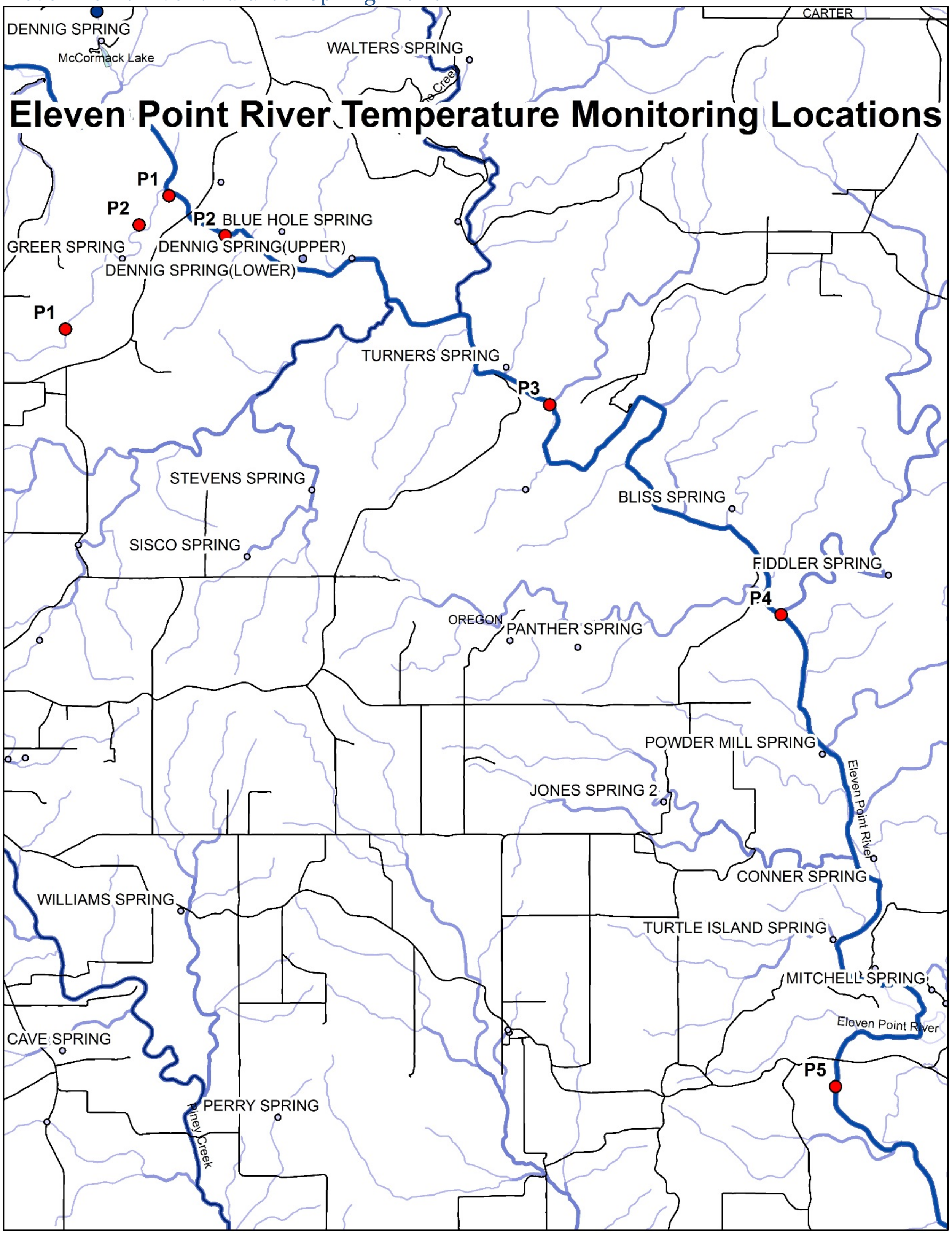
Crane and Spring (Stone County) creeks



Current River

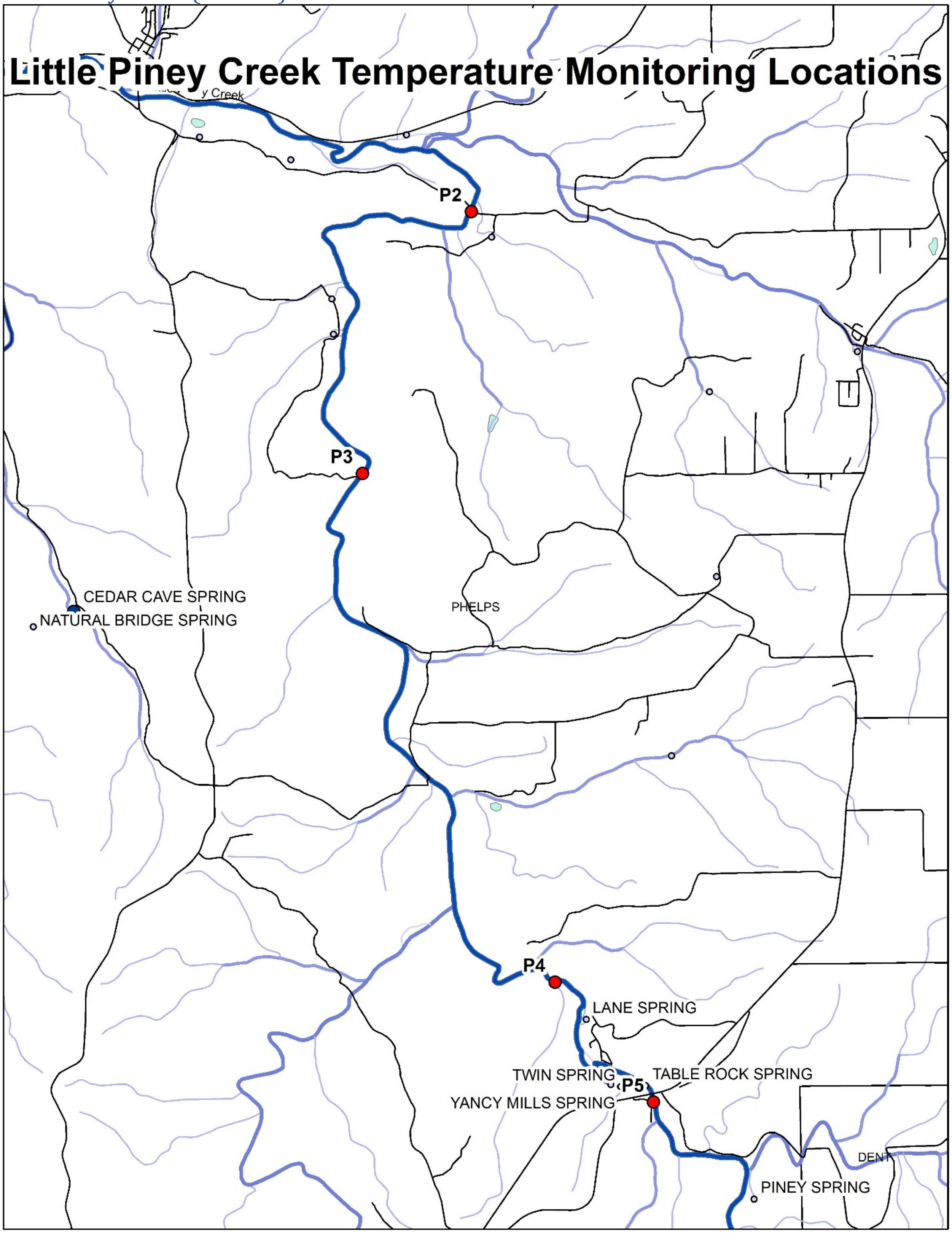


Eleven Point River and Greer Spring Branch

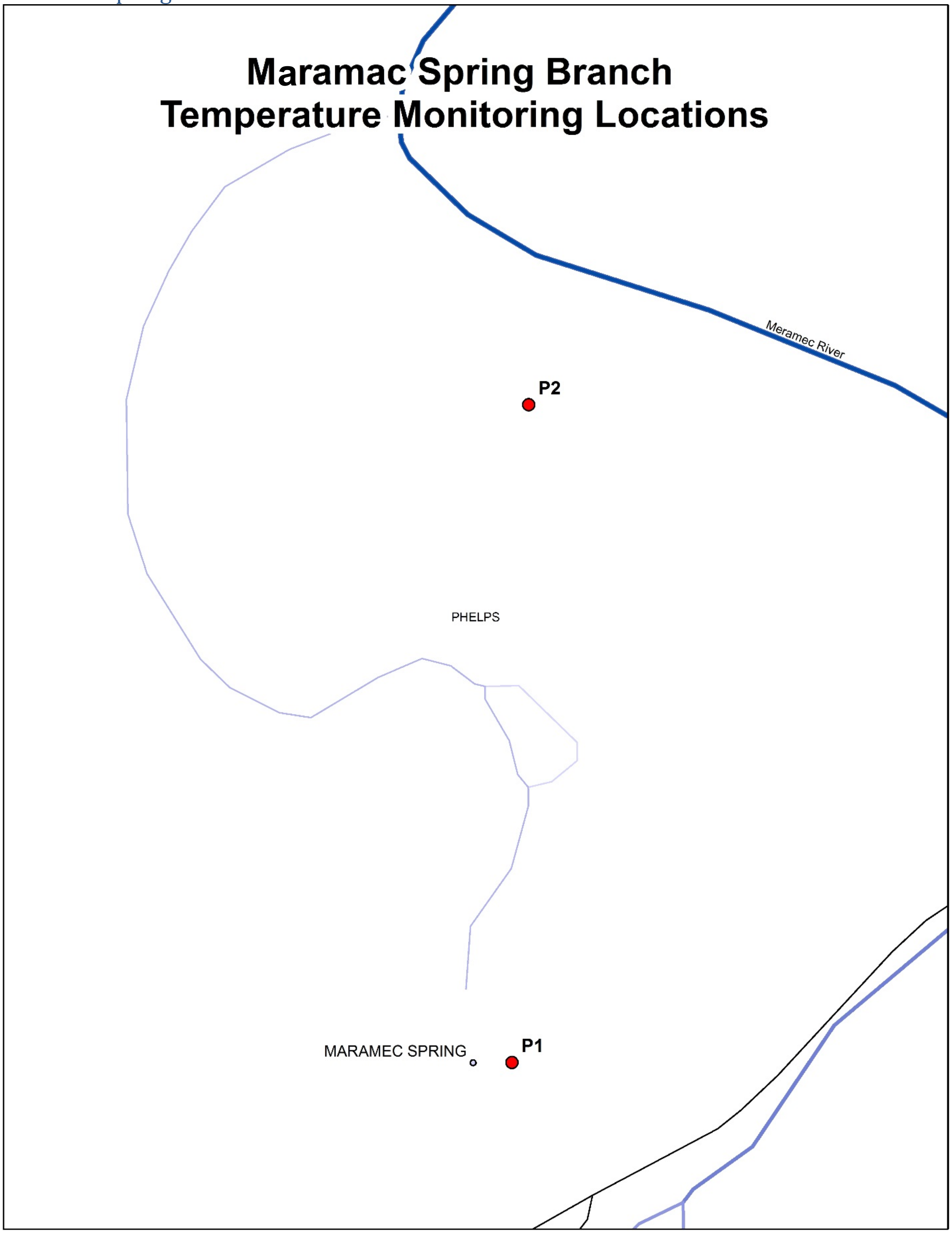


Hickory Creek

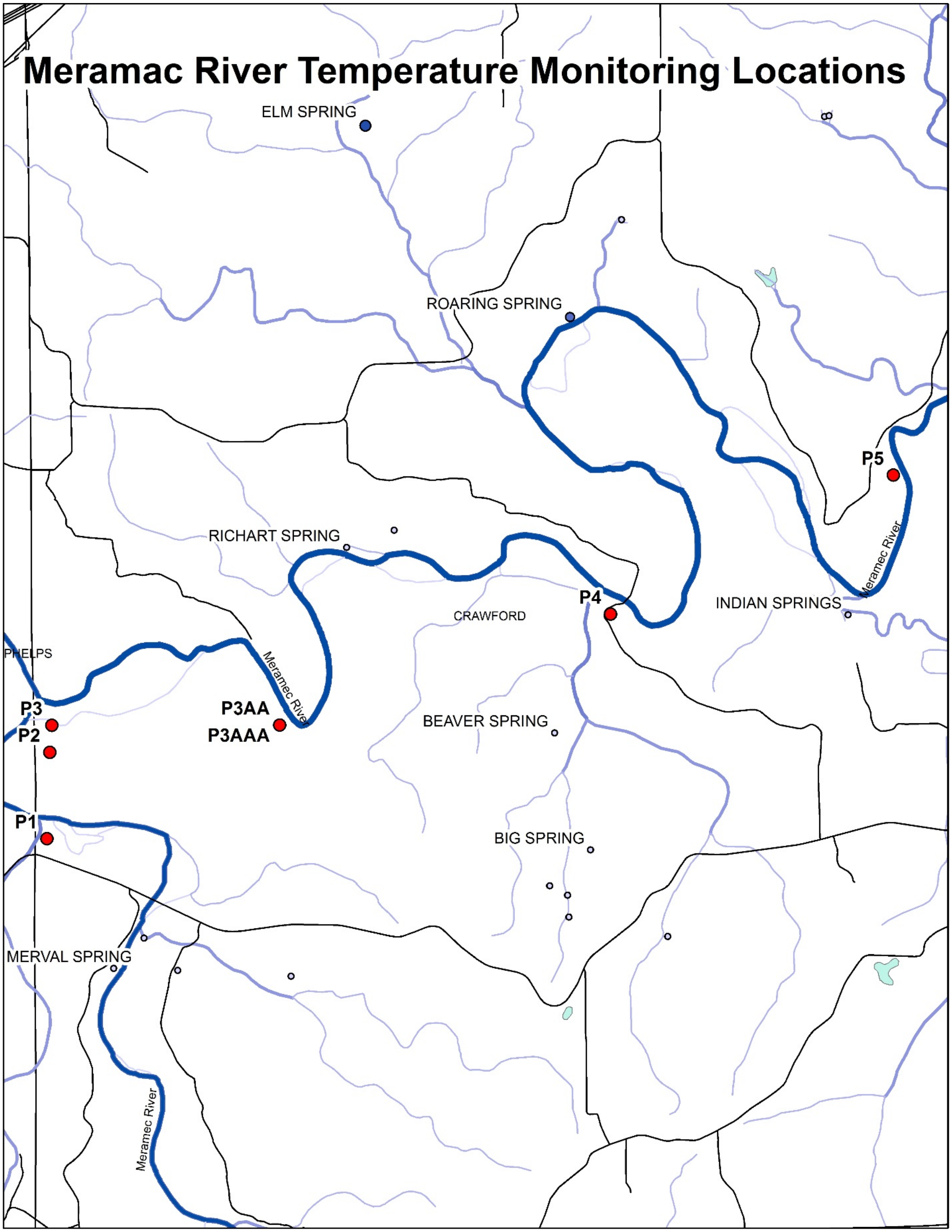
Little Piney Creek (P2 – P5)



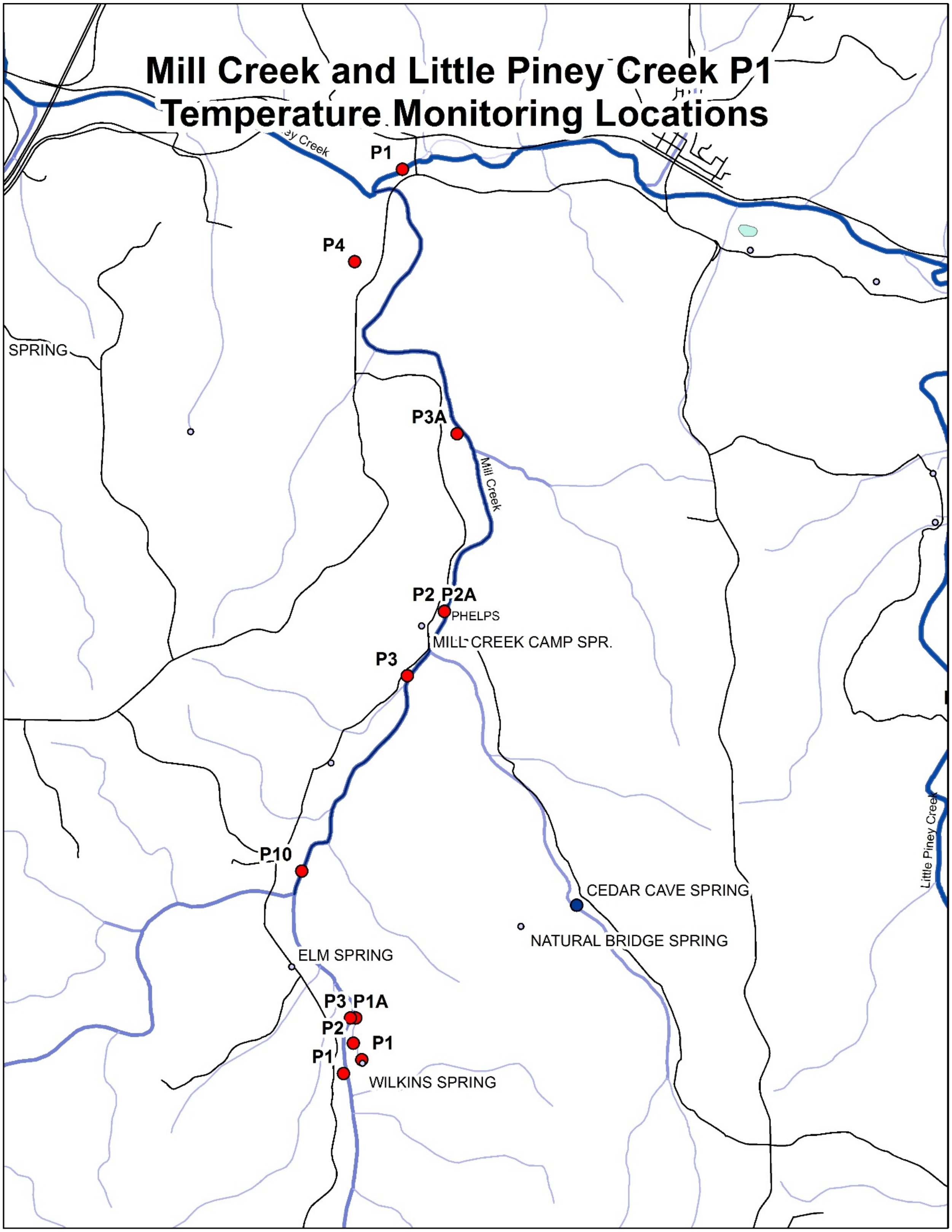
Maramec Spring Branch



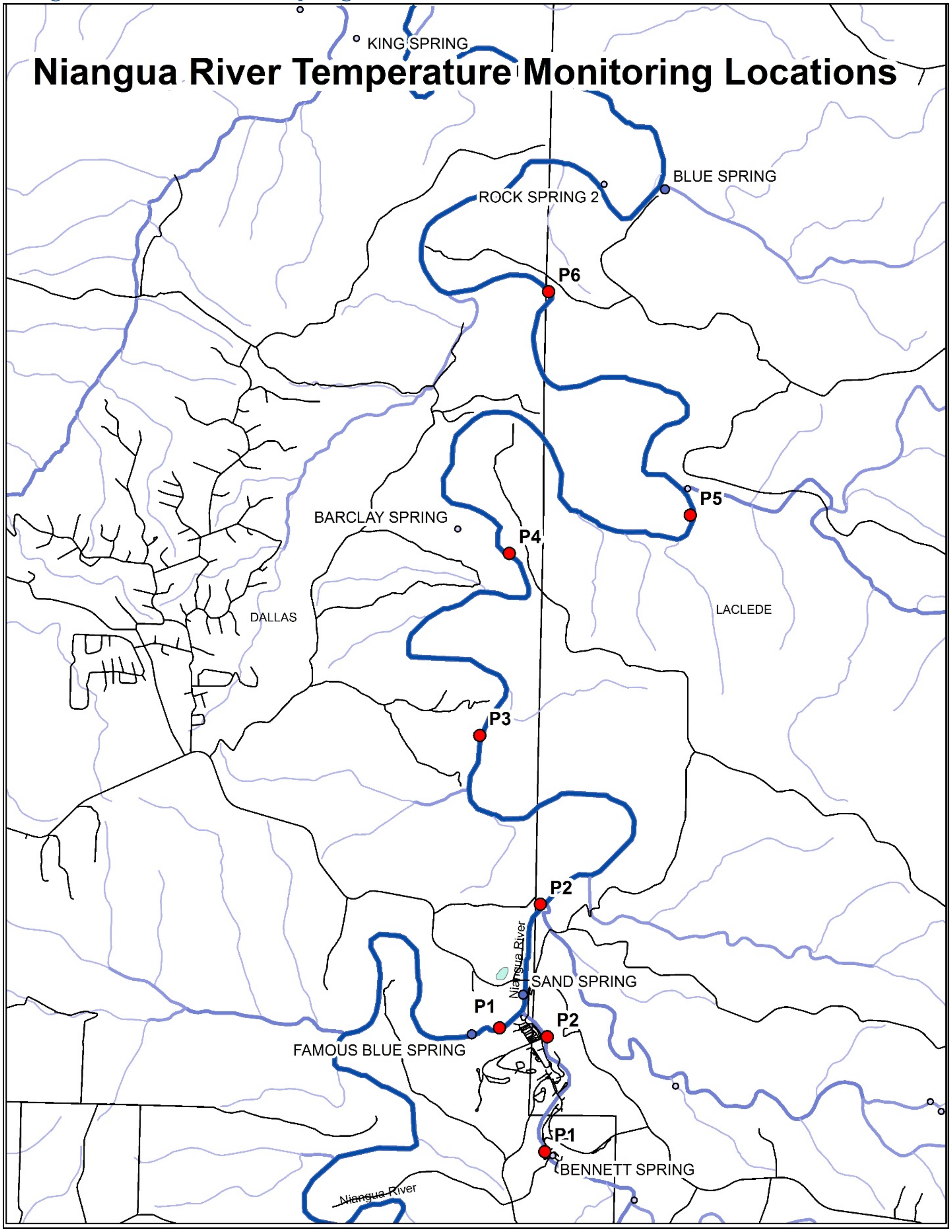
Meramec River



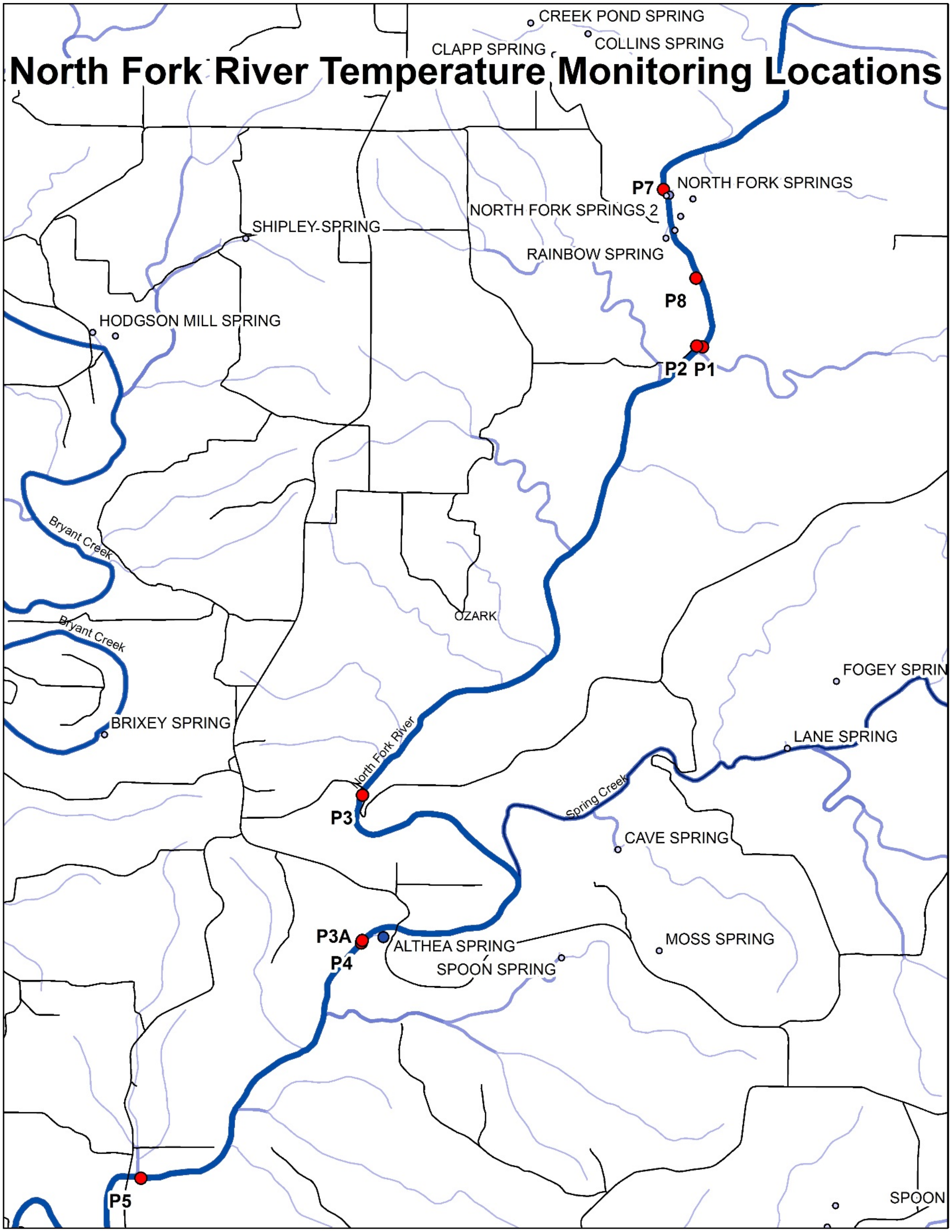
Mill and Little Piney (P1) creeks, and Dewitt-Wilkins Spring – *can't separate Mill and Dewitt sites*



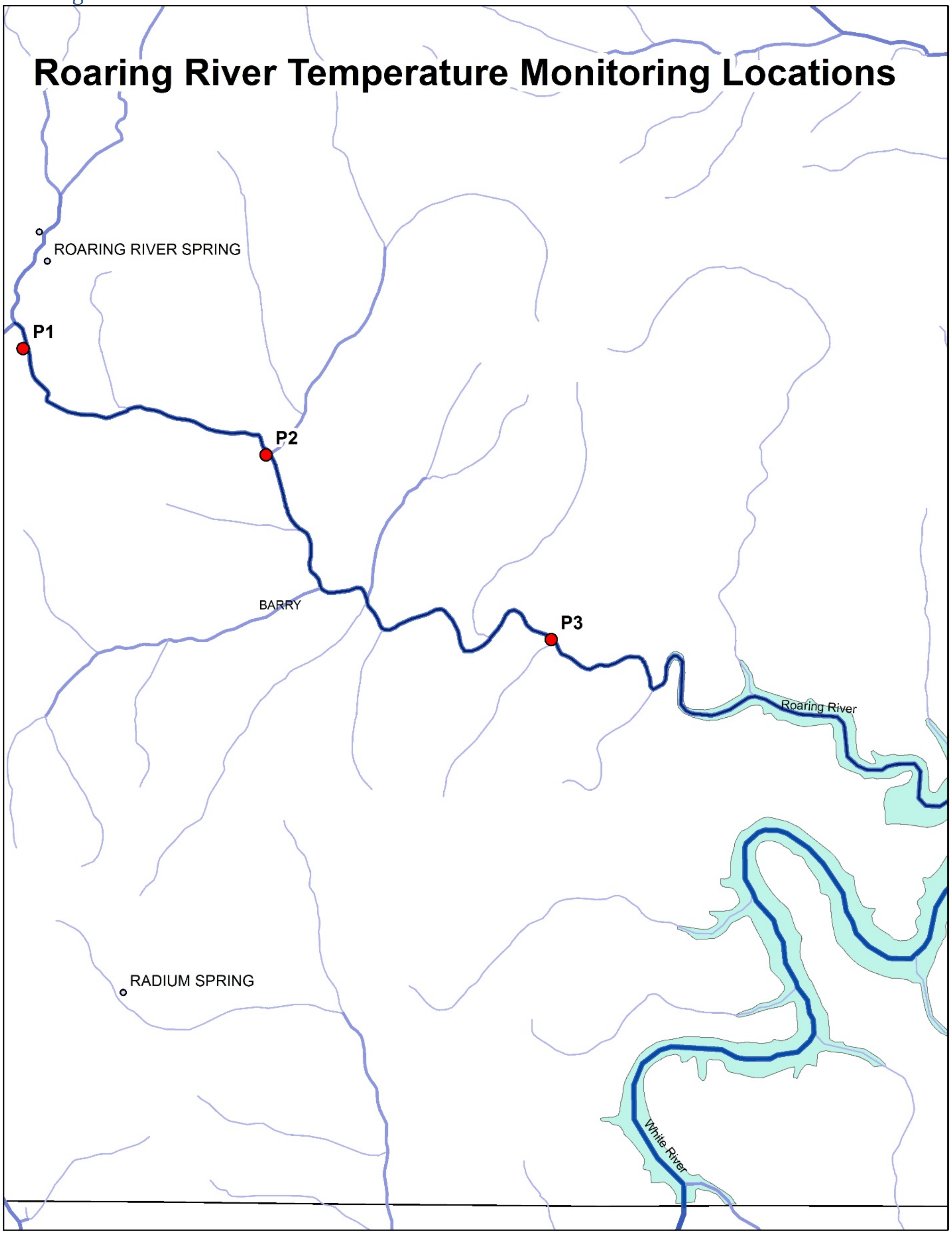
Niangua River and Bennett Spring Branch



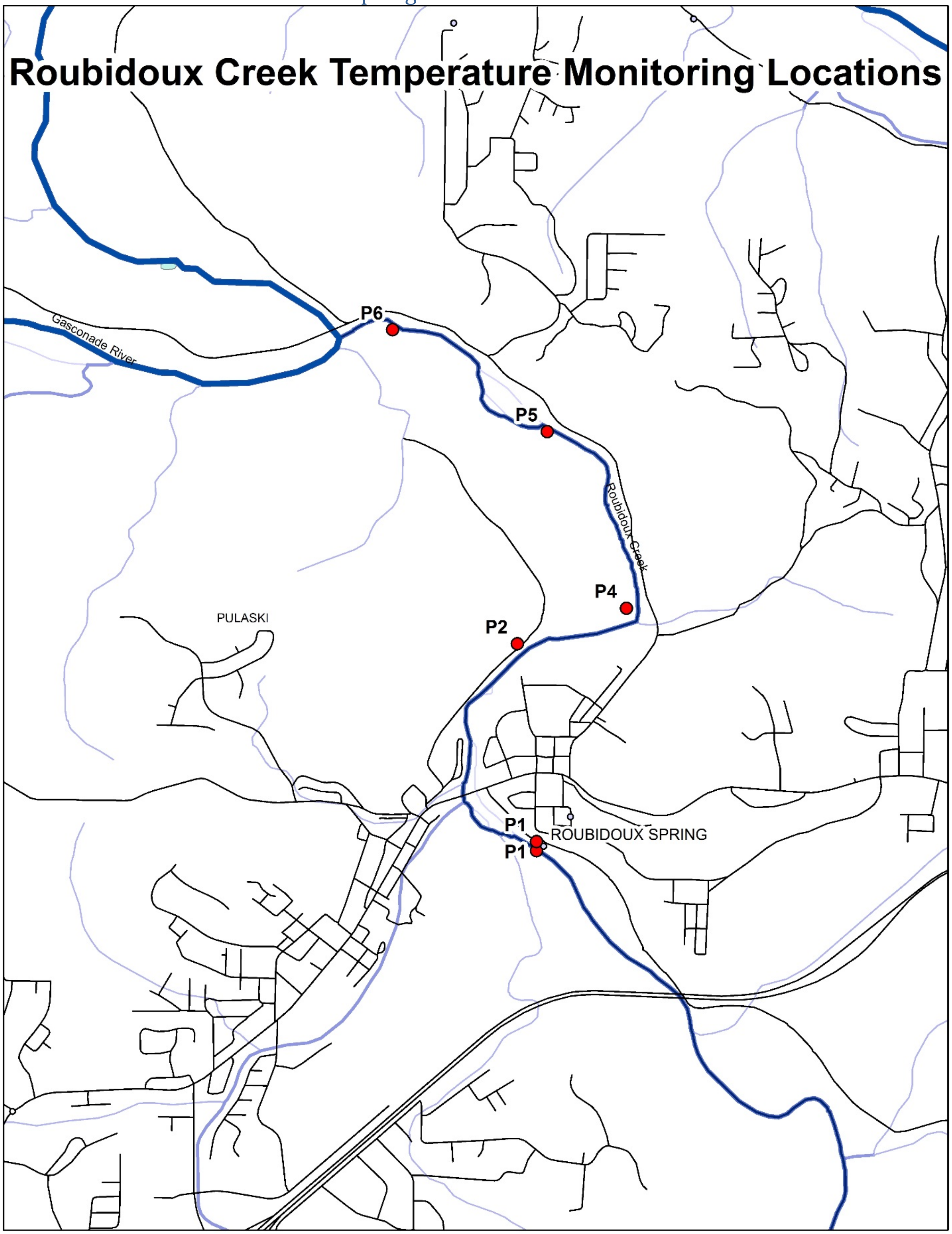
North Fork White River



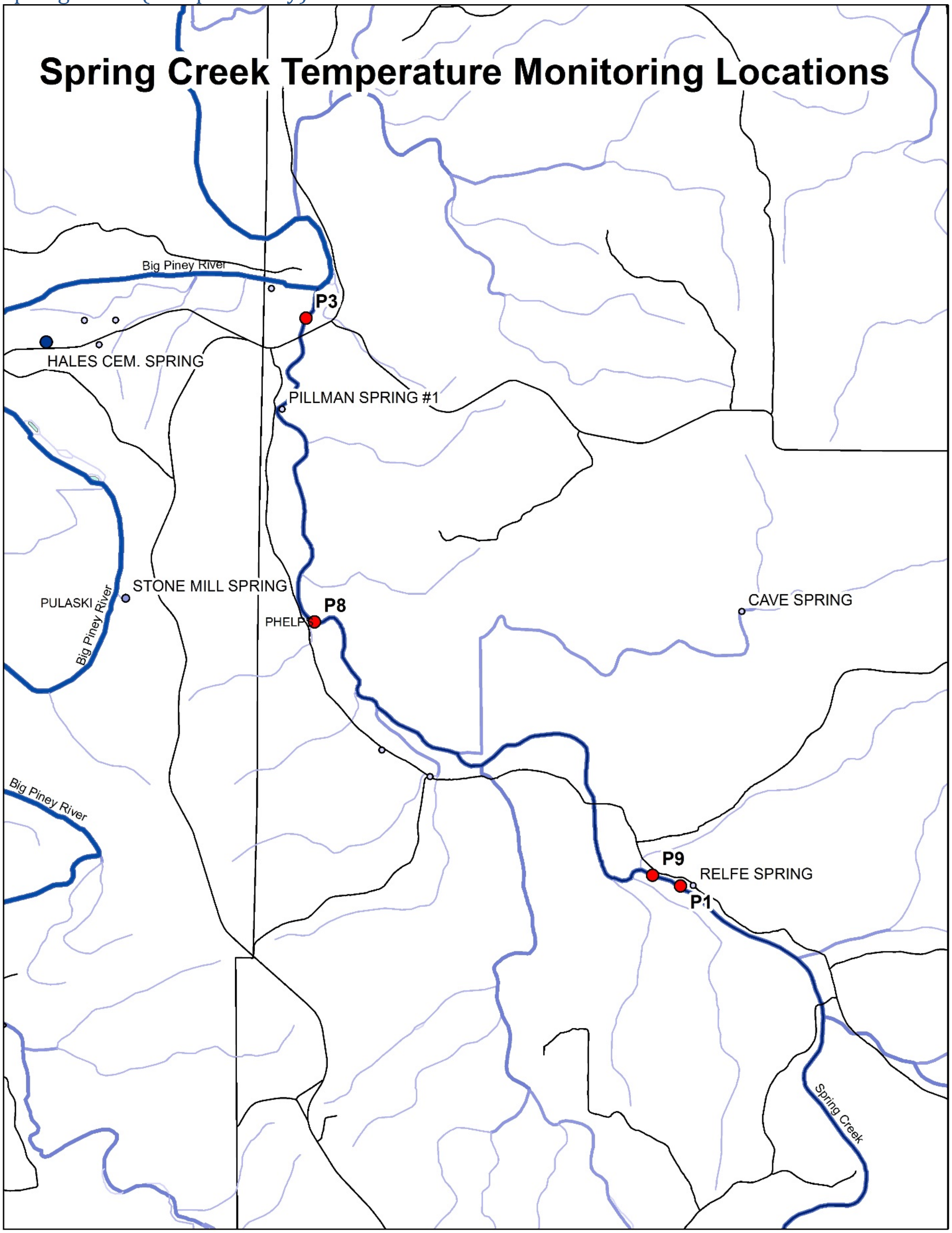
Roaring River



Roubidoux Creek and Roubidoux Spring Branch



Spring Creek (Phelps County)



Appendix B. This appendix contains information regarding quality assessment/quality control checks on the data collected from Ozark Plateau streams associated with trout fishery units in Missouri. Most of these issues were identified from plotting the data using violin plots, but other methods were described in the "Issue Identified" column. We included explanations of what we learned or believed caused the issue and stated the outcome of how we handled the data.

Site	Issue Identified	Explanation	Outcome
Bennett Spring Branch P1 – 2004	11˚C spike in temperature on 8/23 @ 5 pm.	Isolated temperature spikes were observed at this and other sampled sites in the Bennett Spring Branch. Elevated temperatures tended to persist for no more than 5 or 6 hours. Most of the time a spike at P1 coincided with a smaller spike at P2, which was downstream. Conversations with Bennett Spring Hatchery staff confirmed this was almost certainly from flood events.	Used
Bennett Spring Branch P1 – 2005	Spike of 5˚C on 8/15 at 4 am	Same as above	Used
Bennett Spring Branch P1 – 2007	Spike of 14˚C on 8/20 from 2 to 5 pm	Same as above	Used
Bennett Spring Branch P1 – 2008	Could not find raw data	Same as above	Used
Bennett Spring Branch P1 – 2011	Spike on 8/8 at 8 pm	Same as above	Used
Bennett Spring Branch P1 – 2013	Spike on 8/8 at 6 pm	Same as above	Used
Bennett Spring Branch P2 – 2007	Spike on 8/20 from 2 to 5 pm	Same as above	Used
‡Blue Spring Creek P3 2013	Incorrect coordinates	Was not able to determine location	Site removed from analysis; only one year of data for this location

Site	Issue Identified	Explanation	Outcome
Capps Creek P3 - 2003	The data distributions for 2002 and 2003 appeared much different and the mean temperatures differed by about 4.5˚C, which was a lot relative to other datasets. In the raw data the column for 2003 P3 was highlighted in red text (only column like that), which seems to indicate that someone must have seen something strange and flagged it without making notes in the original data.	Suspected case where logger was put in slightly different location in 2003 as opposed to 2002.	Used with caution
Crane Creek P3 – 2006	Mean and variation much different than other years. The normal daily fluctuation in raw data changed around 8/1 and went through 8/28. The graphed data from 2006 looked much different than graphs for other years.	The logger may have been in an unusual location within this site. Data did not appear comparable to the other years at P3.	Removed

Site	Issue Identified	Explanation	Outcome
Crane Creek P3 2011	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	Consulted with Shane Bush and learned that these data were from P7 2011.	We moved data from P3 2011 to P7 2011.
Crane Creek P6 2012	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	Shane Bush informed us he mistakenly placed the P6 data in the P7 spreadsheet.	We moved the data for Crane Creek P7 2012 to P6 2012. However, there is still a record for P7 2012 as the correct data for that site were also listed there.
Crane Creek P7 2014	Outliers present	There were some impossibly high temperatures from 11 am to 11 pm on 8/30	We removed the high records.
Current River P2a – 2002 and 2003	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	The logger may have been in an unusual location within this site during 2002 and 2003. Note: in 2002 it was a tidbit and in 2003 it was watertemp Pro. Conclusion was to remove the 2002 P2a records as these seemed too stable for where the logger actually was in the stream	Removed
Dewitt-Wilkins Spring P1 -2012	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	The raw data were labeled as Dewitt Pond Outfall, which may be P2, not P1. Lack of data for P2 after 2008 would have left a large gap in temporal records. For purpose of analysis, did not use.	Removed

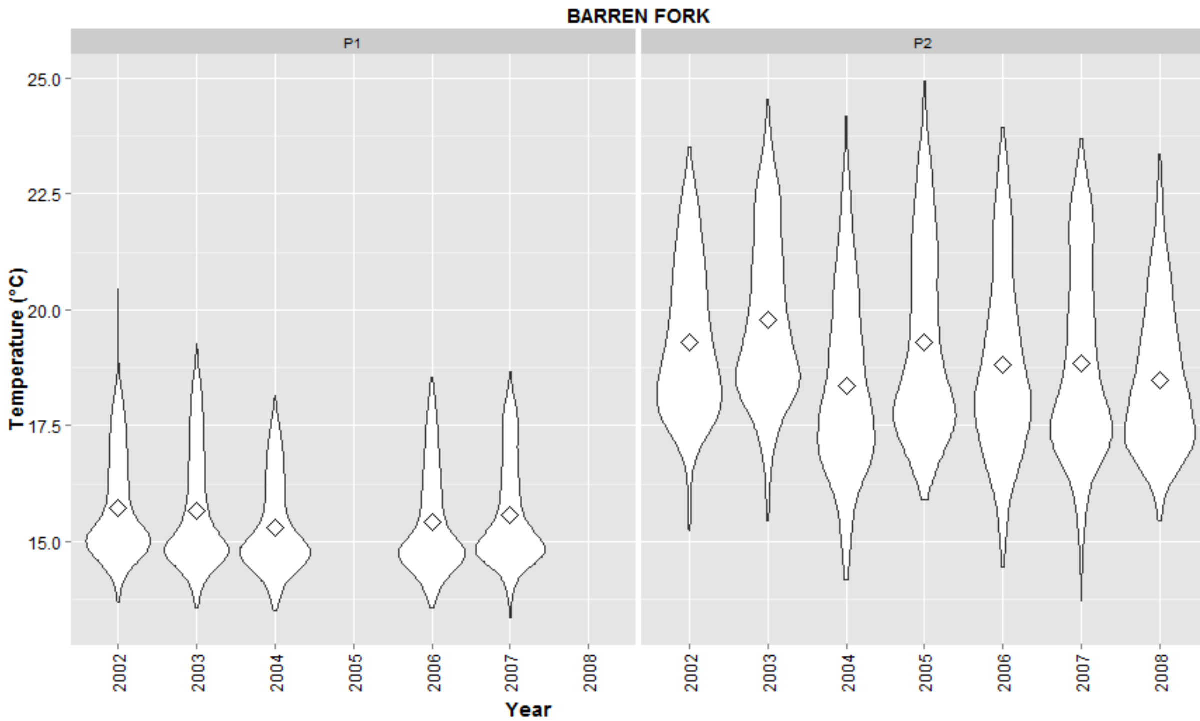
Site	Issue Identified	Explanation	Outcome
Dewitt-Wilkins Spring P2 -2008	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	Patterns in mean and distribution made it seem unlikely that 2007 and 2008 data were recorded from the same location. However, this was at the outflow of a pond so maybe the variation was real.	Used with caution
‡DeWitt Wilkins Spring P2A - 2005	Incorrect coordinates	Was not able to determine location	Site removed from analysis; only one year of data for this location
Geer Spring P1 2007	Outlier on 9/4/2007 in the early afternoon.	Although higher than any other reading over the years at this location, it did not seem to be a mistake. Left as is.	Used
‡Hickory Creek P2 – 2003	Incorrect coordinates	Was not able to determine location	Site removed from analysis; only one year of data for this location
Little Piney P2 - 2012	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	Notes about exact location in 2012 data said "first tree below spring on right bank in roots" while the 2011 notes said "off of big gravel bar below spring branch". Exact location appeared to differ between years with the 2012 location directly below the spring confluence and the 2011 location situated a little bit more downstream or on the other side of the river.	Used with caution
North Fork White River P4 2007 and 2009	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	The coordinates for the loggers matched up, but are also very close to the P3 coordinates. These data may have been collected from P3 or another location that was not P4. GPS coordinates may have been copied and pasted.	Removed

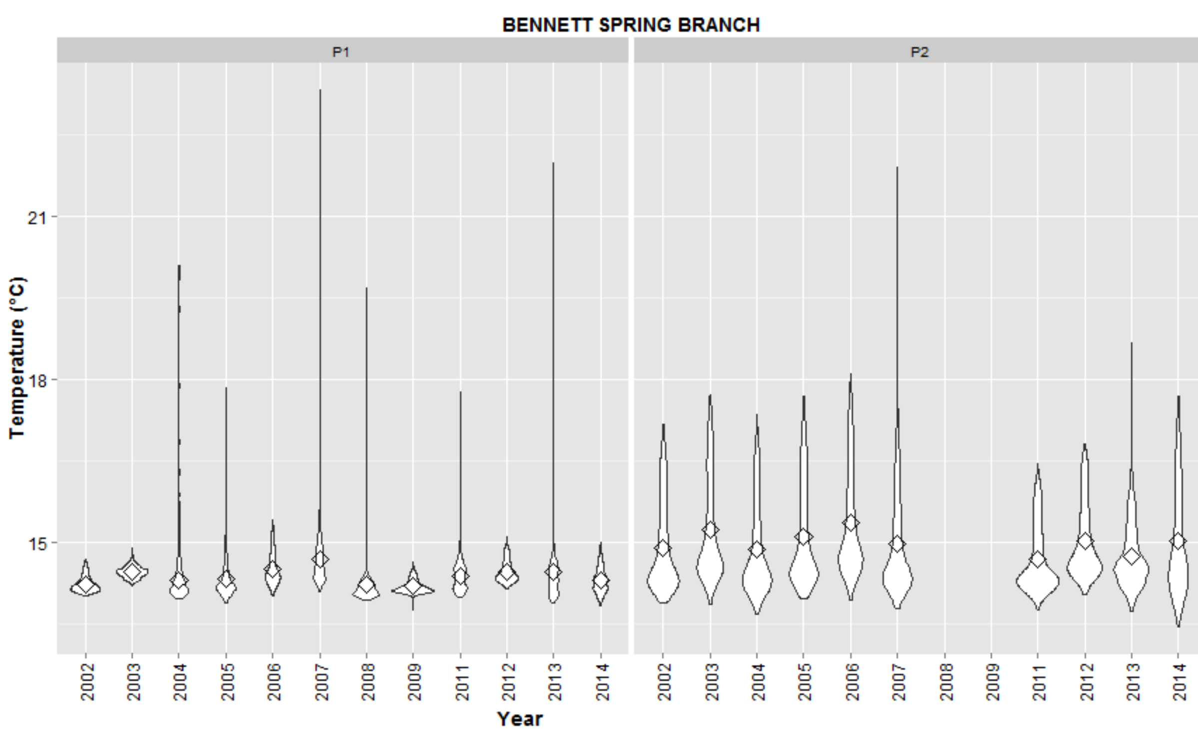
Site	Issue Identified	Explanation	Outcome
Roaring River P2 2009	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	It is likely that these data were from P1. Original data file stated "catch and release zone", which based on the provided map would be P1. The file also indicated that P1 was lost that year, but it may have been that P2 was lost and these data mislabeled. The data were switched to P1.	Switched
Roubidoux Spring Branch 2011	Variation was much greater than other years.	Unexplained variation that was outside of the realm of possibility.	Removed
Spring Creek Stone P1 – 02 and 03	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	Logger may have been in a nearby but not the exact same location.	Used with caution
Spring Creek Phelps P1 2005	The means and distributions of the data did not seem to match patterns of data from the same location in other years.	Based on data patterns, the P1 data from 2005 were almost certainly from the P1A location. Data for P1A did not start until 2006. There are coordinates for P1A, so it was hard to back this with more evidence.	Switched
Spring Creek Phelps P2	GPS coordinates existed for this location on two different Spring Creeks in the Meramec drainage.	Likely a copy and paste mistake	It appeared the coordinates for the Spring Creek closer to St. Louis were incorrect and were deleted. No temperature data were affected.

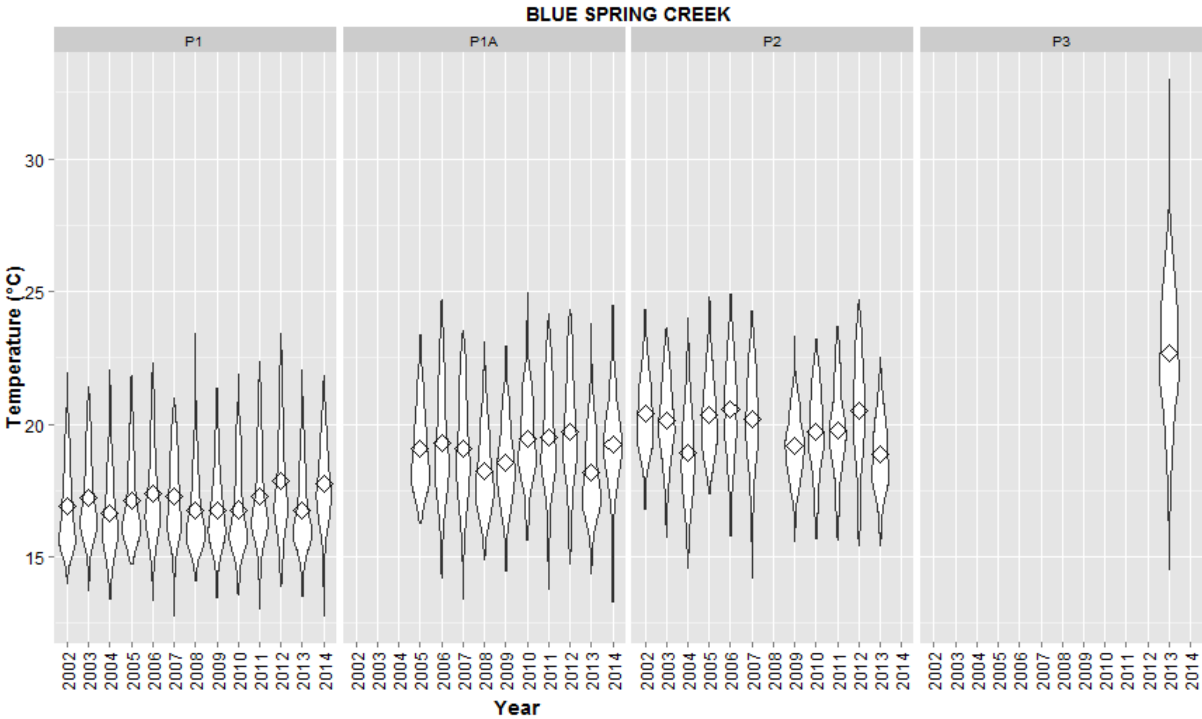
Site	Issue Identified	Explanation	Outcome
Spring Creek Phelps P1A 2005-2008	No GPS coordinates exist Error found on 12-3-2015	Coordinates were likely never obtained	All data were removed because analyses included spatial relationships to other sites.

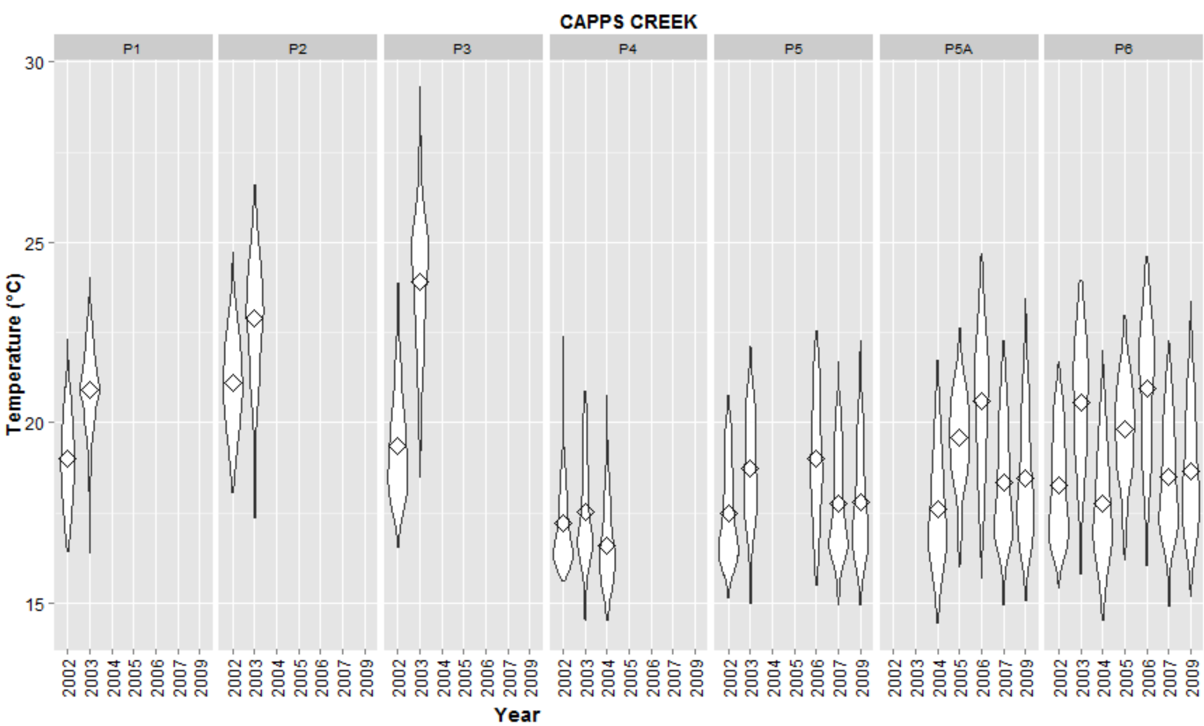
‡These sites were not removed from the violin plots although these were not used in the final analyses.

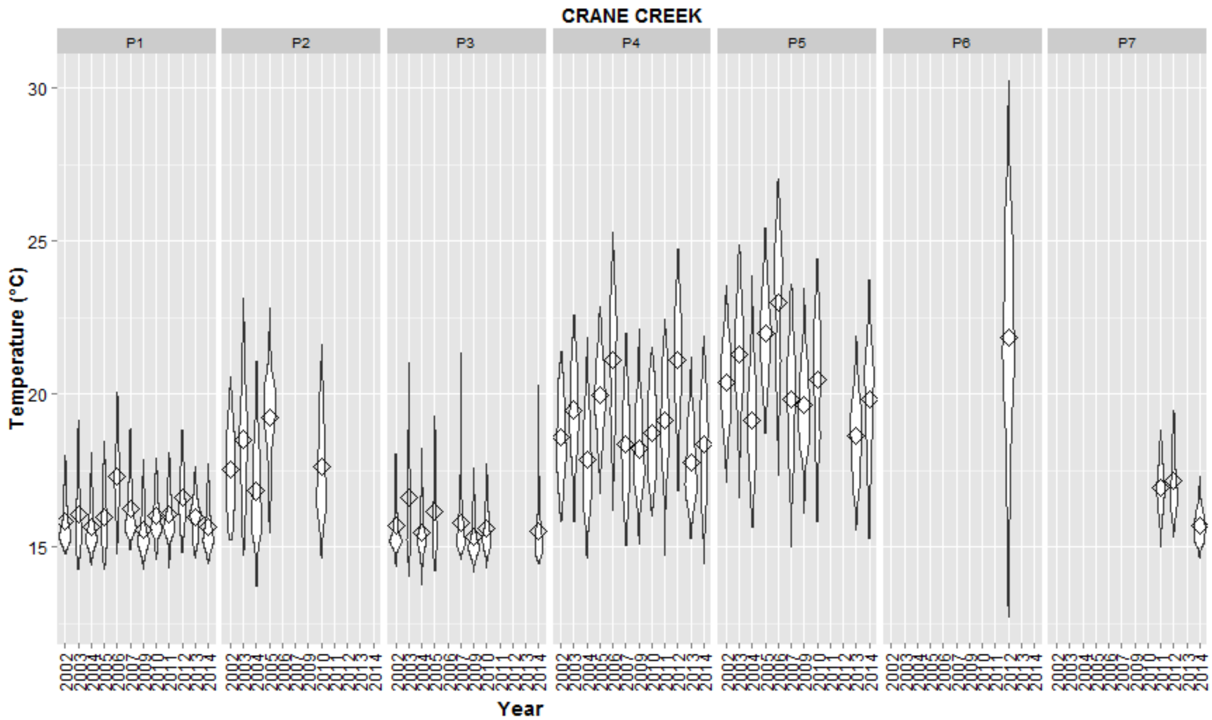
Appendix C. Violin plots used to aid in the QA/QC of data for Section 2. Blue Spring Creek P3 2013, DeWitt Wilkins Spring P2A – 2005, and Hickory Creek P2 – 2003 were not used in the final analyses. Diamonds represent mean values.

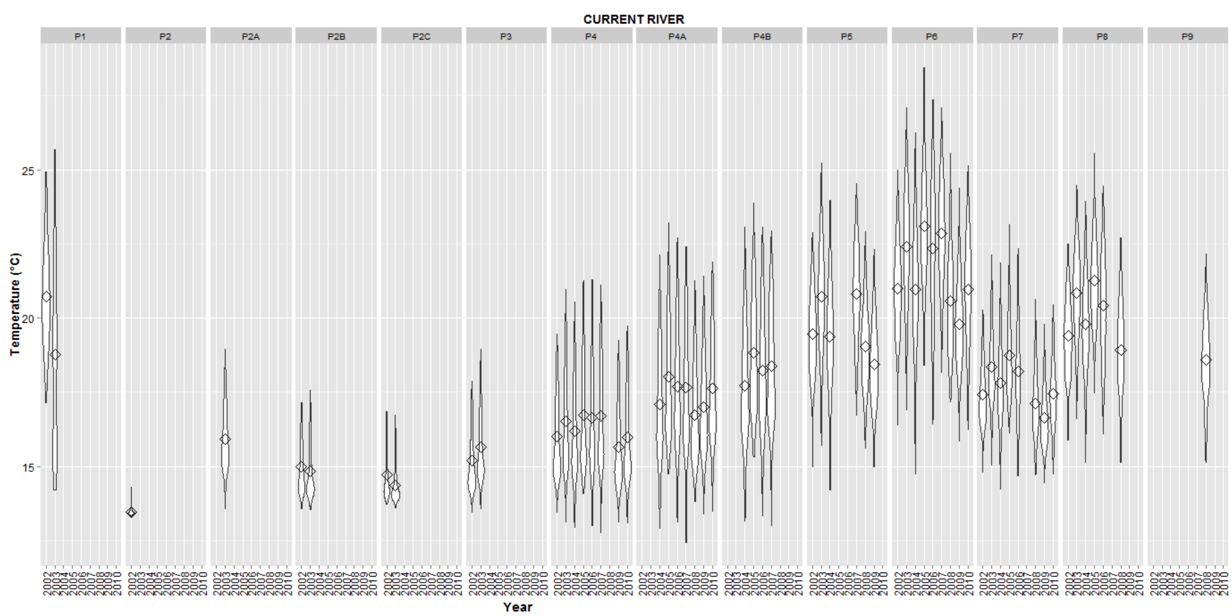


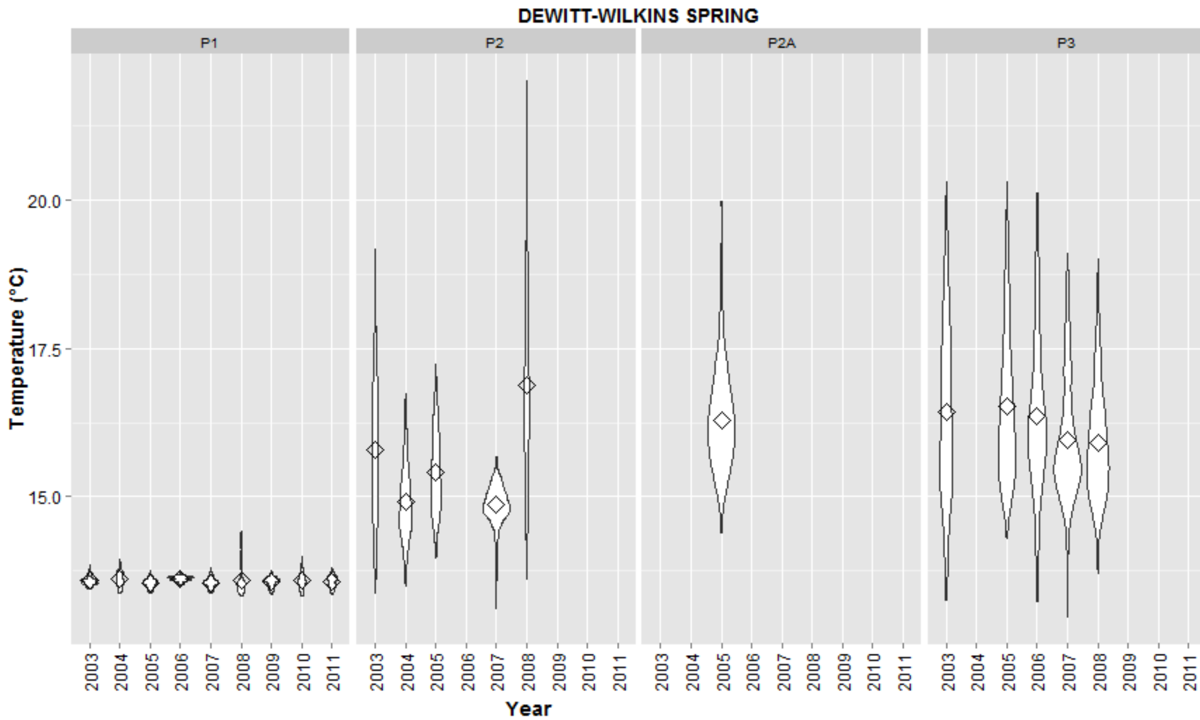


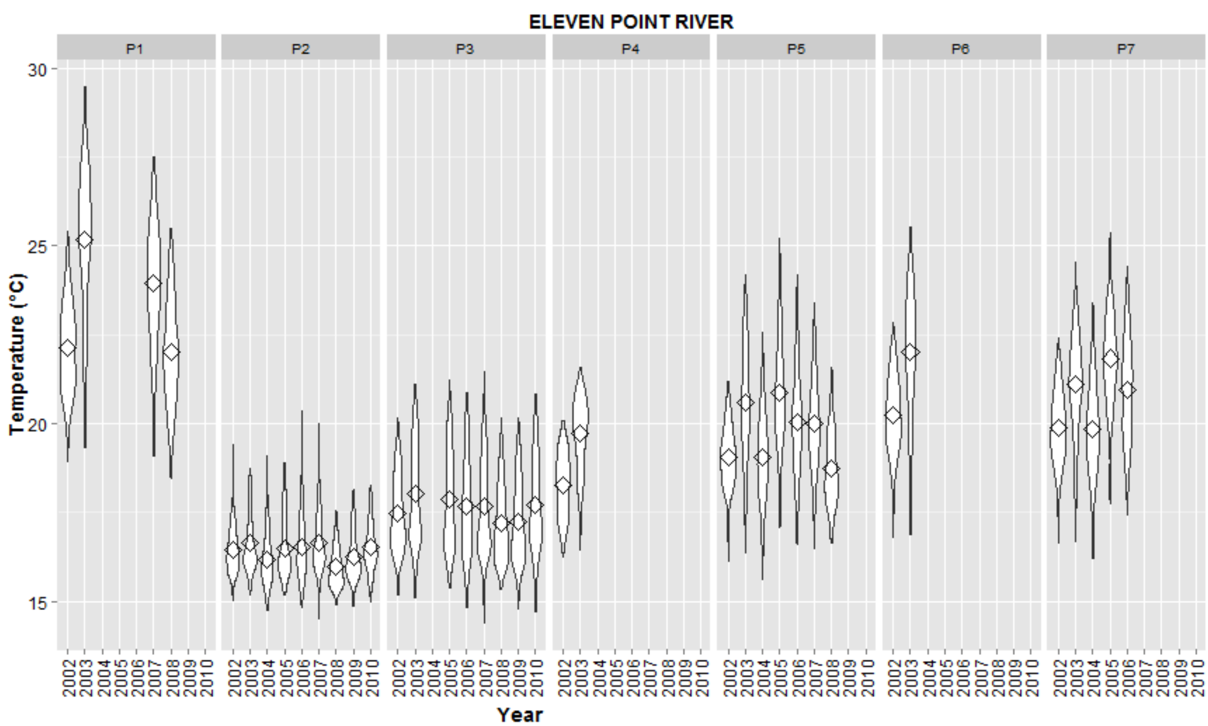

BLUE SPRING CREEK
P1
P1A
P2
P3
Temperature (°C)
30
25
20
15
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
Year

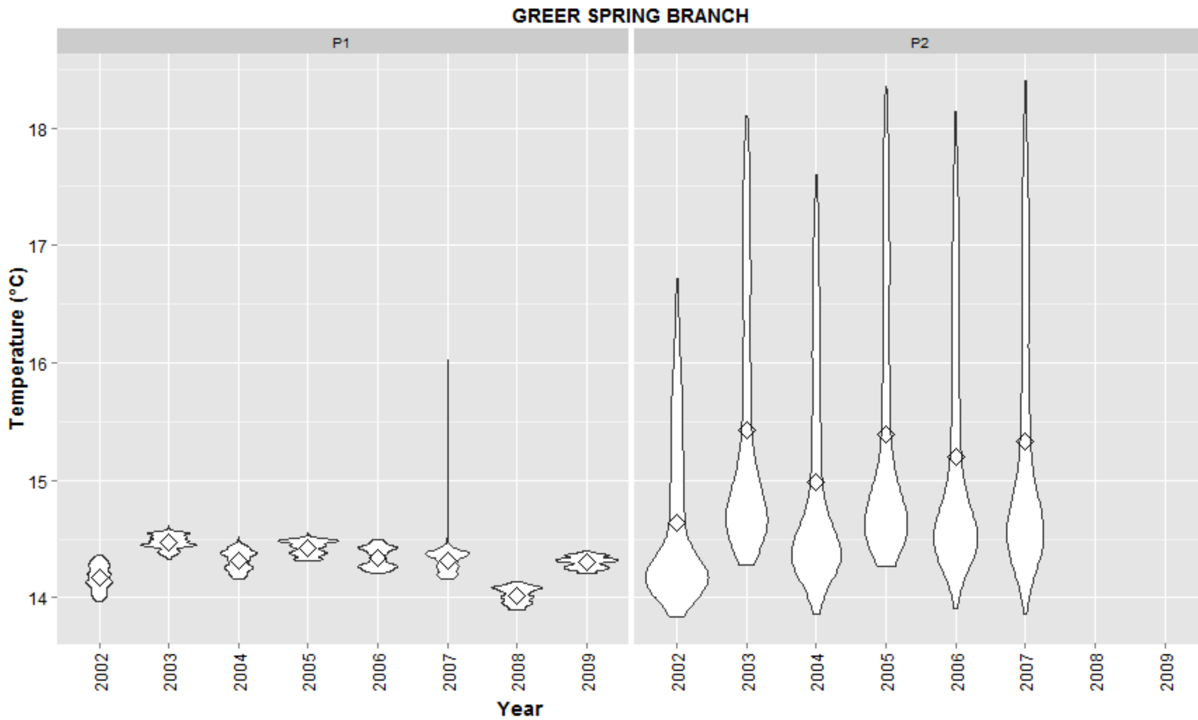

CAPPS CREEK
P1
P2
P3
P4
P5
P5A
P6
Temperature (°C)
30
25
20
15
2002
2003
2004
2005
2006
2007
2009
Year

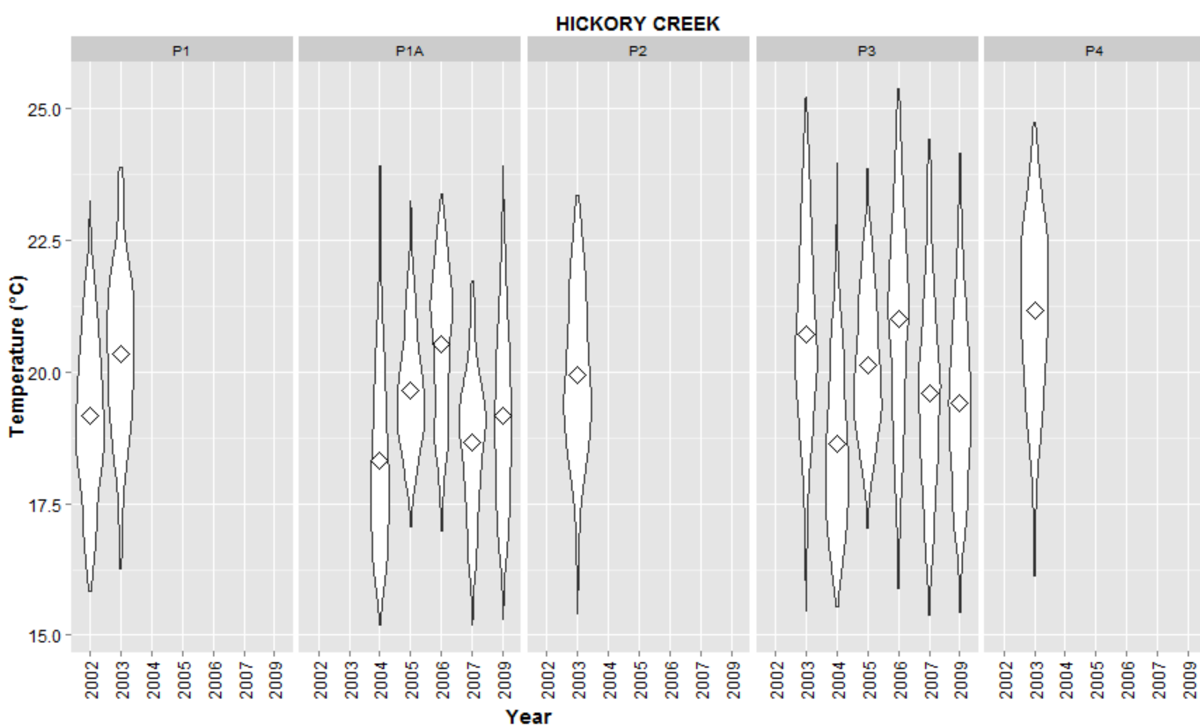

CRANE CREEK
P1
P2
P3
P4
P5
P6
P7
Temperature (°C)
Year

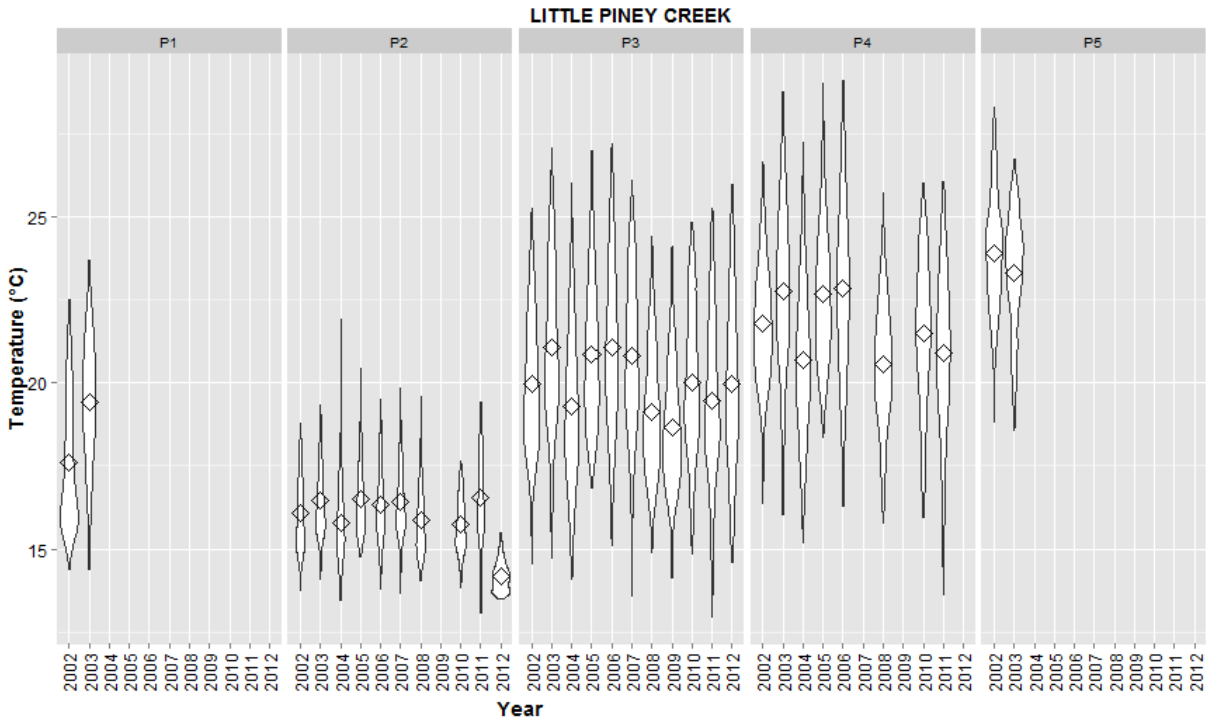

CURRENT RIVER
P1
P2
P2A
P2B
P2C
P3
P4
P4A
P4B
P5
P6
P7
P8
P9
Temperature (°C)
Year

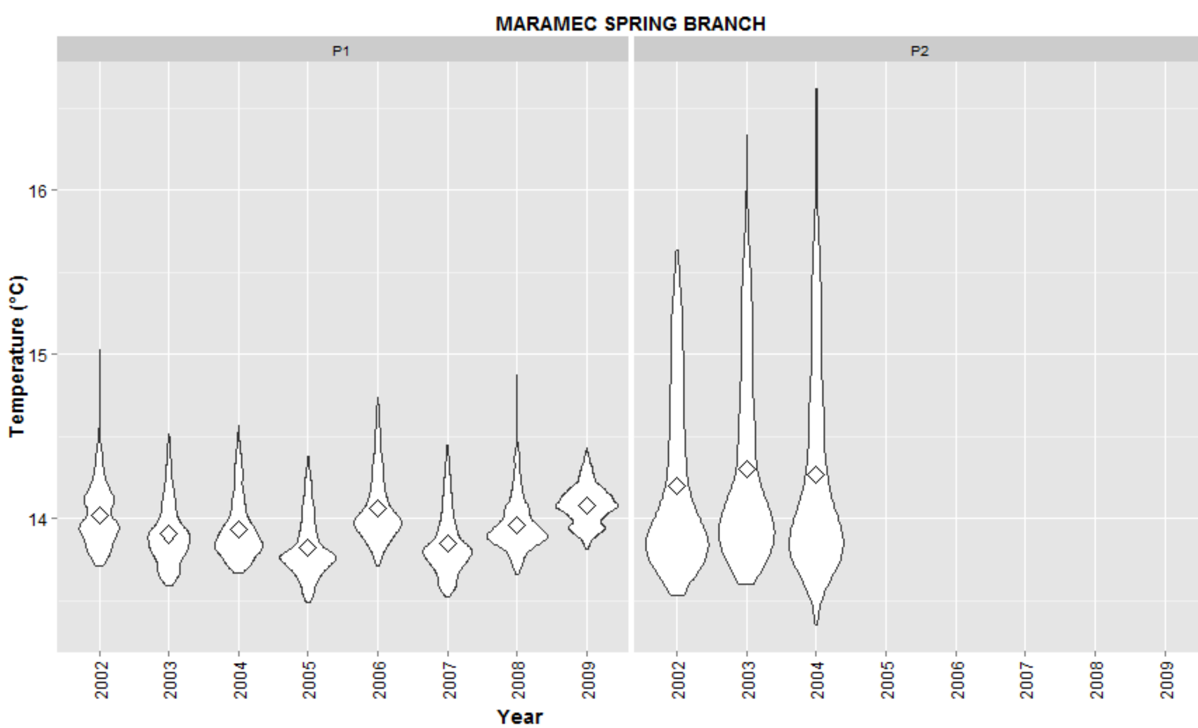

DEWITT-WILKINS SPRING
P1
P2
P2A
P3
Temperature (°C)
20.0
17.5
15.0
2003
2004
2005
2006
2007
2008
2009
2010
2011
Year

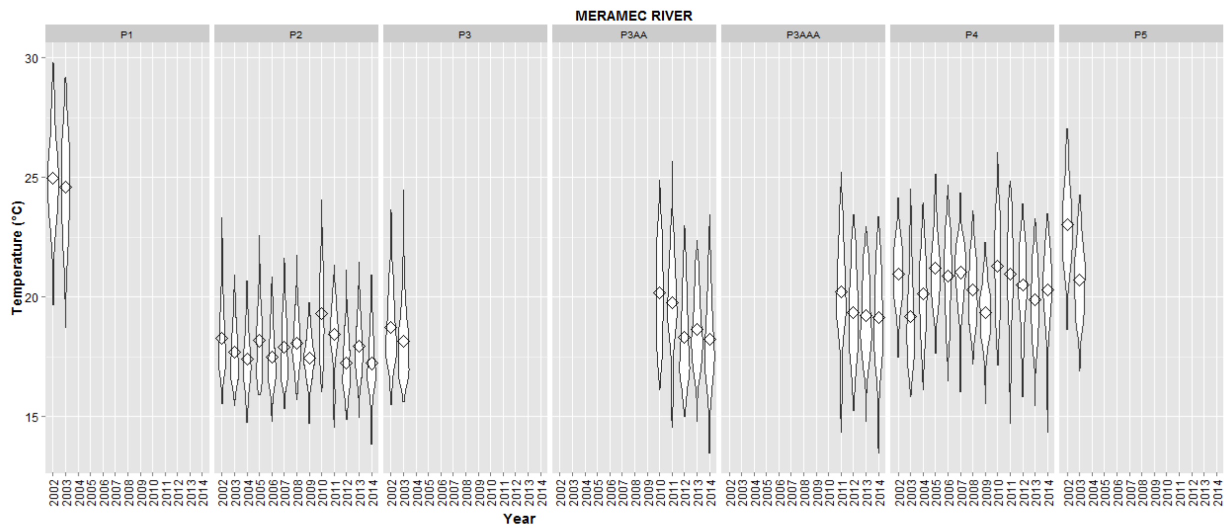

ELEVEN POINT RIVER
P1
P2
P3
P4
P5
P6
P7
Temperature (°C)
30
25
20
15
2002
2003
2004
2005
2006
2007
2008
2009
2010
Year

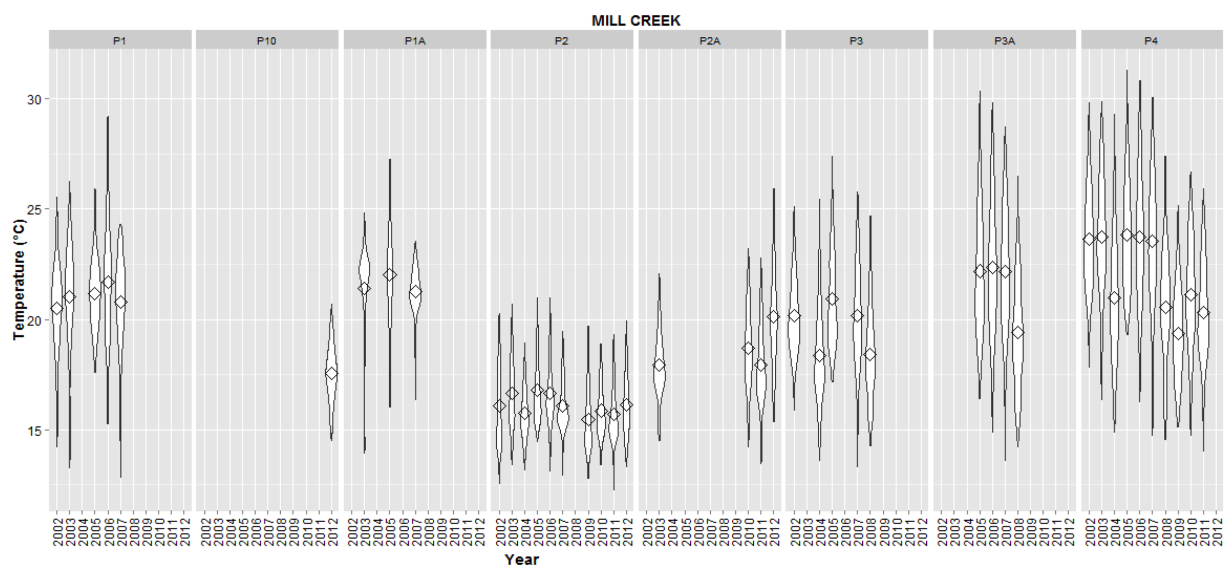

GREER SPRING BRANCH
P1
P2
Temperature (°C)
18
17
16
15
14
2002
2003
2004
2005
2006
2007
2008
2009
Year

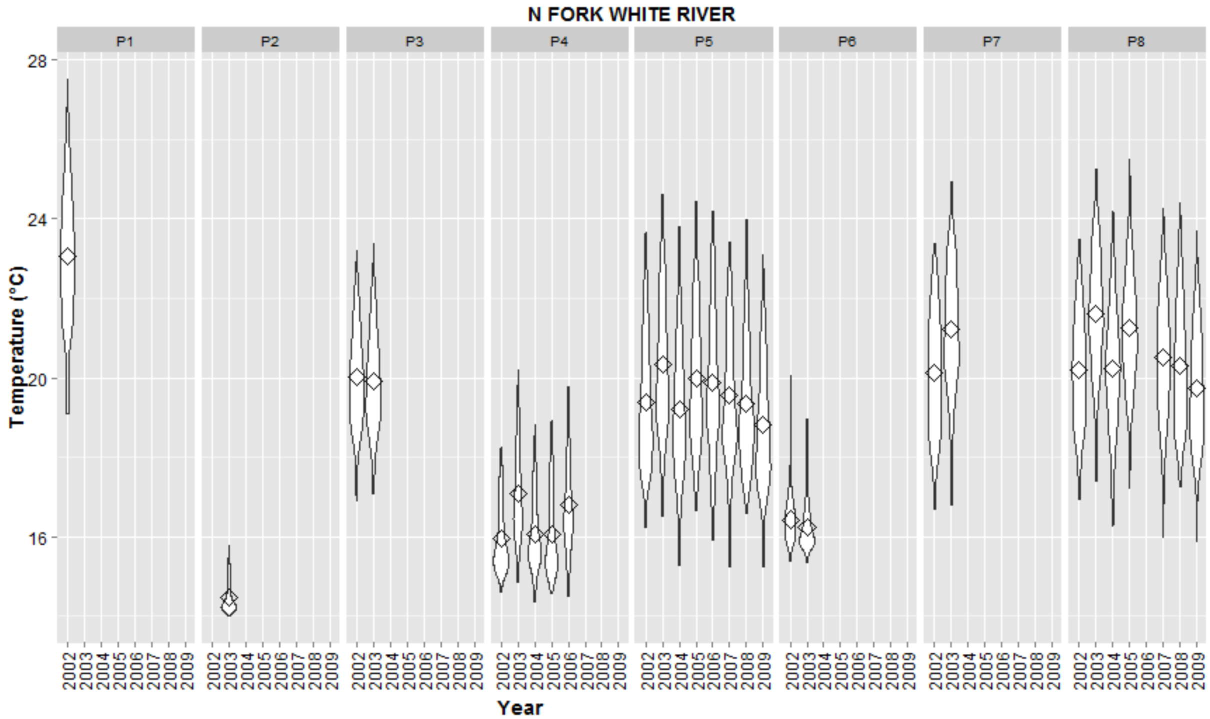

HICKORY CREEK
P1
P1A
P2
P3
P4
Temperature (°C)
25.0
22.5
20.0
17.5
15.0
2002
2003
2004
2005
2006
2007
2009
Year

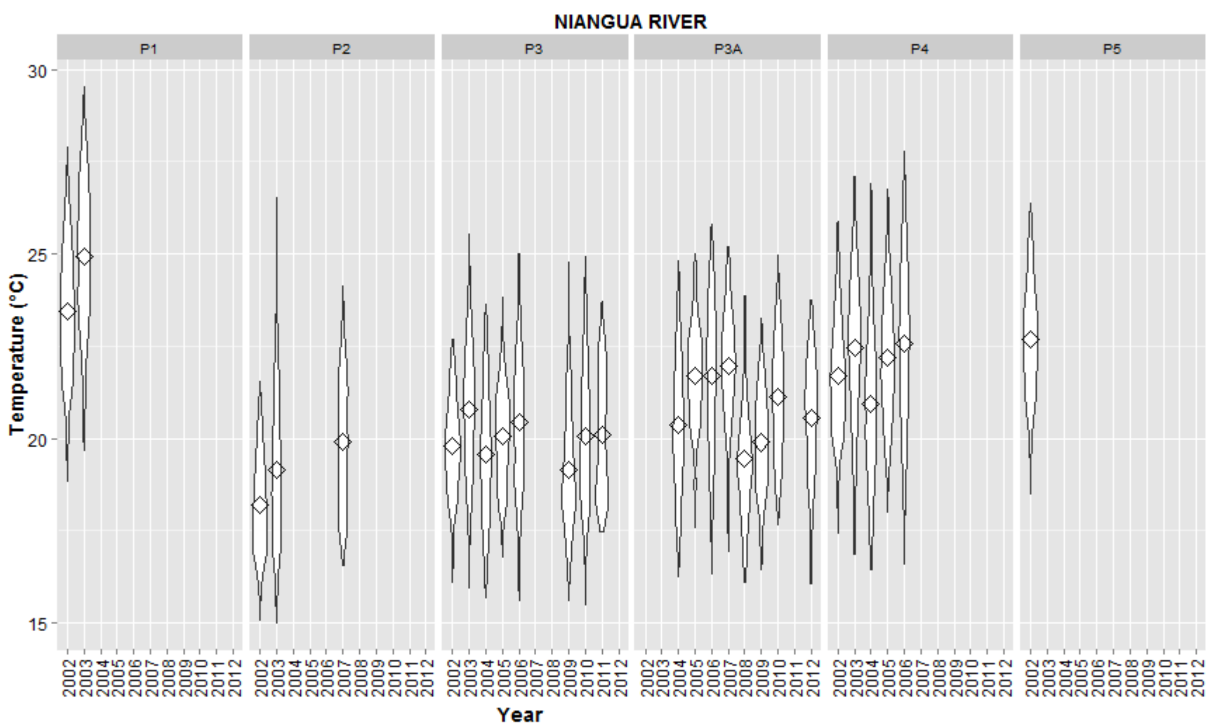

LITTLE PINEY CREEK
P1
P2
P3
P4
P5
Temperature (°C)
25
20
15
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
Year

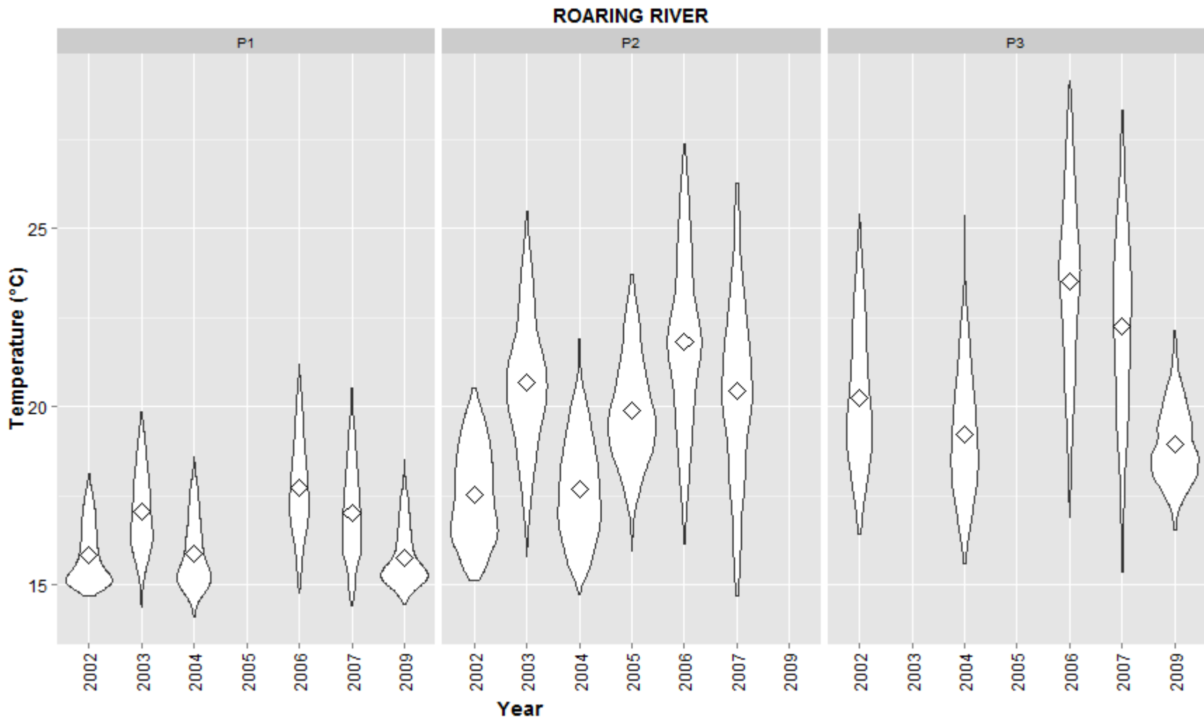

MARAMEC SPRING BRANCH
P1
P2
Temperature (°C)
16
15
14
2002
2003
2004
2005
2006
2007
2008
2009
Year

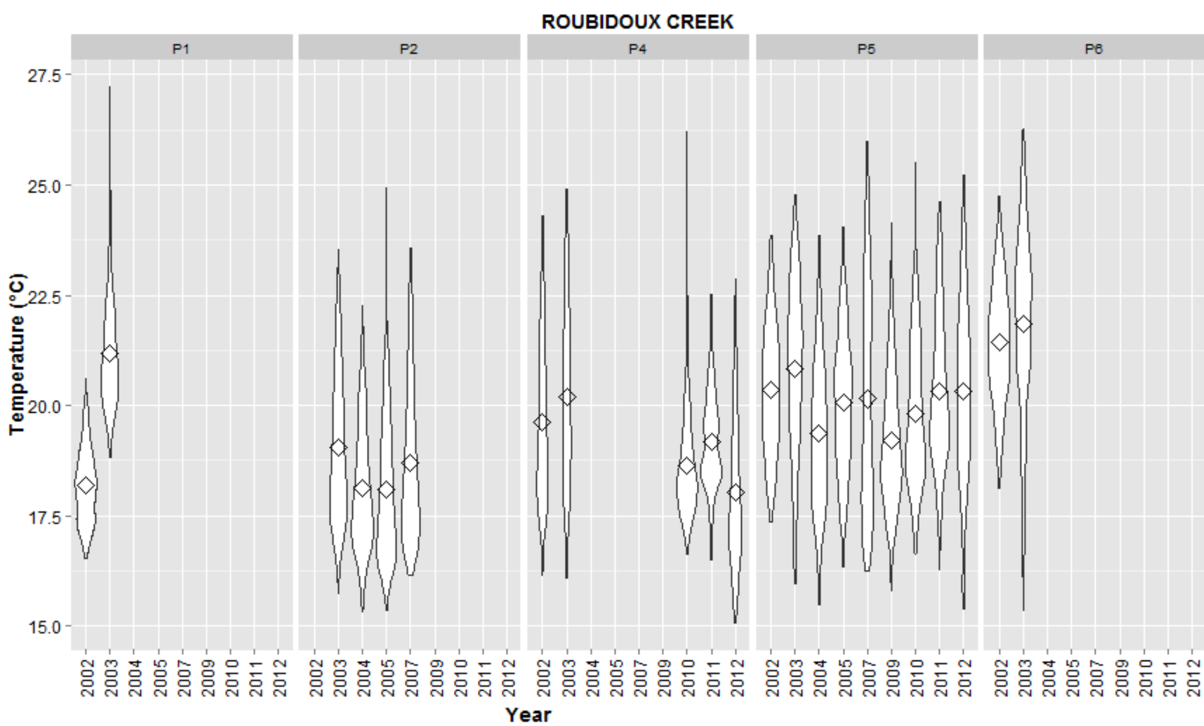

MERAMEC RIVER
P1
P2
P3
P3AA
P3AAA
P4
P5
Temperature (°C)
Year

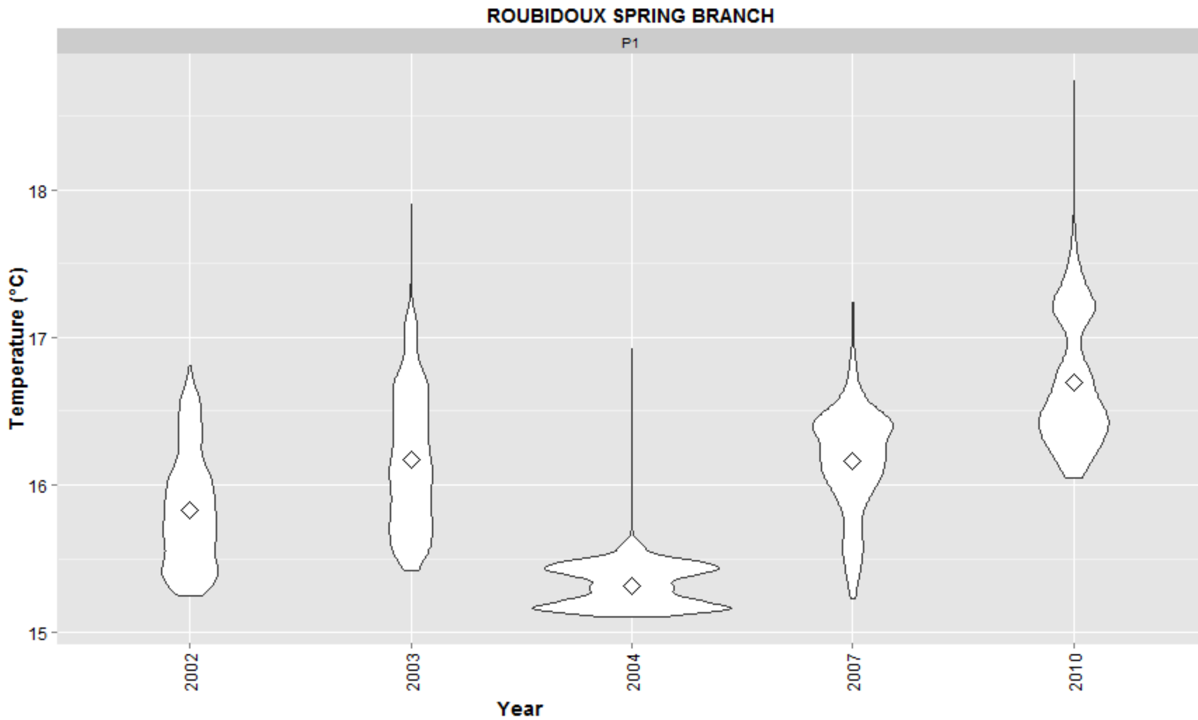

MILL CREEK
P1
P10
P1A
P2
P2A
P3
P3A
P4
Temperature (°C)
Year

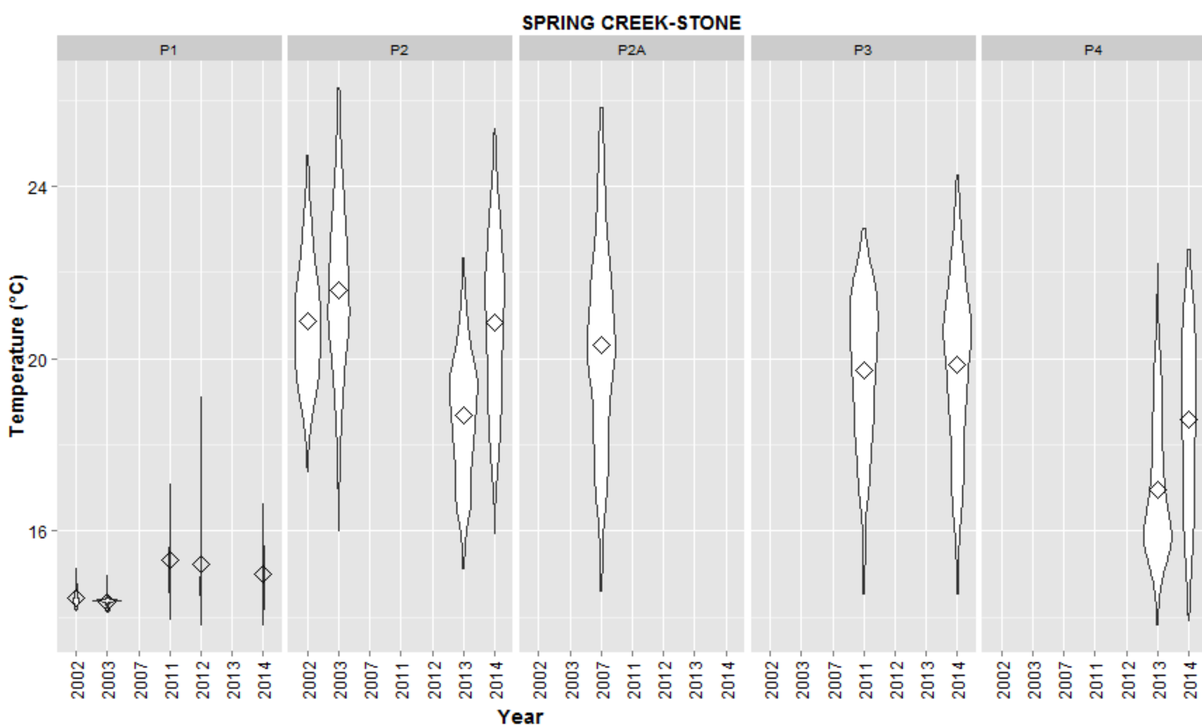

N FORK WHITE RIVER
P1
P2
P3
P4
P5
P6
P7
P8
Temperature (°C)
Year

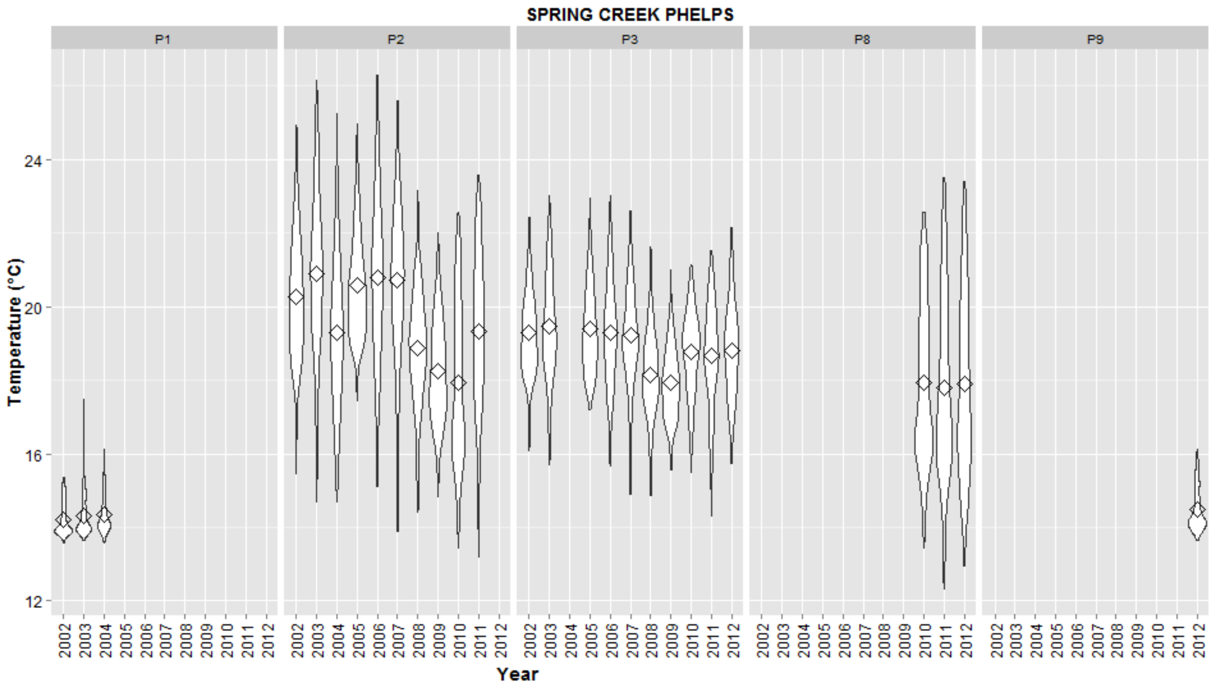

NIANGUA RIVER
P1
P2
P3
P3A
P4
P5
Temperature (°C)
Year


ROARING RIVER
P1
P2
P3
Temperature (°C)
25
20
15
2002
2003
2004
2005
2006
2007
2009
Year


ROUBIDOUX CREEK
P1
P2
P4
P5
P6
Temperature (°C)
27.5
25.0
22.5
20.0
17.5
15.0
2002
2003
2004
2005
2007
2009
2010
2011
2012
Year


ROUBIDOUX SPRING BRANCH
P1
Temperature (°C)
18
17
16
15
2002
2003
2004
2007
2010
Year


SPRING CREEK-STONE
P1
P2
P2A
P3
P4
Temperature (°C)
24
20
16
2002
2003
2007
2011
2012
2013
2014
Year



SPRING CREEK PHELPS
P1
P2
P3
P8
P9
Temperature (°C)
24
20
16
12
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
Year

Appendix D. List of thermal metrics in five categories calculated by "StreamThermal" package (version 1.0). Reproduced from Tsang et al. 2016.

Metrics	Definition	Unit
Magnitude (58)		
Static average		
Monthly[1]		
ADmax	Average daily max temperature	°C
ADmin	Average daily minimum temperature	°C
ADmean	Average daily mean temperature	°C
Seasonal[2]*		
MaxDmean	Maximum daily mean temperature	°C
MinDmean	Minimum daily mean temperature	°C
AvgDmean	Average daily mean temperature	°C
Moving average		
Max30MovingAMeanT Max21MovingAMeanT Max14MovingAMeanT Max7MovingAMeanT Max3MovingAMeanT	Maximum of 30-, 21-, 14-, 7-, 3-day moving average of daily mean	°C
Max30MovingAMaxT Max21MovingAMaxT Max14MovingAMaxT Max7MovingAMaxT Max3MovingAMaxT	Maximum of 30-, 21-, 14-, 7-, 3-day moving average of daily maximum	°C
Variability (82)		
Static variability		
Monthly[1]		
ADrange	Average daily range in temperature	°C
Rmean	Range of daily mean temperature	°C
CVDmax	Coefficient of variation of daily maximum temperature	-
CVDmin	Coefficient of variation of daily minimum temperature	-
CVDmean	Coefficient of variation of daily mean temperature	-
Seasonal[2]*		
Rmax	Range of daily maximum temperature	°C
Rmin	Range of daily minimum temperature	°C
Rmean	Range of daily mean temperature	°C
Moving variability		
Moving average of variability		
Max30MovingADRT Max21MovingADRT Max14MovingADRT Max7MovingADRT Max3MovingADRT	Maximum of 30-, 21-,14-, 7-, 3-day moving average of daily range	°C
Moving variability in extremes		
DiffExtreme 6-30	The 6-day average high minus the 6 day average low over the warmest 30 day window	°C

Metrics	Definition	Unit
DiffExtreme 5-21	The 5-day average high minus the 5 day average low over the warmest 21 day window	°C
DiffExtreme 4-14	The 4-day average high minus the 4 day average low over the warmest 14 day window	°C
DiffExtreme 2-7	The 2-day average high minus the 2 day average low over the warmest 7 day window	°C
DiffExtreme 1-3	The 1-day average high minus the 1 day average low over the warmest 3 day window	°C
Frequency (48)		
Monthly[1]		
FmaxcT*	Number of days that daily maximum temperature exceeds temperature of interest	days
FmincT*	Number of days that daily minimum temperature exceeds temperature of interest	days
FmeancT*	Number of days that daily mean temperature exceeds temperature of interest	days
Seasonal[2]*		
FmaxcT*	Number of days that daily maximum temperature exceeds temperature of interest	days
FmincT*	Number of days that daily minimum temperature exceeds temperature of interest	days
FmeancT*	Number of days that daily mean temperature exceeds temperature of interest	days
Timing (63)		
Timing of static metrics		
Monthly[1]		
JDmaxMaxT	Julian day of maximum daily maximum temperature	day
JDminMinT	Julian day of minimum daily minimum temperature	day
JDmaxMeanT	Julian day of maximum daily mean temperature	day
Seasonal[2]*		
JDmaxMaxT	Julian day of maximum daily maximum temperature	day
JDminMinT	Julian day of minimum daily minimum temperature	day
JDmaxMeanT	Julian day of maximum daily mean temperature	day
Timing of moving metrics		
JDM30MAMeanT JDM21MAMeanT JDM14MAMeanT JDM7MAMeanT JDM3MAMeanT	Julian day of maximum daily mean of 30-, 21-, 14-, 7-, 3-day moving window	day
JDM30MAMaxT JDM21MAMaxT JDM14MAMaxT JDM7MAMaxT JDM3MAMaxT	Julian day of maximum daily maximum of 30-, 21-, 14-, 7-, 3-day moving window	day
JDM30MADRT JDM21MADRT	Julian day of maximum daily range of 30-, 21-, 14-, 7-, 3-day moving window	day

Metrics	Definition	Unit
JDM14MADRT		
JDM7MADRT		
JDM3MADRT		
Rate of change (16)		
Monthly[1]		
RC	The difference in maximum and minimum daily mean temperature divided by the number of days between events	°C/day
Seasonal[2]*		
RC	The difference in maximum and minimum daily mean temperature divided by the number of days between events	°C/day

[1] Monthly calculated for each month January (1) through December (12).

[2] Metrics are calculated for spring (Sp), summer (Su), fall (Fa), winter (Wi). These season maybe defined by the users.

*Metrics including user defined parameters (e.g. seasons, temperature of interest)

Appendix E. Graphical results of hierarchical clustering analysis based on daily water temperatures for 57 Ozark Plateau monitoring sites, descriptions of the water temperature metrics used to cluster sites, and histograms of temperature metrics for groups identified.

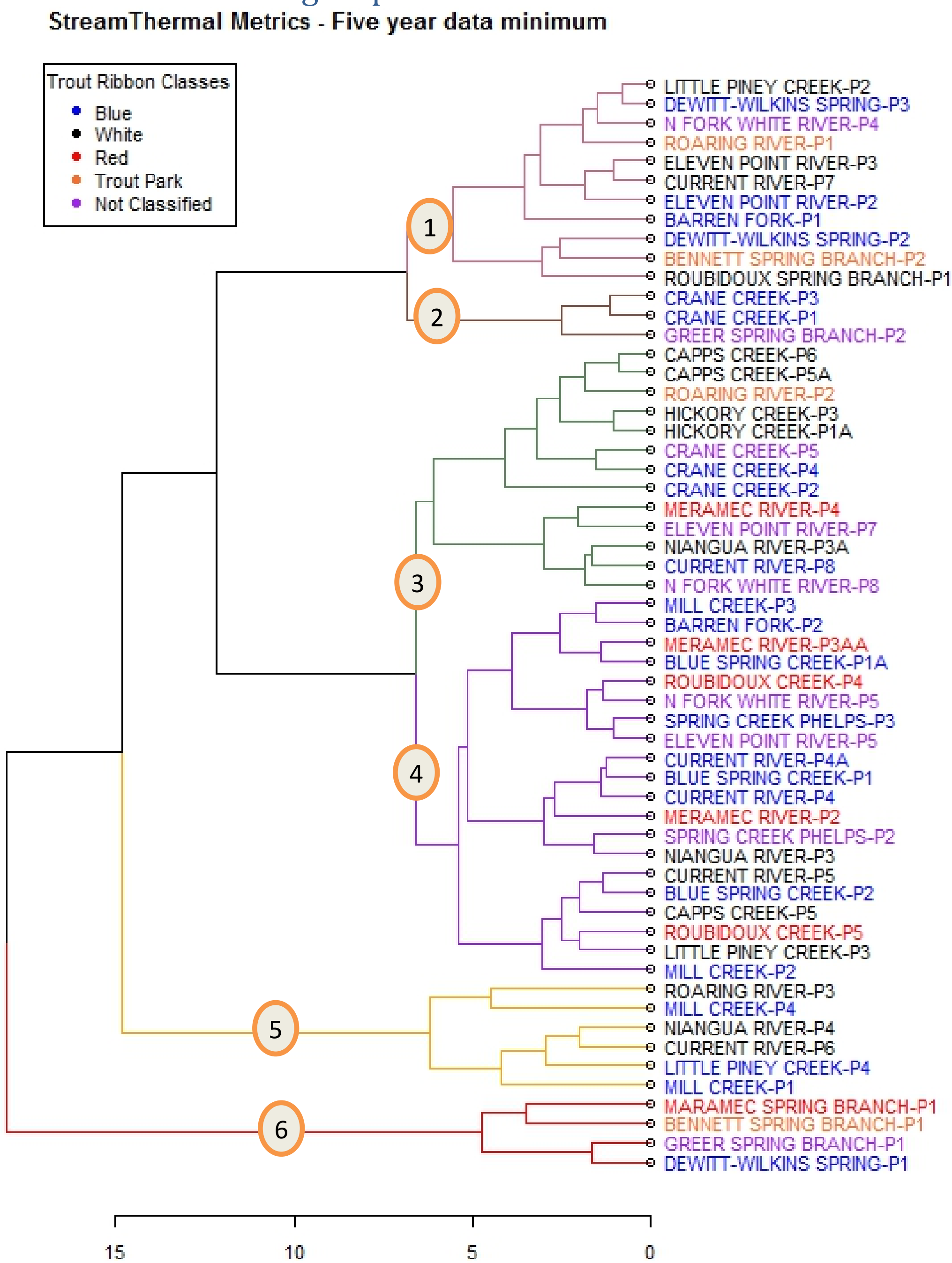


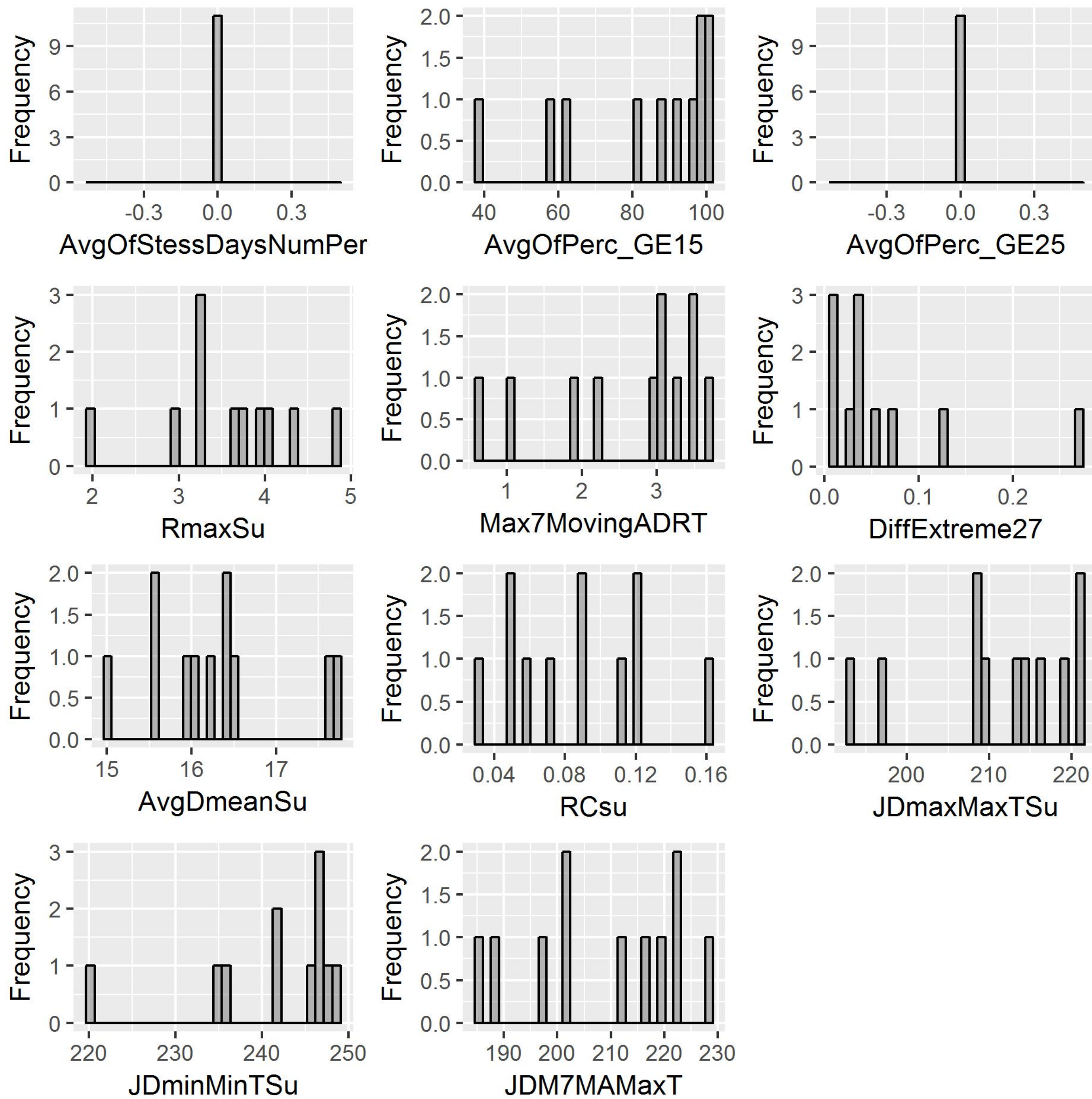
Figure 1. Dendrogram of hierarchical cluster analysis results obtained from the 57 temperature monitoring locations with at least five years of data covering the period of July 1st through September 15th. The analysis was based on 11 metrics from Table 2-3. Line colors represent six different clusters of locations. Label colors depict the MDC trout stream management classification.

Table 1. List of 11 thermal metrics in five categories used in the hierarchical cluster analysis. Excluding the frequency category, metrics were calculated using the "StreamThermal" package v1.0.

Category	Metric	Definition
Magnitude	AvgDmeanSU	Average daily mean temperature (°C)
Frequency	AvgOfStressDayNumPer	Average number of stress days (percentage of total days)
	AvgOfPerc_GE15	Average number of days when temperatures exceeded 15*°C* (percentage of total days)
	AvgOfPerc_GE25	Average number of days when temperatures exceeded 25*°C* (percentage of total days)
Variability	RmaxSu	Range of daily maximum temperature (°C)
	Max7MovingADRT	Maximum of 7-day moving average of daily range (°C)
	DiffExtreme2.7	The 2-day average high minus the 2 day average low over the warmest seven day window (°C)
Timing	JDmaxMaxTSu	Julian day of maximum daily maximum temperature (day)
	JDminMinTSu	Julian day of minimum daily minimum temperature (day)
	JDM7MAMaxT	Julian day of maximum daily maximum of 7-day moving window (day)
Rate of change	RCsu	Difference in maximum and minimum daily mean temperature divided by the number of days between events (°C/day)

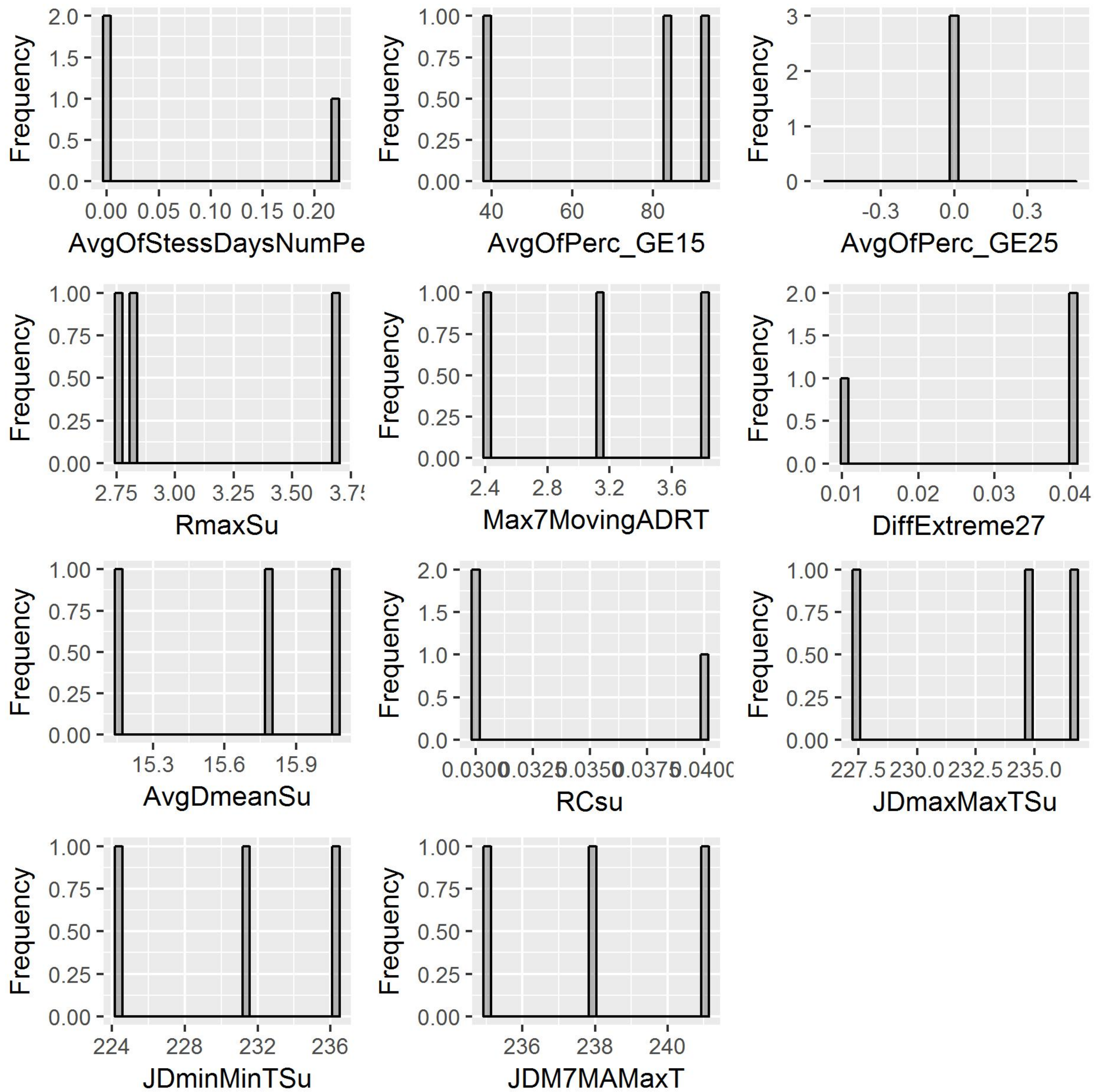
Hclust Group 1 (ex. Little Piney Creek-P2)

N = 11



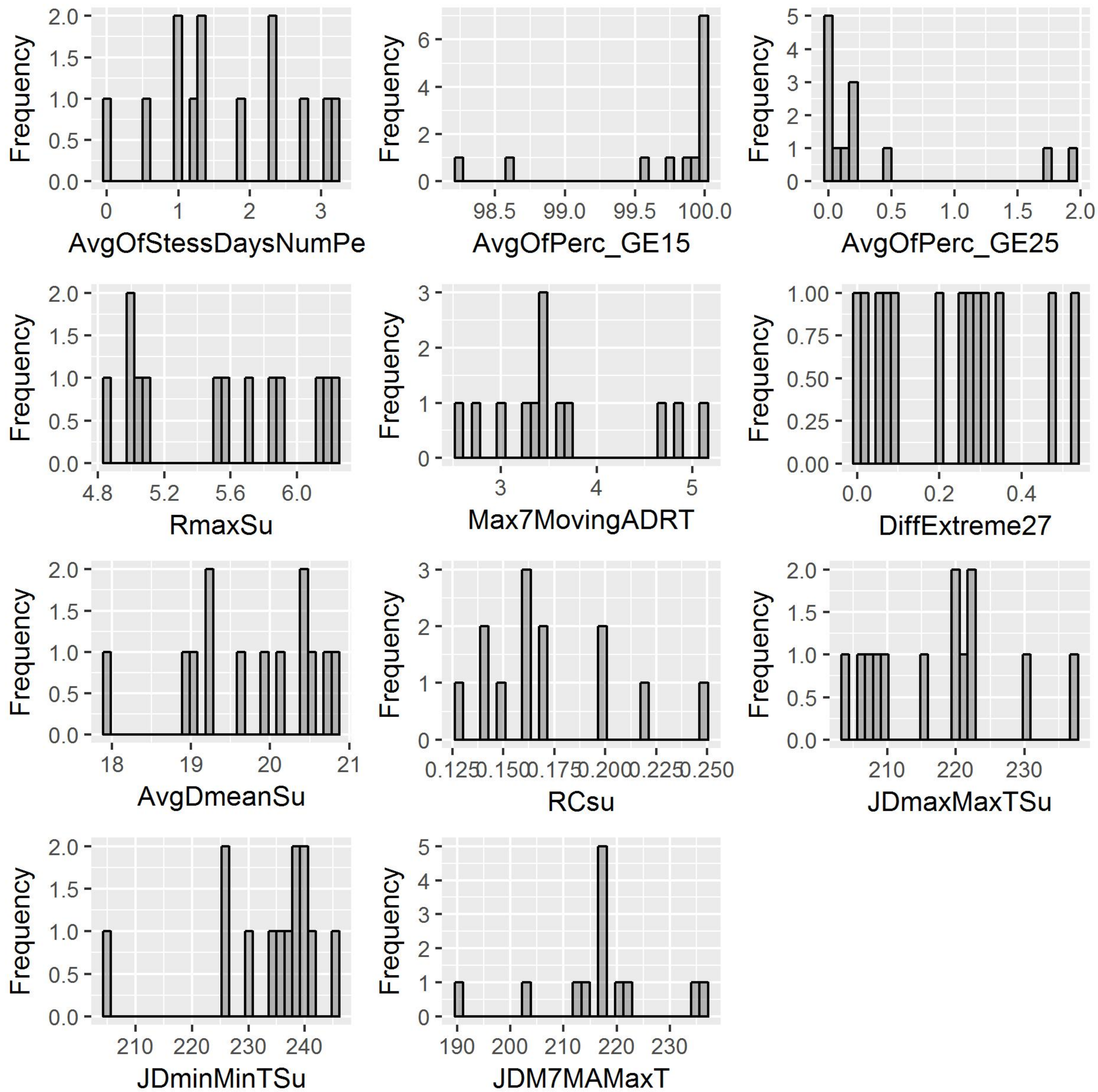
Hclust Group 2 (ex. Current River–P6)

N = 3



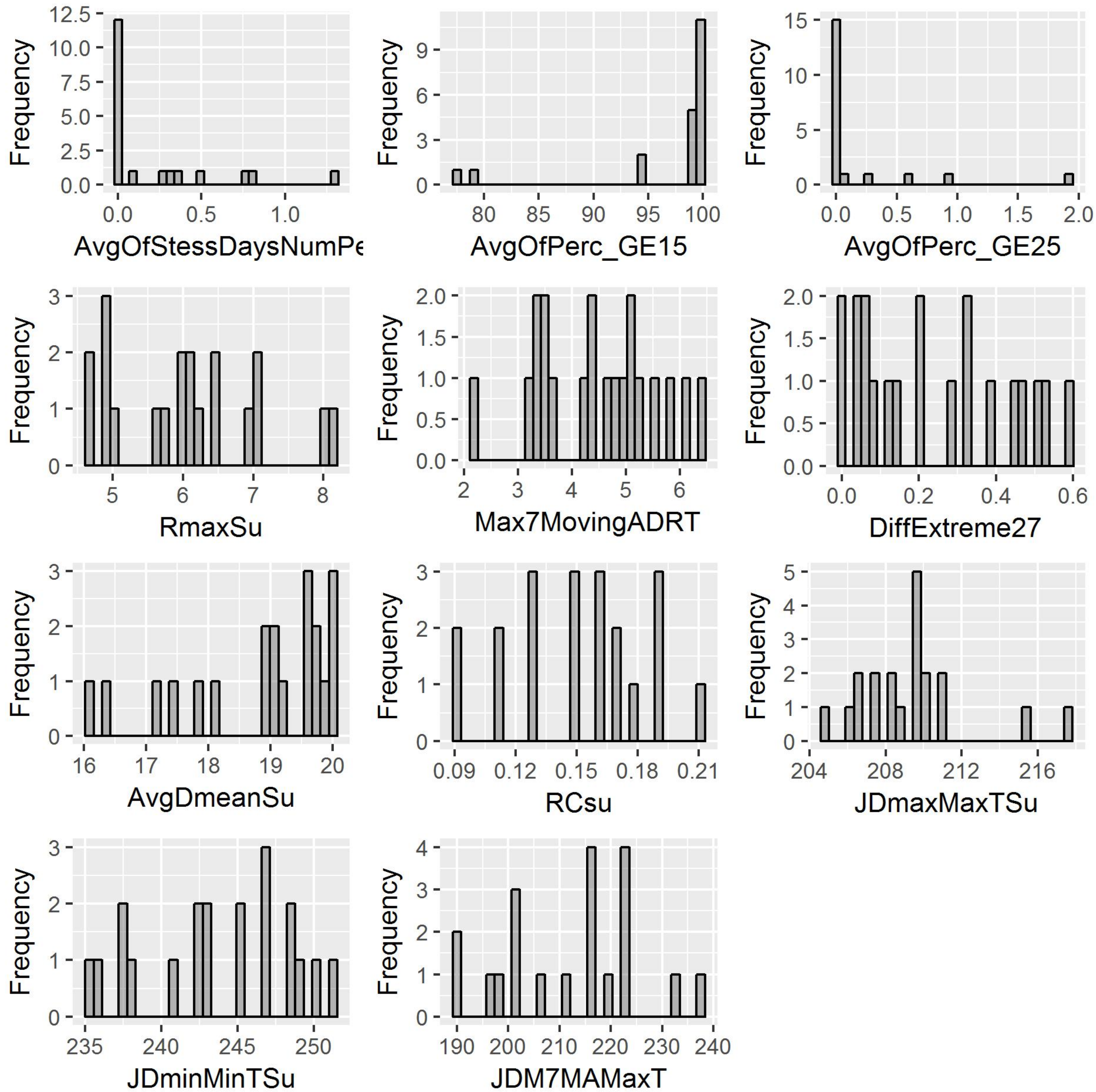
Hclust Group 3 (ex. Capps Creek-P6)

N = 13



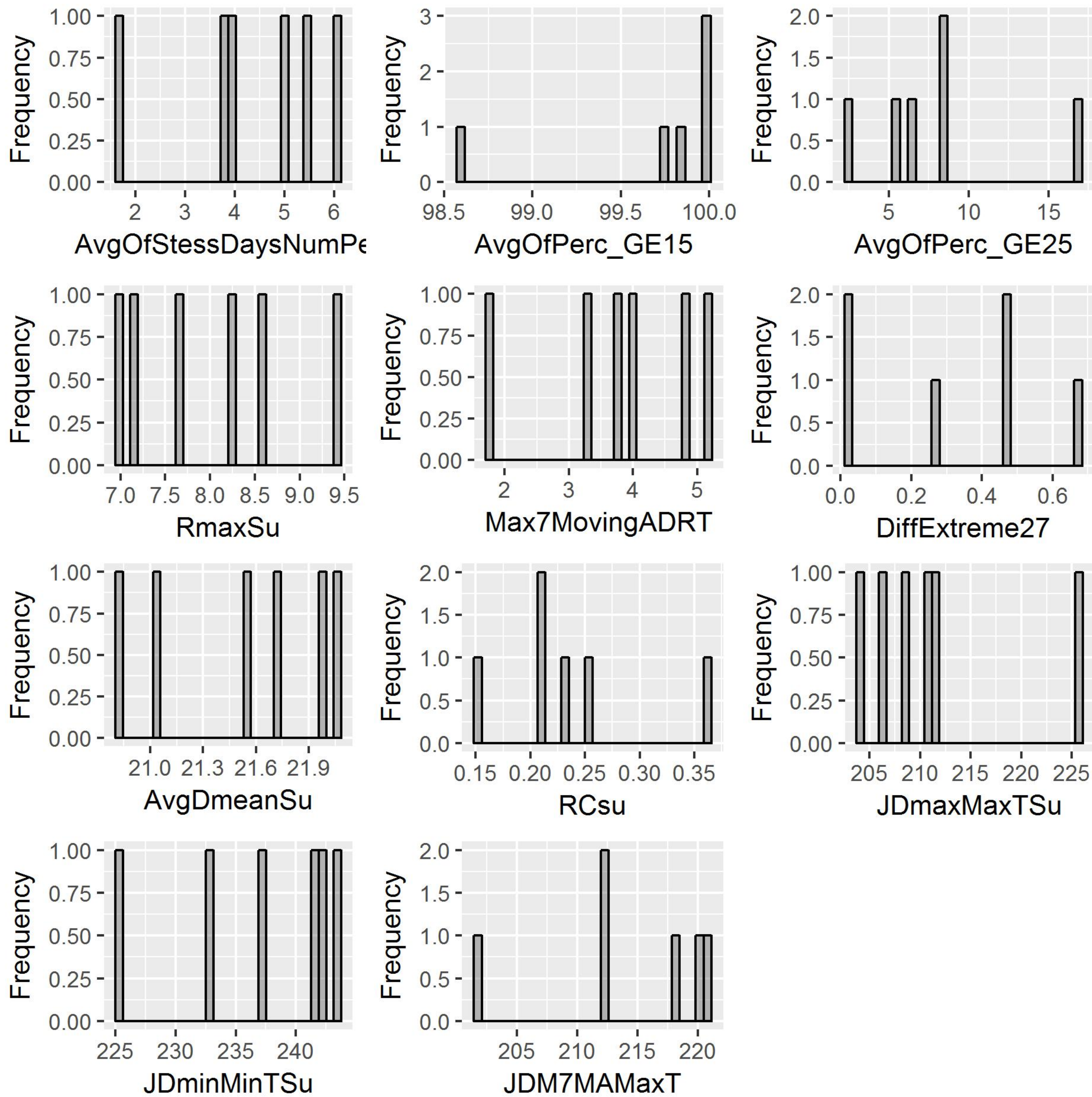
Hclust Group 4 (ex. Mill Creek-P3)

N = 20



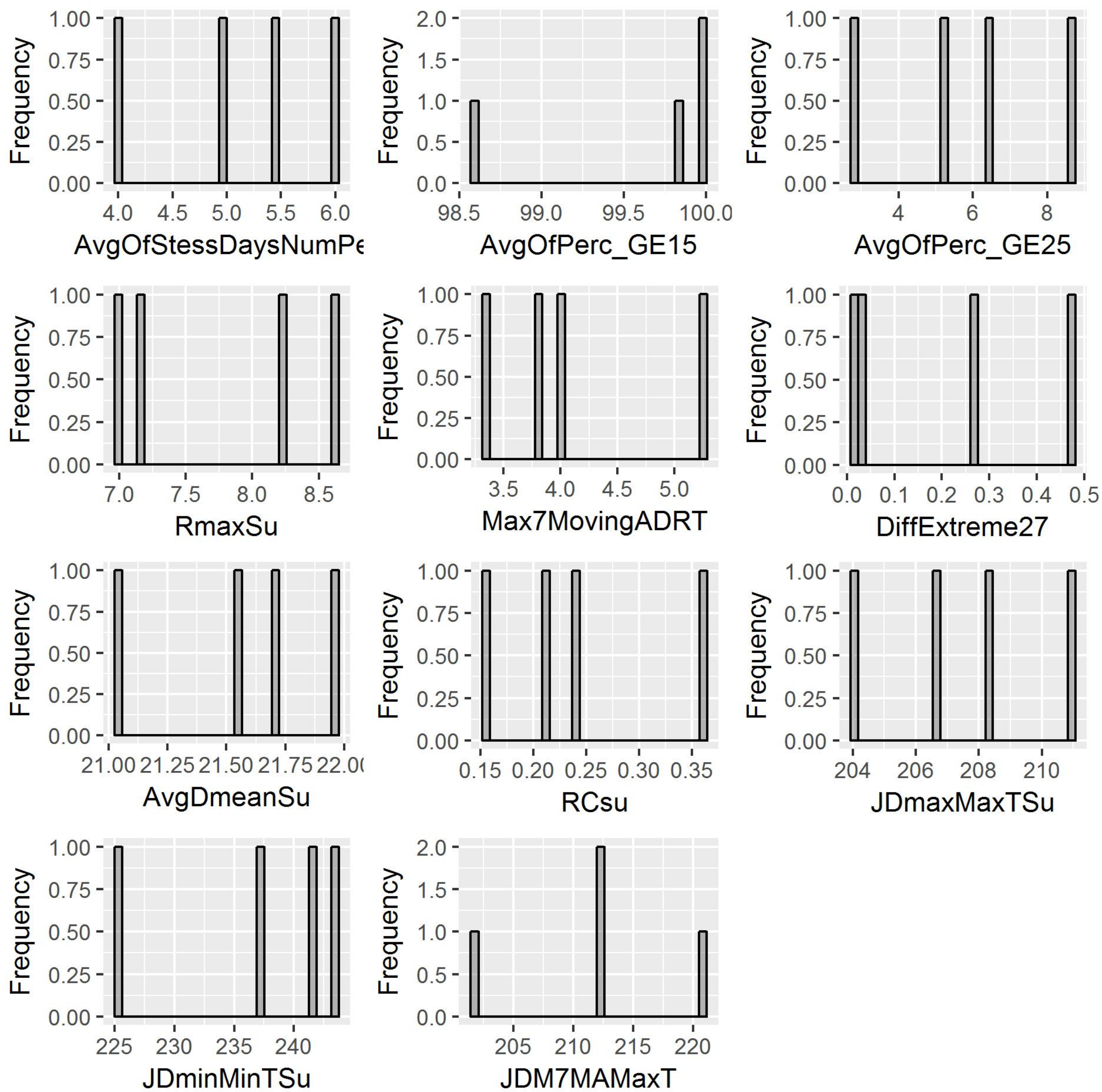
Hclust Group 5 (ex. Roaring River-P3)

N = 6



Hclust Group 6 (ex. Maramec Spring Branch-P1)

N = 4



Appendix F: Effect of climatological variables on summer water temperature (by site).

Refer to Appendix A for site names associated with the site numbers listed in this table. Interpretation for air temperature and solar radiation variables: For every 1 unit (°C or W/m^2) increase in the climatological variable, water temperature typically changes by the reported number of degrees Celsius.

Interpretation for precipitation: When total daily precipitation, area-weighted over the upstream watershed area, is greater than 3 mm, water temperature typically changes by the reported number of degrees Celsius.

The top number in each cell is water temperature (°C) and the numbers in parentheses are the corresponding 95% credible interval. The current day's air temperature is by far the strongest predictor of changes in water temperature.

Site number	Climate variables				
	Air temperature	**Air temperature 3 days previous**	**Air temperature 5 days previous**	**Precipitation > 3 mm**	**Solar radiation**
1	0.06 (0.00, 0.13)	0.02 (-0.01, 0.04)	0.02 (-0.01, 0.05)	-0.06 (-0.26, 0.15)	0.0001 (-0.0066, 0.0067)
2	0.20 (0.14, 0.25)	0.03 (0.00, 0.06)	0.03 (0.00, 0.06)	-0.07 (-0.27, 0.13)	0.0012 (-0.0045, 0.0070)
3	0.02 (-0.03, 0.06)	0.00 (-0.01, 0.02)	0.01 (-0.01, 0.03)	-0.01 (-0.22, 0.20)	0.0000 (-0.0043, 0.0045)
4	0.05 (0.00, 0.10)	0.01 (-0.01, 0.03)	0.00 (-0.02, 0.03)	-0.02 (-0.23, 0.18)	0.0007 (-0.0040, 0.0056)
5	0.16 (0.12, 0.20)	0.02 (0.00, 0.04)	0.01 (-0.01, 0.03)	-0.02 (-0.22, 0.19)	0.0015 (-0.0028, 0.0059)
6	0.22 (0.18, 0.27)	0.04 (0.01, 0.06)	0.02 (-0.01, 0.05)	-0.01 (-0.22, 0.19)	0.0013 (-0.0035, 0.0062)
7	0.25 (0.20, 0.30)	0.06 (0.04, 0.08)	0.03 (0.01, 0.06)	-0.03 (-0.24, 0.18)	0.0012 (-0.0034, 0.0060)
9	0.33 (0.21, 0.45)	0.05 (0.00, 0.10)	0.03 (-0.02, 0.08)	-0.03 (-0.25, 0.18)	-0.0006 (-0.0114, 0.0095)
10	0.29 (0.14, 0.45)	0.04 (-0.02, 0.10)	0.02 (-0.03, 0.07)	-0.03 (-0.25, 0.19)	0.0010 (-0.0105, 0.0129)
11	0.17 (0.09, 0.26)	0.06 (0.02, 0.10)	0.04 (0.01, 0.08)	-0.03 (-0.25, 0.19)	0.0015 (-0.0073, 0.0103)
12	0.15 (0.09, 0.22)	0.03 (0.00, 0.07)	0.01 (-0.03, 0.04)	-0.02 (-0.23, 0.19)	0.0007 (-0.0062, 0.0075)
13	0.25 (0.18, 0.32)	0.05 (0.01, 0.08)	0.04 (0.00, 0.07)	-0.03 (-0.25, 0.18)	0.0007 (-0.0061, 0.0077)
14	0.28 (0.21, 0.34)	0.05 (0.01, 0.08)	0.04 (0.00, 0.07)	-0.03 (-0.24, 0.17)	0.0010 (-0.0050, 0.0071)
15	0.08 (0.03, 0.12)	0.02 (0.00, 0.04)	0.02 (0.00, 0.04)	-0.04 (-0.24, 0.16)	0.0005 (-0.0040, 0.0049)
16	0.28 (0.20, 0.35)	0.05 (0.01, 0.09)	0.03 (0.00, 0.07)	-0.06 (-0.26, 0.15)	0.0000 (-0.0070, 0.0069)

Site number	Climate variables				
	Air temperature	Air temperature 3 days previous	Air temperature 5 days previous	Precipitation > 3 mm	Solar radiation
17	0.09 (0.03, 0.14)	0.02 (-0.01, 0.05)	0.01 (-0.01, 0.04)	-0.06 (-0.26, 0.14)	-0.0001 (-0.0055, 0.0052)
18	0.27 (0.22, 0.32)	0.06 (0.03, 0.08)	0.04 (0.01, 0.07)	-0.07 (-0.27, 0.13)	0.0012 (-0.0032, 0.0057)
19	0.36 (0.30, 0.41)	0.08 (0.04, 0.11)	0.05 (0.02, 0.09)	-0.09 (-0.31, 0.12)	0.0010 (-0.0040, 0.0060)
20	0.39 (0.25, 0.52)	0.05 (0.00, 0.09)	0.02 (-0.03, 0.06)	-0.06 (-0.27, 0.14)	-0.0068 (-0.0209, 0.0063)
21	0.11 (0.03, 0.19)	0.03 (0.00, 0.07)	0.03 (-0.01, 0.06)	-0.05 (-0.25, 0.15)	-0.0004 (-0.0089, 0.0082)
22	0.02 (-0.12, 0.17)	0.03 (-0.03, 0.09)	0.01 (-0.04, 0.07)	-0.06 (-0.27, 0.14)	-0.0015 (-0.0122, 0.0099)
23	0.06 (-0.07, 0.18)	0.02 (-0.03, 0.06)	0.01 (-0.03, 0.06)	-0.01 (-0.25, 0.23)	-0.0003 (-0.0139, 0.0138)
24	0.12 (0.00, 0.25)	0.02 (-0.03, 0.07)	0.03 (-0.02, 0.07)	-0.05 (-0.26, 0.16)	0.0009 (-0.0133, 0.0156)
25	0.06 (-0.04, 0.16)	0.02 (-0.02, 0.06)	0.01 (-0.03, 0.05)	-0.05 (-0.26, 0.16)	0.0002 (-0.0101, 0.0106)
26	0.04 (-0.06, 0.14)	0.02 (-0.02, 0.06)	0.01 (-0.03, 0.05)	-0.06 (-0.26, 0.15)	-0.0006 (-0.0108, 0.0088)
27	0.07 (-0.03, 0.17)	0.01 (-0.03, 0.05)	0.02 (-0.02, 0.06)	-0.06 (-0.27, 0.16)	0.0012 (-0.0089, 0.0112)
28	0.11 (0.06, 0.17)	0.02 (-0.01, 0.04)	0.01 (-0.01, 0.04)	-0.05 (-0.25, 0.15)	0.0012 (-0.0040, 0.0065)
29	0.19 (0.13, 0.25)	0.03 (0.00, 0.06)	0.02 (-0.01, 0.04)	-0.05 (-0.25, 0.15)	0.0013 (-0.0045, 0.0071)
30	0.21 (0.14, 0.28)	0.04 (0.00, 0.07)	0.02 (-0.01, 0.06)	-0.08 (-0.29, 0.13)	0.0009 (-0.0068, 0.0083)
31	0.30 (0.24, 0.36)	0.02 (-0.01, 0.06)	0.03 (0.00, 0.07)	-0.09 (-0.30, 0.12)	0.0024 (-0.0038, 0.0087)
32	0.36 (0.30, 0.41)	0.05 (0.02, 0.08)	0.03 (0.00, 0.06)	-0.09 (-0.31, 0.11)	0.0028 (-0.0023, 0.0080)
33	0.19 (0.13, 0.24)	0.03 (0.00, 0.06)	0.02 (-0.01, 0.05)	-0.08 (-0.28, 0.13)	0.0010 (-0.0042, 0.0064)
34	0.29 (0.22, 0.35)	0.05 (0.02, 0.09)	0.03 (-0.01, 0.06)	-0.07 (-0.27, 0.15)	0.0041 (-0.0022, 0.0106)
35	0.20 (0.07, 0.33)	0.05 (0.00, 0.10)	0.02 (-0.03, 0.07)	-0.07 (-0.29, 0.15)	0.0037 (-0.0102, 0.0176)
36	0.01 (-0.05, 0.05)	0.00 (-0.02, 0.02)	0.00 (-0.02, 0.03)	0.02 (-0.24, 0.27)	0.0000 (-0.0050, 0.0050)
37	0.06 (-0.01, 0.12)	0.00 (-0.04, 0.03)	0.00 (-0.03, 0.04)	0.00 (-0.28, 0.28)	-0.0006 (-0.0075, 0.0063)
38	0.12 (0.06, 0.19)	0.02 (-0.01, 0.05)	0.02 (-0.01, 0.05)	0.01 (-0.26, 0.28)	0.0009 (-0.0058, 0.0074)

Site number	Climate variables				
	Air temperature	Air temperature 3 days previous	Air temperature 5 days previous	Precipitation > 3 mm	Solar radiation
39	0.35 (0.25, 0.44)	0.06 (0.02, 0.11)	0.03 (-0.01, 0.08)	-0.07 (-0.28, 0.14)	0.0041 (-0.0033, 0.0118)
40	0.08 (0.03, 0.13)	0.02 (0.00, 0.04)	0.01 (-0.02, 0.03)	-0.07 (-0.28, 0.14)	-0.0004 (-0.0054, 0.0047)
41	0.11 (0.05, 0.16)	0.03 (0.01, 0.06)	0.01 (-0.02, 0.04)	-0.08 (-0.29, 0.13)	0.0003 (-0.0051, 0.0057)
42	0.14 (0.03, 0.25)	0.04 (-0.01, 0.09)	0.01 (-0.04, 0.05)	-0.08 (-0.29, 0.14)	0.0023 (-0.0080, 0.0128)
43	0.23 (0.17, 0.29)	0.04 (0.01, 0.07)	0.03 (-0.01, 0.06)	-0.09 (-0.30, 0.11)	0.0020 (-0.0038, 0.0080)
44	0.24 (0.12, 0.36)	0.03 (-0.02, 0.09)	0.02 (-0.03, 0.06)	-0.08 (-0.30, 0.13)	0.0035 (-0.0066, 0.0136)
45	0.26 (0.19, 0.33)	0.05 (0.01, 0.08)	0.03 (0.00, 0.07)	-0.11 (-0.34, 0.12)	0.0019 (-0.0050, 0.0089)
46	0.01 (-0.04, 0.06)	0.00 (-0.02, 0.03)	0.01 (-0.02, 0.03)	0.01 (-0.24, 0.27)	0.0001 (-0.0052, 0.0056)
47	0.03 (-0.03, 0.09)	0.00 (-0.03, 0.03)	0.01 (-0.02, 0.03)	0.02 (-0.25, 0.28)	0.0006 (-0.0055, 0.0069)
48	0.29 (0.18, 0.39)	0.06 (0.01, 0.11)	0.03 (-0.02, 0.08)	-0.03 (-0.24, 0.19)	0.0016 (-0.0086, 0.0114)
49	0.26 (0.18, 0.33)	0.04 (0.01, 0.08)	0.01 (-0.03, 0.05)	-0.03 (-0.25, 0.17)	0.0004 (-0.0067, 0.0072)
50	0.30 (0.23, 0.36)	0.05 (0.01, 0.08)	0.03 (0.00, 0.06)	-0.04 (-0.25, 0.18)	-0.0003 (-0.0064, 0.0061)
51	0.33 (0.20, 0.46)	0.04 (-0.01, 0.10)	0.04 (-0.01, 0.09)	-0.03 (-0.24, 0.18)	-0.0005 (-0.0133, 0.0127)
52	0.19 (0.08, 0.30)	0.05 (0.01, 0.11)	0.03 (-0.02, 0.07)	-0.08 (-0.30, 0.14)	0.0016 (-0.0090, 0.0121)
53	0.10 (0.05, 0.15)	0.02 (-0.01, 0.04)	0.00 (-0.03, 0.03)	-0.07 (-0.27, 0.13)	0.0007 (-0.0042, 0.0055)
54	0.31 (0.26, 0.36)	0.04 (0.01, 0.07)	0.02 (-0.01, 0.05)	-0.08 (-0.29, 0.12)	0.0020 (-0.0026, 0.0067)
55	0.38 (0.32, 0.44)	0.04 (0.01, 0.07)	0.02 (-0.01, 0.05)	0.01 (-0.25, 0.27)	0.0033 (-0.0023, 0.0087)
56	0.35 (0.24, 0.45)	0.07 (0.02, 0.12)	0.04 (0.00, 0.09)	-0.08 (-0.29, 0.14)	0.0031 (-0.0070, 0.0133)
57	0.01 (-0.05, 0.06)	0.00 (-0.02, 0.02)	0.00 (-0.03, 0.02)	-0.01 (-0.70, 0.62)	0.0001 (-0.0053, 0.0055)
58	0.05 (-0.04, 0.13)	0.01 (-0.02, 0.05)	0.01 (-0.03, 0.04)	-0.08 (-0.29, 0.14)	0.0007 (-0.0081, 0.0090)
59	0.32 (0.22, 0.43)	0.06 (0.01, 0.11)	0.03 (-0.01, 0.08)	-0.03 (-0.25, 0.19)	0.0019 (-0.0079, 0.0117)
60	0.12 (0.08, 0.17)	0.03 (0.00, 0.05)	0.02 (-0.01, 0.04)	-0.09 (-0.31, 0.13)	-0.0021 (-0.0065, 0.0024)

Site number	Climate variables				
	Air temperature	Air temperature 3 days previous	Air temperature 5 days previous	Precipitation > 3 mm	Solar radiation
61	0.10 (-0.02, 0.21)	0.05 (0.00, 0.10)	0.03 (-0.02, 0.07)	-0.11 (-0.35, 0.13)	-0.0029 (-0.0139, 0.0074)
62	0.17 (0.10, 0.24)	0.05 (0.01, 0.09)	0.03 (-0.01, 0.06)	-0.09 (-0.33, 0.15)	-0.0025 (-0.0092, 0.0044)
63	0.19 (0.12, 0.27)	0.05 (0.01, 0.08)	0.01 (-0.03, 0.04)	-0.1 (-0.33, 0.14)	-0.0009 (-0.0085, 0.0065)
64	0.25 (0.20, 0.29)	0.05 (0.03, 0.08)	0.02 (0.00, 0.05)	-0.11 (-0.33, 0.11)	0.0005 (-0.0039, 0.0048)
65	0.32 (0.19, 0.44)	0.06 (0.01, 0.11)	0.05 (0.00, 0.09)	-0.11 (-0.35, 0.13)	0.0038 (-0.0067, 0.0142)
66	0.31 (0.23, 0.38)	0.07 (0.03, 0.11)	0.03 (-0.01, 0.06)	-0.05 (-0.26, 0.16)	-0.0029 (-0.0100, 0.0039)
67	0.18 (0.05, 0.32)	0.04 (-0.01, 0.09)	0.02 (-0.02, 0.06)	-0.05 (-0.26, 0.15)	0.0011 (-0.0117, 0.0144)
68	0.27 (0.18, 0.37)	0.05 (0.01, 0.10)	0.03 (-0.01, 0.08)	-0.03 (-0.24, 0.18)	-0.0029 (-0.0118, 0.0056)
69	0.13 (0.08, 0.17)	0.01 (-0.01, 0.04)	0.01 (-0.02, 0.03)	-0.03 (-0.23, 0.17)	0.0009 (-0.0037, 0.0056)
70	0.22 (0.15, 0.30)	0.04 (0.00, 0.08)	0.02 (-0.02, 0.06)	-0.06 (-0.27, 0.14)	-0.0001 (-0.0075, 0.0074)
71	0.32 (0.24, 0.39)	0.06 (0.02, 0.10)	0.05 (0.01, 0.08)	-0.05 (-0.25, 0.15)	0.0026 (-0.0043, 0.0095)
72	0.40 (0.32, 0.49)	0.07 (0.02, 0.11)	0.04 (0.00, 0.08)	-0.05 (-0.26, 0.16)	0.0027 (-0.0050, 0.0104)
73	0.40 (0.34, 0.46)	0.06 (0.02, 0.09)	0.03 (-0.01, 0.06)	-0.06 (-0.26, 0.15)	0.0033 (-0.0017, 0.0085)
74	0.23 (0.11, 0.35)	0.06 (0.01, 0.11)	0.01 (-0.03, 0.06)	-0.08 (-0.29, 0.14)	0.0015 (-0.0091, 0.0121)
75	0.05 (-0.04, 0.15)	0.01 (-0.04, 0.05)	0.03 (-0.02, 0.07)	-0.09 (-0.31, 0.13)	-0.0006 (-0.0095, 0.0082)
76	0.16 (0.10, 0.22)	0.03 (0.00, 0.07)	0.01 (-0.03, 0.04)	-0.09 (-0.30, 0.11)	0.0014 (-0.0042, 0.0070)
77	0.29 (0.24, 0.35)	0.06 (0.03, 0.09)	0.02 (-0.02, 0.05)	-0.07 (-0.27, 0.14)	0.0034 (-0.002, 0.0092)
78	0.32 (0.24, 0.39)	0.06 (0.03, 0.10)	0.02 (-0.01, 0.06)	-0.08 (-0.30, 0.12)	0.0036 (-0.0032, 0.0105)
79	0.32 (0.19, 0.47)	0.05 (0.00, 0.10)	0.02 (-0.03, 0.07)	-0.08 (-0.30, 0.14)	0.0043 (-0.0095, 0.0181)
80	0.35 (0.21, 0.49)	0.07 (0.02, 0.13)	0.04 (-0.01, 0.09)	-0.10 (-0.34, 0.14)	0.0087 (-0.0056, 0.0222)
81	0.07 (-0.06, 0.21)	0.03 (-0.02, 0.07)	0.02 (-0.02, 0.06)	-0.10 (-0.35, 0.13)	0.0007 (-0.0136, 0.015)
82	0.14 (0.03, 0.24)	0.06 (0.01, 0.11)	0.01 (-0.04, 0.05)	-0.10 (-0.34, 0.13)	-0.0004 (-0.0113, 0.0101)

Site number	Climate variables				
	Air temperature	Air temperature 3 days previous	Air temperature 5 days previous	Precipitation > 3 mm	Solar radiation
83	0.08 (0.02, 0.15)	0.03 (0.00, 0.06)	0.01 (-0.02, 0.04)	-0.11 (-0.34, 0.13)	-0.0011 (-0.0077, 0.0056)
84	0.19 (0.13, 0.24)	0.06 (0.03, 0.09)	0.02 (-0.01, 0.04)	-0.12 (-0.35, 0.11)	0.0003 (-0.0050, 0.0056)
85	0.06 (-0.04, 0.16)	0.04 (0.00, 0.08)	0.00 (-0.04, 0.04)	-0.10 (-0.33, 0.15)	-0.0002 (-0.0104, 0.0099)
86	0.21 (0.10, 0.31)	0.05 (0.00, 0.1)	0.02 (-0.02, 0.07)	-0.11 (-0.35, 0.13)	0.0024 (-0.0082, 0.0130)
87	0.26 (0.20, 0.32)	0.05 (0.02, 0.09)	0.02 (-0.01, 0.05)	-0.12 (-0.35, 0.11)	0.0014 (-0.0044, 0.0072)
88	0.14 (0.07, 0.20)	0.03 (0.00, 0.07)	0.03 (0.00, 0.06)	-0.06 (-0.27, 0.15)	0.0007 (-0.0056, 0.0068)
89	0.32 (0.23, 0.40)	0.06 (0.02, 0.11)	0.05 (0.01, 0.09)	-0.06 (-0.27, 0.15)	0.0020 (-0.0044, 0.0086)
90	0.40 (0.31, 0.48)	0.08 (0.04, 0.13)	0.07 (0.02, 0.11)	-0.05 (-0.26, 0.15)	0.0025 (-0.0047, 0.0096)
91	-0.07 (-0.20, 0.06)	0.01 (-0.04, 0.07)	0.01 (-0.04, 0.06)	-0.05 (-0.25, 0.17)	0.0017 (-0.0092, 0.0125)
92	0.14 (0.06, 0.22)	0.03 (-0.01, 0.07)	0.03 (-0.01, 0.07)	-0.05 (-0.26, 0.17)	0.0011 (-0.0066, 0.0091)
93	0.13 (0.06, 0.21)	0.02 (-0.01, 0.06)	0.00 (-0.04, 0.03)	-0.04 (-0.24, 0.16)	0.0030 (-0.0038, 0.0099)
94	0.24 (0.19, 0.30)	0.04 (0.01, 0.07)	0.01 (-0.02, 0.04)	-0.03 (-0.23, 0.17)	0.0040 (-0.0012, 0.0092)
95	0.33 (0.22, 0.44)	0.06 (0.01, 0.10)	0.04 (0.00, 0.09)	-0.05 (-0.26, 0.16)	0.0037 (-0.0067, 0.0138)
96	0.02 (-0.04, 0.09)	0.01 (-0.02, 0.04)	0.01 (-0.02, 0.04)	-0.05 (-0.25, 0.15)	-0.0003 (-0.0072, 0.0065)
97	0.03 (-0.05, 0.11)	0.01 (-0.03, 0.04)	0.01 (-0.02, 0.04)	-0.06 (-0.26, 0.14)	0.0002 (-0.0080, 0.0088)
98	0.29 (0.24, 0.34)	0.04 (0.01, 0.07)	0.01 (-0.02, 0.04)	-0.03 (-0.23, 0.18)	0.0040 (-0.0009, 0.0090)
99	0.21 (0.16, 0.26)	0.04 (0.01, 0.06)	0.02 (-0.01, 0.04)	-0.05 (-0.25, 0.14)	0.0017 (-0.0032, 0.0066)
100	0.20 (0.11, 0.29)	0.02 (-0.01, 0.06)	0.02 (-0.02, 0.05)	-0.06 (-0.27, 0.14)	0.0006 (-0.0079, 0.0095)
101	0.07 (-0.05, 0.20)	0.02 (-0.02, 0.07)	0.02 (-0.03, 0.06)	-0.05 (-0.26, 0.16)	-0.0003 (-0.0143, 0.0133)
102	0.05 (-0.02, 0.11)	0.01 (-0.02, 0.04)	0.02 (-0.01, 0.05)	0.00 (-0.24, 0.23)	0.0003 (-0.0063, 0.0068)
103	0.37 (0.28, 0.46)	0.07 (0.03, 0.12)	0.04 (0.00, 0.09)	-0.07 (-0.27, 0.14)	-0.0002 (-0.0079, 0.0078)
104	0.29 (0.15, 0.44)	0.03 (-0.03, 0.08)	0.04 (-0.01, 0.09)	-0.06 (-0.27, 0.16)	0.0004 (-0.0128, 0.0134)

Site number	Climate variables				
	Air temperature	Air temperature 3 days previous	Air temperature 5 days previous	Precipitation > 3 mm	Solar radiation
105	0.29 (0.19, 0.39)	0.03 (-0.02, 0.07)	-0.01 (-0.05, 0.03)	-0.05 (-0.26, 0.16)	0.0002 (-0.0099, 0.0108)
106	0.25 (0.14, 0.37)	0.04 (-0.01, 0.09)	0.04 (-0.01, 0.08)	-0.06 (-0.27, 0.15)	0.0000 (-0.0107, 0.0105)

Appendix G. Mean summer water temperature for three future time periods (by site).

The top number in each cell is the predicted mean summer water temperature and the numbers in parentheses are the corresponding 95% credible interval. We expect predicted increases in water temperature to be conservative with this model because upwards shifts (or other changes) in the seasonal trend curve are not modeled.

Our predictions for the Current River P1 and Roubidoux Creek P1 sites should be further explored and not used as listed due to the pattern of seasonal trend that was counter to the other sites.

Site name	2040 – 2044	2060 – 2064	2085 – 2089
BARREN FORK_P1	15.67 (15.53, 15.82)	15.76 (15.59, 15.96)	15.81 (15.66, 16.01)
BARREN FORK_P2	19.49 (19.31, 19.77)	19.77 (19.53, 19.99)	19.91 (19.68, 20.14)
BENNETT SPRING BRANCH_P1	14.40 (14.35, 14.47)	14.41 (14.35, 14.46)	14.43 (14.36, 14.49)
BENNETT SPRING BRANCH_P2	15.13 (15.05, 15.25)	15.21 (15.15, 15.27)	15.25 (15.19, 15.31)
BLUE SPRING CREEK_P1	17.30 (17.15, 17.54)	17.52 (17.41, 17.66)	17.62 (17.46, 17.80)
BLUE SPRING CREEK_P1A	19.22 (18.90, 19.67)	19.54 (19.25, 19.83)	19.70 (19.31, 20.09)
BLUE SPRING CREEK_P2	20.36 (20.11, 20.75)	20.83 (20.61, 21.06)	21.02 (20.70, 21.36)
CAPPS CREEK_P2	22.22 (21.75, 22.88)	22.57 (21.95, 23.23)	22.73 (22.32, 23.24)
CAPPS CREEK_P3	21.83 (21.19, 22.62)	22.13 (21.43, 22.90)	22.28 (21.70, 22.91)
CAPPS CREEK_P4	17.44 (17.14, 17.86)	17.71 (17.30, 18.18)	17.73 (17.39, 18.14)
CAPPS CREEK_P5	18.46 (18.16, 18.87)	18.64 (18.32, 18.99)	18.74 (18.50, 19.03)
CAPPS CREEK_P5A	19.65 (19.29, 20.16)	20.00 (19.56, 20.44)	20.09 (19.74, 20.47)
CAPPS CREEK_P6	19.90 (19.54, 20.48)	20.26 (19.77, 20.69)	20.42 (20.19, 20.68)
CRANE CREEK_P1	16.33 (16.15, 16.61)	16.42 (16.35, 16.51)	16.51 (16.43, 16.60)
CRANE CREEK_P2	18.41 (18.05, 18.91)	18.76 (18.26, 19.21)	18.91 (18.57, 19.27)
CRANE CREEK_P3	16.02 (15.75, 16.39)	16.12 (15.84, 16.36)	16.23 (16.07, 16.40)

Site name	2040 – 2044	2060 – 2064	2085 – 2089
CRANE CREEK_P4	19.70 (19.34, 20.25)	20.07 (19.67, 20.43)	20.20 (19.89, 20.52)
CRANE CREEK_P5	21.39 (21.02, 21.96)	21.88 (21.35, 22.36)	22.04 (21.63, 22.48)
CRANE CREEK_P6	21.55 (21.04, 22.20)	21.89 (21.29, 22.59)	22.11 (21.54, 22.78)
CRANE CREEK_P7	16.56 (16.22, 16.95)	16.71 (16.31, 17.15)	16.77 (16.36, 17.21)
CURRENT RIVER_P1	19.75 (19.29, 20.18)	19.81 (19.29, 20.35)	19.79 (19.20, 20.37)
CURRENT RIVER_P2	13.56 (13.21, 13.97)	13.63 (13.19, 14.07)	13.67 (13.15, 14.16)
CURRENT RIVER_P2A	16.13 (15.82, 16.55)	16.31 (15.89, 16.81)	16.38 (15.96, 16.93)
CURRENT RIVER_P2B	14.98 (14.74, 15.27)	15.06 (14.75, 15.39)	15.08 (14.74, 15.46)
CURRENT RIVER_P2C	14.59 (14.34, 14.86)	14.65 (14.32, 14.97)	14.66 (14.34, 15.02)
CURRENT RIVER_P3	15.52 (15.26, 15.83)	15.59 (15.28, 15.92)	15.63 (15.31, 16.00)
CURRENT RIVER_P4	16.58 (16.42, 16.82)	16.72 (16.60, 16.85)	16.80 (16.66, 16.95)
CURRENT RIVER_P4A	17.89 (17.64, 18.28)	18.16 (17.89, 18.47)	18.29 (17.95, 18.66)
CURRENT RIVER_P4B	18.69 (18.41, 19.07)	18.99 (18.68, 19.33)	19.15 (18.81, 19.51)
CURRENT RIVER_P5	20.36 (20.01, 20.91)	20.71 (20.35, 21.10)	20.90 (20.56, 21.31)
CURRENT RIVER_P6	22.44 (22.04, 23.05)	22.93 (22.54, 23.31)	23.13 (22.77, 23.52)
CURRENT RIVER_P7	18.24 (18.04, 18.54)	18.49 (18.27, 18.70)	18.58 (18.36, 18.82)
CURRENT RIVER_P8	20.74 (20.41, 21.20)	21.11 (20.81, 21.38)	21.27 (20.97, 21.60)
CURRENT RIVER_P9	19.08 (18.63, 19.69)	19.39 (18.80, 20.04)	19.51 (18.93, 20.21)
DEWITT-WILKINS SPRING_P1	13.58 (13.49, 13.66)	13.57 (13.46, 13.68)	13.57 (13.43, 13.71)
DEWITT-WILKINS SPRING_P2	15.71 (15.49, 15.92)	15.81 (15.56, 16.09)	15.86 (15.61, 16.13)

Site name	2040 – 2044	2060 – 2064	2085 – 2089
DEWITT-WILKINS SPRING_P3	16.41 (16.19, 16.71)	16.60 (16.36, 16.86)	16.69 (16.42, 17.02)
ELEVEN POINT RIVER_P1	23.83 (23.40, 24.51)	24.25 (23.70, 24.73)	24.44 (23.98, 24.95)
ELEVEN POINT RIVER_P2	16.54 (16.47, 16.63)	16.62 (16.52, 16.72)	16.68 (16.59, 16.78)
ELEVEN POINT RIVER_P3	17.81 (17.62, 18.05)	17.95 (17.71, 18.15)	18.01 (17.80, 18.23)
ELEVEN POINT RIVER_P4	19.18 (18.84, 19.61)	19.35 (18.96, 19.75)	19.40 (19.04, 19.83)
ELEVEN POINT RIVER_P5	20.33 (20.09, 20.70)	20.63 (20.34, 20.86)	20.71 (20.47, 20.97)
ELEVEN POINT RIVER_P6	21.50 (21.10, 22.05)	21.77 (21.31, 22.25)	21.88 (21.48, 22.40)
ELEVEN POINT RIVER_P7	21.27 (21.02, 21.67)	21.61 (21.30, 21.84)	21.70 (21.43, 21.99)
GREER SPRING BRANCH_P1	14.31 (14.29, 14.35)	14.32 (14.29, 14.34)	14.31 (14.28, 14.34)
GREER SPRING BRANCH_P2	15.22 (15.14, 15.33)	15.24 (15.17, 15.30)	15.23 (15.15, 15.29)
HICKORY CREEK_P1	20.00 (19.55, 20.59)	20.33 (19.76, 20.91)	20.47 (20.08, 20.94)
HICKORY CREEK_P1A	19.87 (19.56, 20.29)	20.17 (19.76, 20.60)	20.27 (19.94, 20.61)
HICKORY CREEK_P3	20.57 (20.26, 21.01)	20.91 (20.48, 21.33)	21.07 (20.82, 21.37)
HICKORY CREEK_P4	21.51 (21.03, 22.16)	21.88 (21.24, 22.55)	22.07 (21.59, 22.63)
LITTLE PINEY CREEK_P1	18.66 (18.24, 19.25)	18.94 (18.52, 19.34)	19.14 (18.75, 19.55)
LITTLE PINEY CREEK_P2	16.23 (16.08, 16.44)	16.39 (16.26, 16.52)	16.46 (16.29, 16.65)
LITTLE PINEY CREEK_P3	20.65 (20.32, 21.18)	21.08 (20.79, 21.33)	21.31 (21.01, 21.62)
LITTLE PINEY CREEK_P4	22.44 (22.06, 23.04)	22.97 (22.67, 23.26)	23.23 (22.91, 23.57)
LITTLE PINEY CREEK_P5	23.88 (23.46, 24.52)	24.39 (23.94, 24.84)	24.65 (24.15, 25.22)
MARAMEC SPRING BRANCH_P1	13.96 (13.93, 13.98)	13.97 (13.95, 13.98)	13.97 (13.95, 13.99)

Site name	2040 – 2044	2060 – 2064	2085 – 2089
MARAMEC SPRING BRANCH_P2	14.30 (14.11, 14.55)	14.33 (14.11, 14.54)	14.35 (14.14, 14.57)
MERAMEC RIVER_P1	25.10 (24.69, 25.73)	25.58 (25.14, 26.01)	25.81 (25.33, 26.36)
MERAMEC RIVER_P2	17.97 (17.81, 18.17)	18.13 (17.95, 18.33)	18.25 (18.05, 18.48)
MERAMEC RIVER_P3	18.57 (18.26, 18.97)	18.72 (18.34, 19.13)	18.85 (18.45, 19.30)
MERAMEC RIVER_P3AA	19.14 (18.76, 19.62)	19.37 (18.93, 19.84)	19.54 (19.05, 20.06)
MERAMEC RIVER_P3AAA	19.64 (19.27, 20.13)	19.90 (19.48, 20.35)	20.04 (19.59, 20.59)
MERAMEC RIVER_P4	20.80 (20.54, 21.20)	21.18 (20.95, 21.37)	21.36 (21.05, 21.70)
MERAMEC RIVER_P5	22.18 (21.75, 22.80)	22.69 (22.21, 23.18)	22.87 (22.30, 23.53)
MILL CREEK_P1	21.21 (20.83, 21.82)	21.61 (21.26, 21.94)	21.91 (21.56, 22.30)
MILL CREEK_P10	17.63 (17.24, 18.18)	17.88 (17.42, 18.41)	18.01 (17.50, 18.66)
MILL CREEK_P1A	21.65 (21.25, 22.25)	22.05 (21.58, 22.49)	22.31 (21.86, 22.85)
MILL CREEK_P2	16.43 (16.26, 16.68)	16.64 (16.48, 16.77)	16.73 (16.57, 16.90)
MILL CREEK_P2A	18.52 (18.17, 18.98)	18.79 (18.39, 19.21)	18.93 (18.50, 19.45)
MILL CREEK_P3	20.18 (19.77, 20.80)	20.67 (20.24, 21.05)	20.86 (20.39, 21.32)
MILL CREEK_P3A	21.89 (21.42, 22.56)	22.43 (21.98, 22.89)	22.70 (22.17, 23.27)
MILL CREEK_P4	23.04 (22.63, 23.68)	23.64 (23.18, 24.03)	23.89 (23.40, 24.42)
NIANGUA RIVER_P1	24.36 (23.88, 24.99)	24.65 (24.21, 25.15)	24.82 (24.40, 25.31)
NIANGUA RIVER_P2	19.07 (18.73, 19.47)	19.14 (18.80, 19.49)	19.20 (18.80, 19.58)
NIANGUA RIVER_P3	20.38 (20.10, 20.73)	20.62 (20.42, 20.85)	20.78 (20.60, 20.96)
NIANGUA RIVER_P3A	21.54 (21.14, 22.08)	21.94 (21.62, 22.31)	22.14 (21.74, 22.56)

Site name	2040 – 2044	2060 – 2064	2085 – 2089
NIANGUA RIVER_P4	22.46 (22.13, 22.93)	22.88 (22.59, 23.18)	23.10 (22.86, 23.35)
NIANGUA RIVER_P5	22.72 (22.21, 23.45)	23.13 (22.64, 23.68)	23.31 (22.75, 23.95)
NORTH FORK OF WHITE RIVER_P1	23.43 (22.94, 24.14)	23.90 (23.25, 24.58)	24.00 (23.36, 24.70)
NORTH FORK OF WHITE RIVER_P2	14.60 (14.27, 14.96)	14.71 (14.28, 15.19)	14.72 (14.30, 15.21)
NORTH FORK OF WHITE RIVER_P3	20.14 (19.85, 20.51)	20.31 (19.94, 20.70)	20.37 (20.00, 20.77)
NORTH FORK OF WHITE RIVER_P4	16.59 (16.47, 16.78)	16.64 (16.54, 16.76)	16.74 (16.65, 16.84)
NORTH FORK OF WHITE RIVER_P5	20.10 (19.90, 20.42)	20.32 (20.08, 20.55)	20.44 (20.24, 20.66)
NORTH FORK OF WHITE RIVER_P6	16.40 (16.13, 16.73)	16.46 (16.12, 16.84)	16.47 (16.16, 16.85)
NORTH FORK OF WHITE RIVER_P7	21.02 (20.66, 21.52)	21.26 (20.83, 21.74)	21.37 (20.98, 21.81)
NORTH FORK OF WHITE RIVER_P8	21.23 (20.97, 21.69)	21.53 (21.15, 21.87)	21.66 (21.36, 21.98)
ROARING RIVER_P1	16.93 (16.69, 17.26)	17.10 (16.83, 17.37)	17.17 (16.98, 17.37)
ROARING RIVER_P2	20.24 (19.86, 20.81)	20.64 (20.16, 21.15)	20.80 (20.53, 21.12)
ROARING RIVER_P3	22.02 (21.56, 22.70)	22.57 (21.94, 23.23)	22.73 (22.29, 23.20)
ROUBIDOUX CREEK_P1	19.68 (19.32, 20.05)	19.61 (19.20, 20.03)	19.60 (19.10, 20.07)
ROUBIDOUX CREEK_P2	18.66 (18.36, 19.06)	18.83 (18.56, 19.13)	19.00 (18.73, 19.30)
ROUBIDOUX CREEK_P4	19.39 (19.04, 19.86)	19.63 (19.28, 19.99)	19.77 (19.41, 20.14)
ROUBIDOUX CREEK_P5	20.39 (20.06, 20.85)	20.72 (20.41, 21.05)	20.94 (20.68, 21.26)
ROUBIDOUX CREEK_P6	21.82 (21.37, 22.48)	22.26 (21.81, 22.71)	22.51 (22.07, 23.03)
ROUBIDOUX SPRING BRANCH_P1	16.04 (15.84, 16.26)	16.05 (15.83, 16.29)	16.05 (15.83, 16.27)
SPRING CREEK PHELPS_P1	14.34 (14.15, 14.57)	14.36 (14.13, 14.60)	14.37 (14.17, 14.59)

Site name	2040 – 2044	2060 – 2064	2085 – 2089
SPRING CREEK PHELPS_P2	20.43 (20.09, 21.00)	20.94 (20.66, 21.21)	21.14 (20.82, 21.51)
SPRING CREEK PHELPS_P3	19.23 (18.99, 19.59)	19.52 (19.24, 19.77)	19.66 (19.38, 19.98)
SPRING CREEK PHELPS_P8	18.00 (17.66, 18.47)	18.23 (17.81, 18.68)	18.37 (17.90, 18.95)
SPRING CREEK PHELPS_P9	14.58 (14.28, 15.00)	14.69 (14.24, 15.17)	14.77 (14.27, 15.30)
SPRING CREEK-STONE_P1	14.73 (14.49, 14.99)	14.77 (14.50, 15.04)	14.77 (14.51, 15.04)
SPRING CREEK-STONE_P2	21.16 (20.66, 21.83)	21.59 (20.97, 22.22)	21.75 (21.24, 22.31)
SPRING CREEK-STONE_P2A	20.51 (20.05, 21.15)	20.83 (20.29, 21.48)	20.95 (20.42, 21.57)
SPRING CREEK-STONE_P3	20.01 (19.57, 20.55)	20.27 (19.77, 20.81)	20.38 (19.90, 20.92)
SPRING CREEK-STONE_P4	18.33 (17.88, 18.88)	18.61 (18.10, 19.21)	18.72 (18.22, 19.34)

Appendix H: Number of 24-hour periods above 21.1°C (70°F) per summer (by site).

For 2002 – 2014, the number in the cell is an estimate of the average number of 24-hour periods above 21.1°C (70°F) per summer. It is calculated based on the observed days, accounting for missing days. For example, if 5% of observed summer days were above 21.1°C, then it is assumed that 5% of unobserved summer days were also above 21.1°C. For future predictions, the top number in each cell is the number of 24-hour periods above 21.1°C per summer and the numbers in parentheses are the corresponding 95% credible interval. We expect predictions from this model to be conservative because upwards shifts (or other changes) in the seasonal trend curve are not modeled.

Site name	2002 – 2014	2040 – 2044	2060 – 2064	2085 – 2089
BARREN FORK_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
BARREN FORK_P2	0	0 (0, 0)	0 (0, 1)	0 (0, 0)
BENNETT SPRING BRANCH_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
BENNETT SPRING BRANCH_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
BLUE SPRING CREEK_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
BLUE SPRING CREEK_P1A	0	0 (0, 2)	0 (0, 2)	0 (0, 4)
BLUE SPRING CREEK_P2	1	4 (0, 35)	8 (0, 31)	10 (0, 33)
CAPPS CREEK_P2	32	40 (24, 61)	45 (26, 61)	49 (28, 64)
CAPPS CREEK_P3	33	33 (19, 51)	36 (19, 52)	37 (22, 54)
CAPPS CREEK_P4	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CAPPS CREEK_P5	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CAPPS CREEK_P5A	2	4 (0, 39)	4 (0, 21)	5 (0, 24)
CAPPS CREEK_P6	4	7 (0, 45)	8 (0, 28)	10 (0, 33)
CRANE CREEK_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CRANE CREEK_P2	0	0 (0, 4)	1 (0, 12)	1 (0, 10)
CRANE CREEK_P3	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CRANE CREEK_P4	3	6 (0, 52)	8 (0, 32)	8 (0, 39)
CRANE CREEK_P5	12	26 (10, 60)	34 (9, 54)	37 (12, 61)
CRANE CREEK_P6	10	6 (0, 23)	8 (0, 25)	9 (0, 24)
CRANE CREEK_P7	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P1	2	6 (1, 14)	6 (1, 15)	6 (1, 16)
CURRENT RIVER_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P2A	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P2B	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P2C	0	0 (0, 0)	0 (0, 0)	0 (0, 0)

CURRENT RIVER_P3	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P4	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P4A	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P4B	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P5	1	7 (0, 33)	11 (0, 30)	12 (0, 30)
CURRENT RIVER_P6	23	40 (18, 61)	46 (19, 61)	50 (22, 65)
CURRENT RIVER_P7	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
CURRENT RIVER_P8	5	15 (0, 42)	21 (0, 46)	23 (0, 47)
CURRENT RIVER_P9	0	2 (0, 17)	3 (0, 21)	3 (0, 20)
DEWITT-WILKINS SPRING_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
DEWITT-WILKINS SPRING_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
DEWITT-WILKINS SPRING_P3	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
ELEVEN POINT RIVER_P1	50	60 (47, 71)	63 (50, 72)	66 (51, 75)
ELEVEN POINT RIVER_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
ELEVEN POINT RIVER_P3	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
ELEVEN POINT RIVER_P4	0	2 (0, 10)	2 (0, 13)	3 (0, 14)
ELEVEN POINT RIVER_P5	0	5 (0, 30)	8 (0, 23)	7 (0, 24)
ELEVEN POINT RIVER_P6	21	26 (6, 52)	32 (8, 56)	33 (8, 57)
ELEVEN POINT RIVER_P7	11	22 (2, 51)	29 (2, 53)	32 (3, 56)
GREER SPRING BRANCH_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
GREER SPRING BRANCH_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
HICKORY CREEK_P1	4	5 (0, 26)	8 (0, 29)	9 (0, 31)
HICKORY CREEK_P1A	2	5 (0, 35)	8 (0, 25)	8 (0, 25)
HICKORY CREEK_P3	2	6 (0, 43)	9 (0, 29)	11 (0, 28)
HICKORY CREEK_P4	13	24 (6, 53)	30 (5, 54)	33 (9, 54)
LITTLE PINEY CREEK_P1	0	1 (0, 6)	1 (0, 6)	1 (0, 9)
LITTLE PINEY CREEK_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
LITTLE PINEY CREEK_P3	0	4 (0, 29)	5 (0, 15)	6 (0, 20)
LITTLE PINEY CREEK_P4	18	35 (19, 58)	43 (23, 56)	47 (22, 61)
LITTLE PINEY CREEK_P5	66	61 (51, 70)	65 (55, 71)	68 (59, 75)
MARAMEC SPRING BRANCH_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
MARAMEC SPRING BRANCH_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
MERAMEC RIVER_P1	71	68 (60, 75)	70 (64, 76)	72 (67, 77)

MERAMEC RIVER_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
MERAMEC RIVER_P3	0	0 (0, 4)	1 (0, 5)	1 (0, 5)
MERAMEC RIVER_P3AA	2	2 (0, 9)	2 (0, 9)	2 (0, 11)
MERAMEC RIVER_P3AAA	1	1 (0, 8)	1 (0, 9)	2 (0, 10)
MERAMEC RIVER_P4	6	15 (2, 49)	22 (2, 42)	24 (3, 46)
MERAMEC RIVER_P5	30	40 (22, 60)	48 (27, 63)	51 (35, 69)
MILL CREEK_P1	17	20 (7, 45)	27 (9, 45)	30 (11, 47)
MILL CREEK_P10	0	0 (0, 1)	0 (0, 1)	0 (0, 2)
MILL CREEK_P1A	31	29 (13, 53)	34 (16, 53)	39 (19, 57)
MILL CREEK_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
MILL CREEK_P2A	0	0 (0, 3)	0 (0, 4)	0 (0, 4)
MILL CREEK_P3	0	2 (0, 19)	5 (0, 20)	4 (0, 18)
MILL CREEK_P3A	11	13 (2, 47)	19 (3, 40)	23 (4, 42)
MILL CREEK_P4	24	37 (24, 57)	44 (31, 57)	48 (31, 61)
NIANGUA RIVER_P1	67	65 (54, 73)	67 (57, 74)	69 (60, 75)
NIANGUA RIVER_P2	2	1 (0, 6)	1 (0, 7)	1 (0, 7)
NIANGUA RIVER_P3	2	5 (0, 27)	6 (0, 21)	7 (0, 20)
NIANGUA RIVER_P3A	14	28 (13, 58)	35 (14, 53)	39 (15, 56)
NIANGUA RIVER_P4	30	40 (25, 62)	46 (28, 61)	49 (28, 62)
NIANGUA RIVER_P5	41	47 (30, 62)	52 (36, 65)	55 (39, 68)
NORTH FORK OF WHITE RIVER_P1	54	55 (40, 66)	59 (47, 68)	61 (49, 71)
NORTH FORK OF WHITE RIVER_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
NORTH FORK OF WHITE RIVER_P3	0	2 (0, 20)	4 (0, 25)	4 (0, 21)
NORTH FORK OF WHITE RIVER_P4	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
NORTH FORK OF WHITE RIVER_P5	0	0 (0, 2)	0 (0, 2)	0 (0, 1)
NORTH FORK OF WHITE RIVER_P6	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
NORTH FORK OF WHITE RIVER_P7	0	6 (0, 31)	9 (0, 33)	10 (0, 30)
NORTH FORK OF WHITE RIVER_P8	4	13 (0, 44)	19 (1, 41)	20 (1, 40)
ROARING RIVER_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
ROARING RIVER_P2	7	9 (0, 43)	12 (0, 32)	13 (1, 34)
ROARING RIVER_P3	16	27 (11, 58)	33 (11, 53)	36 (12, 58)
ROUBIDOUX CREEK_P1	4	6 (0, 15)	5 (0, 16)	5 (0, 16)
ROUBIDOUX CREEK_P2	0	0 (0, 0)	0 (0, 0)	0 (0, 1)

ROUBIDOUX CREEK_P4	0	0 (0, 4)	1 (0, 5)	1 (0, 8)
ROUBIDOUX CREEK_P5	4	5 (0, 30)	7 (0, 29)	9 (0, 34)
ROUBIDOUX CREEK_P6	20	32 (16, 54)	38 (16, 54)	42 (21, 58)
ROUBIDOUX SPRING BRANCH_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
SPRING CREEK PHELPS_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
SPRING CREEK PHELPS_P2	3	10 (0, 38)	14 (1, 31)	15 (2, 31)
SPRING CREEK PHELPS_P3	0	0 (0, 4)	1 (0, 7)	0 (0, 4)
SPRING CREEK PHELPS_P8	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
SPRING CREEK PHELPS_P9	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
SPRING CREEK-STONE_P1	0	0 (0, 0)	0 (0, 0)	0 (0, 0)
SPRING CREEK-STONE_P2	11	20 (6, 47)	25 (8, 48)	28 (8, 47)
SPRING CREEK-STONE_P2A	16	14 (3, 36)	18 (3, 38)	19 (4, 37)
SPRING CREEK-STONE_P3	3	4 (0, 20)	6 (0, 23)	6 (0, 21)
SPRING CREEK-STONE_P4	0	0 (0, 2)	0 (0, 2)	0 (0, 3)

Appendix I. Table of stream temperature collections in Missouri. The Pflieger size field is based on a classification by Pflieger (1989).

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MDC	Ozark Plateau	Niangua River	2002	2002	3	5	1290.50
MDC	Ozark Plateau	Niangua River	2002	2006	3	5	1290.50
MDC	Ozark Plateau	Niangua River	2004	2012	3	5	1204.56
MDC	Ozark Plateau	Niangua River	2002	2011	3	5	1190.16
MDC	Ozark Plateau	Niangua River	2002	2007	3	5	1141.31
MDC	Ozark Plateau	Niangua River	2002	2003	3	5	1025.99
MDC	Ozark Plateau	Bennett Spring	2002	2014	2	3	113.23
MDC	Ozark Plateau	Bennett Spring	2002	2014	2	3	110.46
MDC	Ozark Plateau	Bennett Spring	2000	ongoing	2	3	110.46
MDC	Ozark Plateau	Roubidoux Creek	2002	2003	3	4	752.75
MDC	Ozark Plateau	Roubidoux Creek	2002	2012	3	4	750.88
MDC	Ozark Plateau	Roubidoux Creek	2002	2012	3	4	750.88
MDC	Ozark Plateau	Roubidoux Creek	2003	2007	3	4	747.07
MDC	Ozark Plateau	Roubidoux Creek	2002	2010	3	4	723.35
MDC	Ozark Plateau	Roubidoux Creek	2002	2003	3	4	723.32
MDC	Ozark Plateau	Spring Creek	2002	2012	3	4	282.20
MDC	Ozark Plateau	Spring Creek	2002	2011	3	4	282.20
MDC	Ozark Plateau	Spring Creek	2010	2012	3	4	269.50
MDC	Ozark Plateau	Spring Creek	2012	2012	3	4	224.74
MDC	Ozark Plateau	Spring Creek	2002	2004	3	4	224.74
MDC	Ozark Plateau	Little Piney Creek	2002	2003	3	5	531.24
MDC	Ozark Plateau	Mill Creek	2002	2011	2	4	120.71
MDC	Ozark Plateau	Little Piney Creek	2002	2012	3	5	387.89
MDC	Ozark Plateau	Mill Creek	2005	2008	2	4	114.14
MDC	Ozark Plateau	Mill Creek	2003	2012	2	4	106.72
MDC	Ozark Plateau	Mill Creek	2002	2008	2	4	90.42
MDC	Ozark Plateau	Little Piney Creek	2002	2012	3	5	369.52
MDC	Ozark Plateau	Mill Creek	2012	2012	2	4	84.19
MDC	Ozark Plateau	Mill Creek	2002	2012	2	3	47.66
MDC	Ozark Plateau	Dewitt Wilkins Spring	2003	2008	1	1	0.68
MDC	Ozark Plateau	Dewitt Wilkins Spring	2003	2008	1	1	0.68
MDC	Ozark Plateau	Dewitt Wilkins Spring	2003	2011	1	1	0.68
MDC	Ozark Plateau	Mill Creek	2002	2007	2	3	46.81
MDC	Ozark Plateau	Mill Creek	2003	2007	2	3	46.81
MDC	Ozark Plateau	Little Piney Creek	2002	2003	3	5	245.15
MDC	Ozark Plateau	Little Piney Creek	2002	2011	1	1	4.43
MDC	Ozark Plateau	Roaring River	2002	2009	2	4	183.96
MDC	Ozark Plateau	Roaring River	2002	2007	2	4	110.98

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MDC	Ozark Plateau	Roaring River	2002	2009	2	4	133.28
MDC	Ozark Plateau	Spring Creek	2002	2014	1	2	9.53
MDC	Ozark Plateau	Spring Creek	2013	2014	2	4	11.65
MDC	Ozark Plateau	Crane Creek	2002	2014	2	4	118.92
MDC	Ozark Plateau	Crane Creek	2002	2010	2	4	118.92
MDC	Ozark Plateau	Spring Creek	2011	2014	2	4	101.34
MDC	Ozark Plateau	Crane Creek	2002	2014	2	4	159.40
MDC	Ozark Plateau	Spring Creek	2007	2007	2	4	91.64
MDC	Ozark Plateau	Spring Creek	2002	2014	2	4	91.64
MDC	Ozark Plateau	Crane Creek	2002	2014	2	4	26.66
MDC	Ozark Plateau	Crane Creek	2012	2012	2	4	250.43
MDC	Ozark Plateau	Crane Creek	2011	2014	2	4	250.43
MDC	Ozark Plateau	Crane Creek	2002	2014	3	5	394.37
MDC	Ozark Plateau	North Fork River	2002	2002	3	6	924.55
MDC	Ozark Plateau	North Fork River	2003	2003	3	6	1498.70
MDC	Ozark Plateau	North Fork River	2002	2006	3	6	1498.70
MDC	Ozark Plateau	North Fork River	2002	2003	3	6	1498.70
MDC	Ozark Plateau	North Fork River	2002	2009	3	6	3043.20
MDC	Ozark Plateau	North Fork River	2002	2003	3	6	1519.52
MDC	Ozark Plateau	North Fork River	2002	2003	3	6	1519.52
MDC	Ozark Plateau	North Fork River	2002	2009	3	6	523.04
MDC	Ozark Plateau	Pigeon Creek	2002	2002	1	2	1.67
MDC	Ozark Plateau	Pigeon Creek	2002	2003	2	4	389.23
MDC	Ozark Plateau	Pigeon Creek	2002	2003	2	4	415.90
MDC	Ozark Plateau	Pigeon Creek	2003	2003	2	4	415.90
MDC	Ozark Plateau	Pigeon Creek	2002	2003	2	4	415.90
MDC	Ozark Plateau	Pigeon Creek	2002	2003	2	4	415.90
MDC	Ozark Plateau	Pigeon Creek	2002	2010	3	4	232.90
MDC	Ozark Plateau	Pigeon Creek	2004	2010	3	4	95.97
MDC	Ozark Plateau	Current River	2004	2007	3	5	81.17
MDC	Ozark Plateau	Current River	2002	2009	3	5	522.43
MDC	Ozark Plateau	Current River	2002	2010	3	5	1188.46
MDC	Ozark Plateau	Current River	2002	2010	3	5	422.76
MDC	Ozark Plateau	Barren Fork	2002	2008	2	4	536.99
MDC	Ozark Plateau	Barren Fork	2002	2007	2	4	536.99
MDC	Ozark Plateau	Current River	2002	2008	3	5	1514.16
MDC	Ozark Plateau	Current River	2008	2008	3	5	1514.64
MDC	Ozark Plateau	Eleven Point River	2010	2012	3	4	817.12
MDC	Ozark Plateau	Eleven Point River	2011	2012	3	5	1391.59
MDC	Ozark Plateau	Eleven Point River	2002	2008	4	5	1574.33

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MDC	Ozark Plateau	Eleven Point River	2010	2011	4	5	1574.33
MDC	Ozark Plateau	Eleven Point River	2011	2012	4	5	1574.33
MDC	Ozark Plateau	Eleven Point River	2002	2010	4	5	1574.33
MDC	Ozark Plateau	Greer Spring Branch	2002	2007	1	1	3.75
MDC	Ozark Plateau	Greer Spring Branch	2011	2012	1	1	3.75
MDC	Ozark Plateau	Hurricane Creek	2010	2011	3	4	8.31
MDC	Ozark Plateau	Hurricane Creek	2011	2012	3	4	8.31
MDC	Ozark Plateau	Middle Fork Eleven Point River	2010	2012	2	3	407.57
MDC	Ozark Plateau	Barren Fork	2010	2012	2	4	43.14
MDC	Ozark Plateau	Greer Spring Branch	2002	2009	1	1	7.38
MDC	Ozark Plateau	Eleven Point River	2002	2010	4	5	1060.20
MDC	Ozark Plateau	Eleven Point River	2002	2003	4	5	1363.79
MDC	Ozark Plateau	Eleven Point River	2002	2008	4	5	3051.20
MDC	Ozark Plateau	unnamed	2010	2011	1	2	6.43
MDC	Ozark Plateau	Frederick Creek	2010	2011	3	5	208.85
MDC	Ozark Plateau	Eleven Point River	2002	2003	4	5	1473.15
MDC	Ozark Plateau	Eleven Point River	2002	2006	4	6	757.41
MDC	Ozark Plateau	Eleven Point River	2010	2012	4	6	205.15
MDC	Ozark Plateau	Capps Creek	2002	2009	2	3	114.14
MDC	Ozark Plateau	Capps Creek	2002	2004	2	3	114.14
MDC	Ozark Plateau	Capps Creek	2002	2003	2	3	114.14
MDC	Ozark Plateau	Capps Creek	2002	2003	2	3	95.78
MDC	Ozark Plateau	Capps Creek	2002	2009	2	3	118.69
MDC	Ozark Plateau	Capps Creek	2004	2009	2	3	118.69
MDC	Ozark Plateau	Hickory Creek	2003	2003	2	3	99.75
MDC	Ozark Plateau	Hickory Creek	2003	2009	2	3	83.16
MDC	Ozark Plateau	Capps Creek	2002	2003	2	2	37.47
MDC	Ozark Plateau	Hickory Creek	2004	2009	2	3	73.45
MDC	Ozark Plateau	Hickory Creek	2002	2003	2	3	65.67
MDC	Ozark Plateau	Blue Springs Creek	2002	2014	2	3	18.63
MDC	Ozark Plateau	Blue Springs Creek	2005	2014	2	3	29.30
MDC	Ozark Plateau	Blue Springs Creek	2002	2013	2	3	38.71
MDC	Ozark Plateau	Meramec River	2002	2014	4	6	1902.28
MDC	Ozark Plateau	Meramec River	2002	2003	4	6	1975.31
MDC	Ozark Plateau	Meramec River	2002	2014	4	6	1891.58
MDC	Ozark Plateau	Meramec River	2002	2003	4	6	1891.58
MDC	Ozark Plateau	Meramec River	2010	2014	4	6	1894.76
MDC	Ozark Plateau	Meramec River	2011	2014	4	6	1894.76
MDC	Ozark Plateau	Maramec Spring Branch	2002	2004	3	5	891.43

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MDC	Ozark Plateau	Maramec Spring Branch	2002	2009	1	1	0.33
MDC	Ozark Plateau	Meramec River	2002	2003	1	3	30.04
MDC	Ozark Plateau	Saint Francis River	2000		4	5	1313.40
MU	Central Plains	Nodaway River	2012	2013	4	5	8618.07
MU	Central Plains	Platte River	2012	2013	4	6	3511.29
MU	Central Plains	Little Platte River	2011	2014	3	4	71.92
MU	Central Plains	Platte River	2012	2013	4	6	8002.19
MU	Central Plains	One Hundred and Two River	2012	2013	3	5	1865.60
MU	Central Plains	One Hundred and Two River	2014	2016	3	5	1575.89
MU	Central Plains	One Hundred and Two River	2014	2016	3	5	1575.89
MU	Central Plains	Grand River	2014	2016	4	6	5823.16
MU	Central Plains	Grand River	2014	2016	4	6	5823.16
MU	Central Plains	Grand River	2014	2016	4	7	19607.81
MU	Central Plains	Grand River	2014	2016	4	7	19607.81
MU	Central Plains	Locust Creek	2012	2014	3	5	1438.43
MU	Central Plains	Grand River	2012	2013	4	7	17947.24
MU	Central Plains	unnamed	2014	2016	3	5	2242.42
MU	Central Plains	unnamed	2014	2016	3	5	2242.42
MU	Central Plains	Chariton River	2014	2016	4	5	4486.28
MU	Central Plains	Chariton River	2014	2016	4	5	4486.28
MU	Central Plains	Long Branch	2011	2015	2	3	59.73
MU	Central Plains	Little Chariton River	2014	2016	3	5	1743.78
MU	Central Plains	Little Chariton River	2014	2016	3	5	1743.78
MU	Central Plains	South Grand River	2014	2016	3	5	1728.18
MU	Central Plains	South Grand River	2014	2016	3	5	1728.18
MU	Central Plains	Crooked River	2011	2013	3	4	412.52
MU	Central Plains	Lamine River	2014	2016	4	7	6858.44
MU	Central Plains	Lamine River	2014	2016	4	7	6858.44
MU	Central Plains	Lamine River	2014	2016	4	6	2760.13
MU	Central Plains	Lamine River	2014	2016	4	6	2760.13
MU	Central Plains	unnamed	2014	2016	4	6	3968.99
MU	Central Plains	unnamed	2014	2016	4	6	3968.99
MU	Central Plains	South Fabius River	2011	2015	3	4	548.51
MU	Central Plains	South Fabius River	2011	2014	3	5	1569.40
MU	Central Plains	North Fork Salt River	2011	2013	3	5	935.91
MU	Central Plains	North Fork Salt River	2011	2014	3	5	1191.24
MU	Central Plains	Crooked Creek	2011	2015	3	3	212.42
MU	Central Plains	Middle Fork Salt River	2011	2015	3	4	809.08
MU	Central Plains	Elk Fork Salt River	2011	2015	3	5	519.23

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MU	Central Plains	Salt River	2014	2016	4	6	6458.89
MU	Central Plains	Salt River	2014	2016	4	6	6458.89
MU	Central Plains	Cuivre River	2011	2014	3	6	2408.65
MU	Central Plains	Cuivre River	2014	2016	4	6	3189.63
MU	Central Plains	Cuivre River	2014	2016	4	6	3189.63
MU	Ozark Plateau	Galliniper Creek	2010	2012	2	4	42.97
MU	Ozark Plateau	Weaubleau Creek	2011	2015	2	4	332.99
MU	Ozark Plateau	Little Weaubleau Creek	2010	2012	1	2	17.88
MU	Ozark Plateau	Cedar Creek	2011	2015	3	5	1068.90
MU	Ozark Plateau	Cedar Creek	2010	2012	3	5	1068.90
MU	Ozark Plateau	Brush Creek	2010	2012	1	1	17.85
MU	Ozark Plateau	Bear Creek	2010	2012	3	4	248.83
MU	Ozark Plateau	Snag Branch	2010	2012	2	2	29.04
MU	Ozark Plateau	Little Sac River	2012	2015	3	5	610.13
MU	Ozark Plateau	Lousy Branch	2010	2012	2	3	18.98
MU	Ozark Plateau	Sims Branch	2010	2012	2	2	23.26
MU	Ozark Plateau	Clear Creek	2010	2012	2	3	78.87
MU	Ozark Plateau	Sycamore Branch	2010	2012	2	3	40.10
MU	Ozark Plateau	South Dry Sac River	2012	2015	2	3	35.31
MU	Ozark Plateau	Crane Creek	2010	2012	2	2	15.32
MU	Ozark Plateau	Lindley Creek	2010	2012	3	4	344.13
MU	Ozark Plateau	Hominy Creek	2010	2012	2	3	80.54
MU	Ozark Plateau	Schultz Creek	2010	2012	2	3	36.28
MU	Ozark Plateau	Indian Creek	2010	2012	2	3	43.29
MU	Ozark Plateau	Big Buffalo Creek	2010	2012	2	3	36.54
MU	Ozark Plateau	Deer Creek	2010	2012	2	3	46.21
MU	Ozark Plateau	Turkey Creek	2010	2012	2	3	31.78
MU	Ozark Plateau	Wet Glaize Creek	2010	2012	3	5	308.95
MU	Ozark Plateau	Williamson Branch	2010	2012	2	3	15.55
MU	Ozark Plateau	Macks Creek	2010	2012	2	3	33.88
MU	Ozark Plateau	Little Niangua River	2012	2014	3	4	329.33
MU	Ozark Plateau	Little Niangua River	2010	2012	3	4	329.33
MU	Ozark Plateau	Niangua River	2011	2015	3	5	1353.09
MU	Ozark Plateau	Niangua River	2010	2012	3	5	1353.09
MU	Ozark Plateau	Jakes Creek	2010	2012	2	3	48.79
MU	Ozark Plateau	Niangua River	2011	2015	3	5	871.54
MU	Ozark Plateau	Atwell Creek	2010	2012	1	2	25.66
MU	Ozark Plateau	unnamed	2014	2016	1	1	1.61
MU	Ozark Plateau	Osage River	2014	2016	4	7	38878.91
MU	Ozark Plateau	Maries River	2012	2015	3	4	673.30

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MU	Ozark Plateau	Maries River	2010	2012	3	4	673.30
MU	Ozark Plateau	Little Maries Creek	2010	2012	2	3	78.66
MU	Ozark Plateau	Maries River	2010	2012	3	4	551.00
MU	Ozark Plateau	Maries River	2010	2012	3	4	551.00
MU	Ozark Plateau	Maries River	2010	2012	3	4	530.63
MU	Ozark Plateau	Maries River	2010	2012	3	4	487.23
MU	Ozark Plateau	Saline Creek	2010	2012	2	3	17.42
MU	Ozark Plateau	Osage River	2014	2016	4	7	37621.12
MU	Ozark Plateau	Osage River	2014	2016	4	7	37621.12
MU	Ozark Plateau	Sugar Creek	2010	2012	2	2	53.44
MU	Ozark Plateau	Saline Creek	2010	2012	2	4	109.09
MU	Ozark Plateau	Tavern Creek	2010	2012	3	5	786.48
MU	Ozark Plateau	Tavern Creek	2010	2012	3	5	637.81
MU	Ozark Plateau	Little Tavern Creek	2010	2012	2	3	97.46
MU	Ozark Plateau	Tavern Creek	2010	2012	3	5	564.24
MU	Ozark Plateau	Tavern Creek	2010	2012	3	5	528.87
MU	Ozark Plateau	Barren Fork	2010	2012	2	3	99.18
MU	Ozark Plateau	Tavern Creek	2010	2012	3	4	324.14
MU	Ozark Plateau	Maries River	2010	2012	2	3	73.68
MU	Ozark Plateau	Tavern Creek	2010	2012	3	4	261.89
MU	Ozark Plateau	Spring Branch	2010	2012	1	2	15.60
MU	Ozark Plateau	Little Tavern Creek	2010	2012	2	4	97.61
MU	Ozark Plateau	Tavern Creek	2010	2012	2	3	149.08
MU	Ozark Plateau	Gasconade River	2014	2016	4	6	4531.05
MU	Ozark Plateau	Gasconade River	2014	2016	4	6	4531.05
MU	Ozark Plateau	Gasconade River	2012	2015	4	6	3246.68
MU	Ozark Plateau	Big Piney River	2012	2015	3	5	1534.11
MU	Ozark Plateau	Big Piney River	2012	2015	3	5	1426.03
MU	Ozark Plateau	unnamed	2014	2016	1	1	1.58
MU	Ozark Plateau	Gasconade River	2014	2016	4	6	9092.66
MU	Ozark Plateau	Gasconade River	2011	2014	4	6	8259.62
MU	Ozark Plateau	Gasconade River	2012	2015	4	6	7334.21
MU	Ozark Plateau	James River	2012	2015	3	5	2395.67
MU	Ozark Plateau	Finley Creek	2012	2015	3	5	1437.09
MU	Ozark Plateau	James River	2012	2015	4	6	3613.05
MU	Ozark Plateau	Pierson Creek	2012	2015	2	3	78.66
MU	Ozark Plateau	James River	2012	2015	3	4	1634.89
MU	Ozark Plateau	Beaver Creek	2012	2015	3	5	897.39
MU	Ozark Plateau	Bull Creek	2012	2014	3	5	1358.61
MU	Ozark Plateau	North Fork River	2012	2015	3	6	186.93

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MU	Ozark Plateau	Black River	2014	2016	4	6	2720.99
MU	Ozark Plateau	Black River	2014	2016	4	6	2720.99
MU	Ozark Plateau	Current River	2012	2013	4	6	3954.73
MU	Ozark Plateau	Current River	2012	2013	4	6	366.83
MU	Ozark Plateau	Current River	2012	2013	4	6	2916.31
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	1344.81
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	268.74
MU	Ozark Plateau	Current River	2012	2013	4	6	797.30
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	243.21
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	75.25
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	26.96
MU	Ozark Plateau	Current River	2012	2013	4	6	5272.44
MU	Ozark Plateau	Current River	2012	2013	4	6	7750.20
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	1148.92
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	221.15
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	210.23
MU	Ozark Plateau	Jacks Fork	2012	2013	3	5	115.87
MU	Ozark Plateau	Current River	2012	2013	4	6	7979.38
MU	Ozark Plateau	Current River	2013	2014	4	6	31624.40
MU	Ozark Plateau	Current River	2012	2013	4	6	3089.70
MU	Ozark Plateau	Current River	2012	2013	4	6	22243.88
MU	Ozark Plateau	Current River	2012	2013	4	6	1660.35
MU	Ozark Plateau	Current River	2012	2013	4	6	677.79
MU	Ozark Plateau	Pigeon Creek	2012	2015	2	4	415.90
MU	Ozark Plateau	Pigeon Creek	2012	2013	2	4	415.90
MU	Ozark Plateau	Current River	2012	2014	4	6	12854.17
MU	Ozark Plateau	Current River	2012	2013	3	5	522.43
MU	Ozark Plateau	Current River	2012	2013	3	5	1155.54
MU	Ozark Plateau	Current River	2012	2013	3	5	422.76
MU	Ozark Plateau	Current River	2012	2014	3	5	422.76
MU	Ozark Plateau	Current River	2012	2013	3	5	1514.16
MU	Ozark Plateau	Current River	2012	2013	3	5	941.43
MU	Ozark Plateau	Current River	2012	2013	3	6	913.58
MU	Ozark Plateau	Eleven Point River	2012	2014	4	5	3051.20
MU	Ozark Plateau	North Fork Spring River	2011	2015	3	5	1339.74
MU	Ozark Plateau	Spring River	2011	2015	4	6	2997.94
MU	Ozark Plateau	Spring River	2011	2015	3	5	1158.58
MU	Ozark Plateau	Spring River	2011	2015	3	5	792.57
MU	Ozark Plateau	Shoal Creek	2011	2015	3	5	1109.92
MU	Ozark Plateau	Buffalo Creek	2012	2013	2	4	243.22

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
MU	Ozark Plateau	Elk River	2013	2015	1	1	5.14
MU	Ozark Plateau	Big Sugar Creek	2011	2015	3	4	367.50
MU	Ozark Plateau	Indian Creek	2014	2015	3	5	616.45
MU	Ozark Plateau	Meramec River	2011	2015	4	7	9809.73
MU	Ozark Plateau	Meramec River	2014	2016	4	7	7136.62
MU	Ozark Plateau	Meramec River	2014	2016	4	7	7136.62
MU	Ozark Plateau	Meramec River	2014	2016	4	7	4496.67
MU	Ozark Plateau	Meramec River	2011	2015	4	7	3851.10
MU	Ozark Plateau	Meramec River	2011	2015	1	1	6.65
MU	Ozark Plateau	Meramec River	2011	2015	3	5	516.52
MU	Ozark Plateau	Bourbeuse River	2011	2015	4	5	2079.20
MU	Ozark Plateau	Bourbeuse River	2011	2015	3	4	350.97
MU	Ozark Plateau	Big River	2011	2015	4	6	2379.16
MU	Ozark Plateau	Big River	2011	2015	4	6	1916.00
MU	Ozark Plateau	Big River	2014	2015	3	5	461.23
MU	Ozark Plateau	Big Creek	2011	2015	3	4	1189.56
NPS	Ozark Plateau	Current	2013	ongoing	4	6	628.49
NPS	Ozark Plateau	Current	2013	ongoing	4	6	797.30
NPS	Ozark Plateau	Current	2013	ongoing	4	6	7750.20
NPS	Ozark Plateau	Current	2013	ongoing	4	6	7979.38
SIU	Ozark Plateau	Missouri	2009	2012	2	2	14.78
SIU	Ozark Plateau	Missouri	2009	2012	2	2	14.78
SIU	Ozark Plateau	Missouri	2009	2012	2	2	14.78
SIU	Ozark Plateau	Missouri	2009	2012	2	2	14.78
SIU	Ozark Plateau	Missouri	2009	2012	2	2	14.78
SIU	Ozark Plateau	Missouri	2009	2012	1	1	6.53
USGS	Central Plains	Missouri River	2007	ongoing	5	15	34208.52
USGS	Central Plains	Osage River	2013	ongoing	4	7	14688.91
USGS	Central Plains	Missouri River	2011	ongoing	5	15	53.18
USGS	Central Plains	Little Blue River	2007	ongoing	3	4	480.53
USGS	Central Plains	Spring Branch	2007	ongoing	2	2	22.07
USGS	Central Plains	Rock Creek	2011	ongoing	2	2	25.30
USGS	Central Plains	Little Blue River	2006	2009	3	4	403.24
USGS	Central Plains	Adair Creek	2008	ongoing	2	2	14.11
USGS	Central Plains	Little Blue River	2009	ongoing	3	4	256.91
USGS	Central Plains	East Fork Little Blue River	2009	ongoing	2	3	90.35
USGS	Central Plains	Indian Creek	2007	2015	3	4	173.70
USGS	Ozark Plateau	Osage River	2015	ongoing	4	7	36426.50
USGS	Ozark Plateau	Tavern Creek	2014	ongoing	3	5	786.48
USGS	Ozark Plateau	Missouri River	2012	ongoing	5	8	35355.89

Source	Aquatic subregion	Name	Start year	Stop year	Pflieger size	Strahler Order	Upstream watershed (km2)
USGS	Ozark Plateau	Missouri River	2007	ongoing	5	8	47341.10
USGS	Ozark Plateau	Missouri River	2008	ongoing	5	8	54759.47
USGS	Ozark Plateau	Missouri River	2007	ongoing	5	8	51045.04
USGS	Ozark Plateau	Lake Taneycomo	2007	ongoing	4	7	4971.45
USGS	Ozark Plateau	White River	2007	ongoing	4	7	846.38
USGS	Ozark Plateau	East Fork Black River	2007	ongoing	2	4	36.10
USGS	Ozark Plateau	East Fork Black River	2008	ongoing	3	4	54.50
USGS	Ozark Plateau	Jacks Fork	2016	ongoing	3	5	210.23
USGS	Ozark Plateau	Huzzah Creek	2013	ongoing	3	5	663.91
USGS	Ozark Plateau	Big River	2011	ongoing	4	6	2379.16
USGS	Ozark Plateau	Big River	2011	ongoing	3	5	1057.75
USGS	Ozark Plateau	Mississippi River	2014	ongoing	5	15	13527.42

Appendix J. Maps depicting predicted temperatures for stream segments.

List of Figures

Figure 1. Central Plains: mean of July daily means for predicted stream temperatures. Strahler order 1 streams are not displayed in this image.

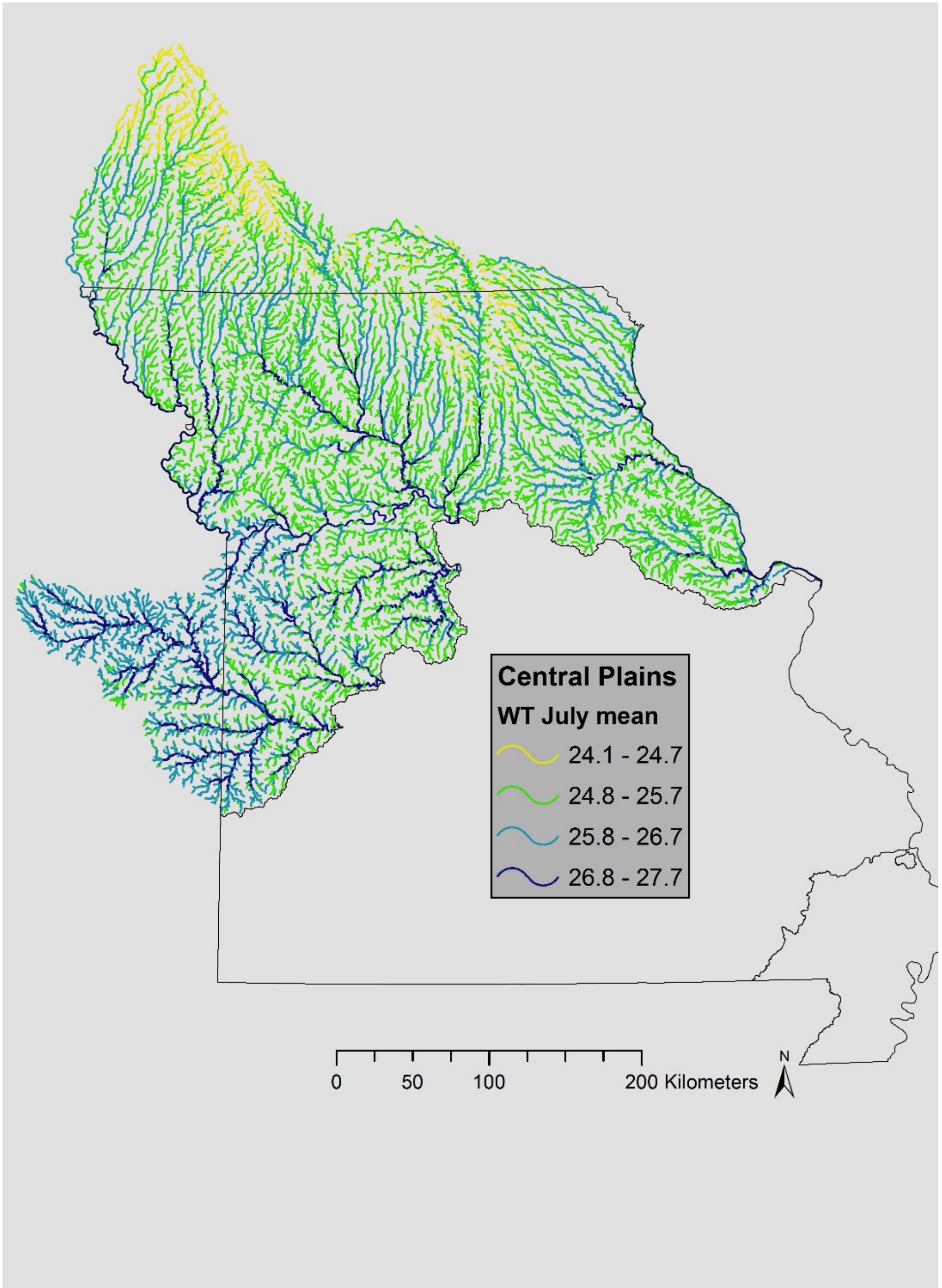


Figure 2. Central Plains: maximum of July daily means for predicted stream temperature. Strahler order 1 streams are not displayed in this image so watersheds are highlighted.

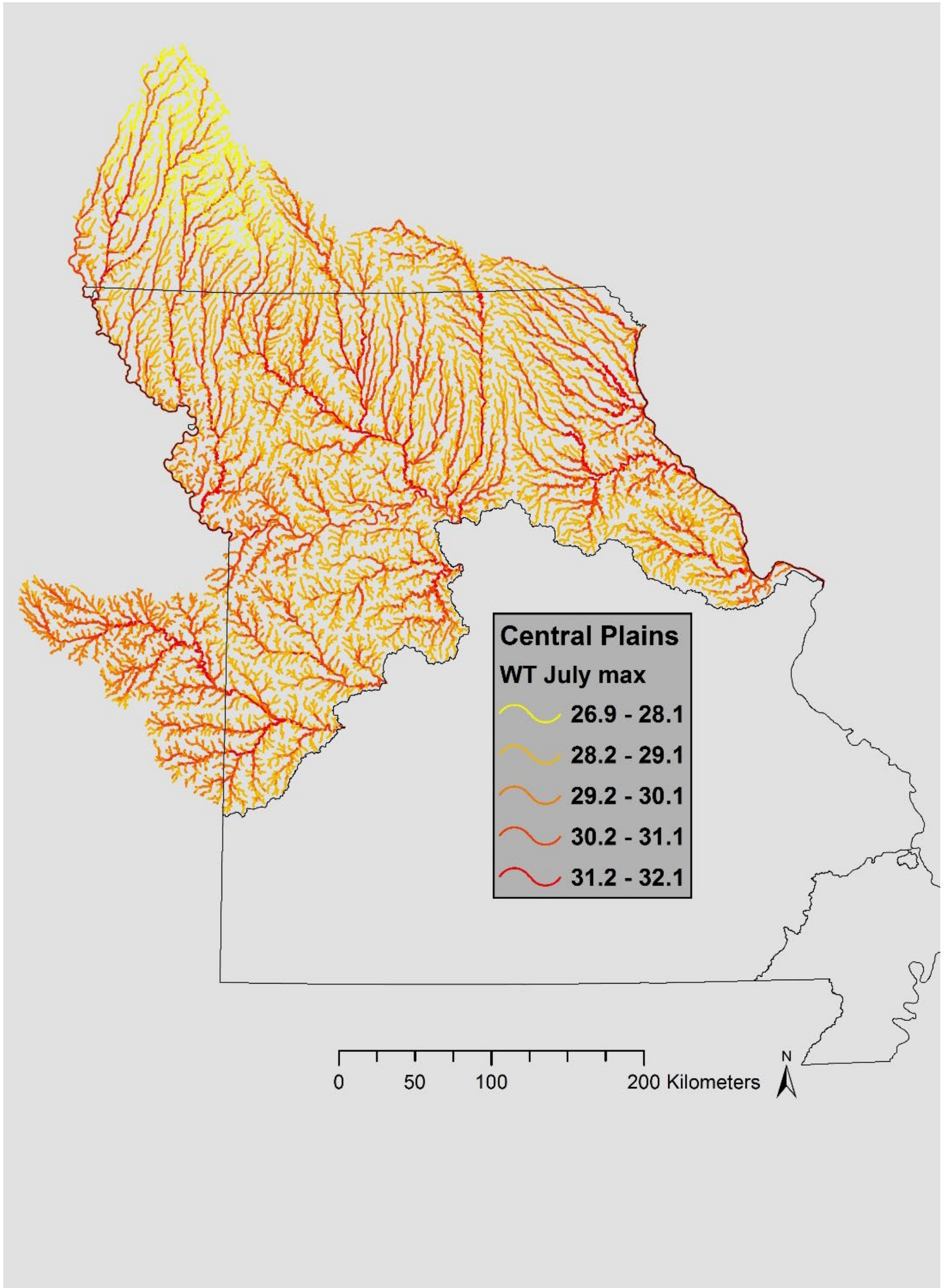


Figure 3. Central Plains: range (maximum – minimum) of July daily mean predicted stream temperature. Strahler order 1 streams are not displayed in this image so watersheds are highlighted.

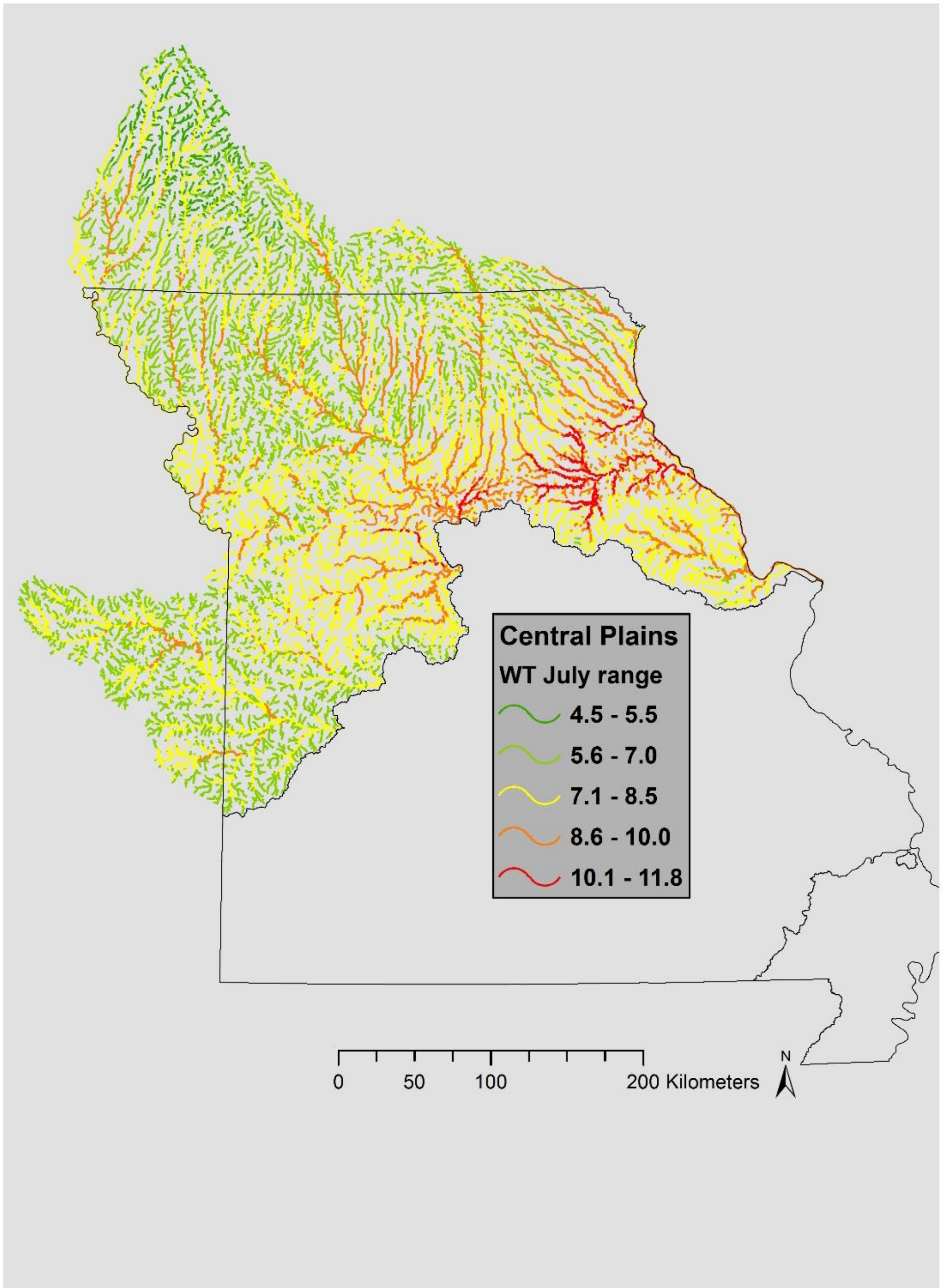


Figure 4. Ozark Plateau: mean of July daily means for predicted water temperatures. Strahler order 1 streams are not displayed in this image so watersheds are highlighted.

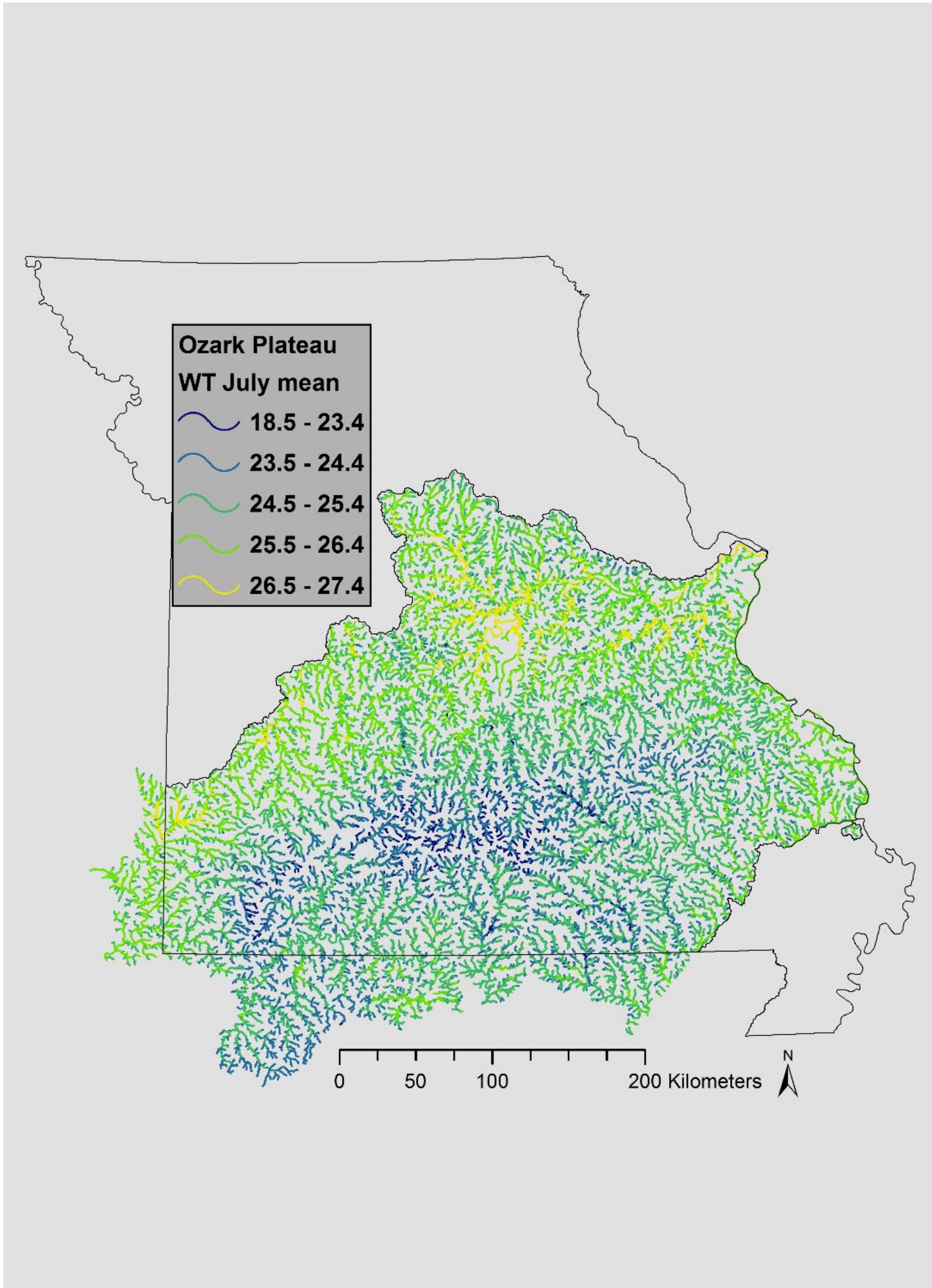


Figure 5. Ozark Plateau: maximum of July daily means for predicted stream temperature. Strahler order 1 streams are not displayed in this image so watersheds are highlighted.

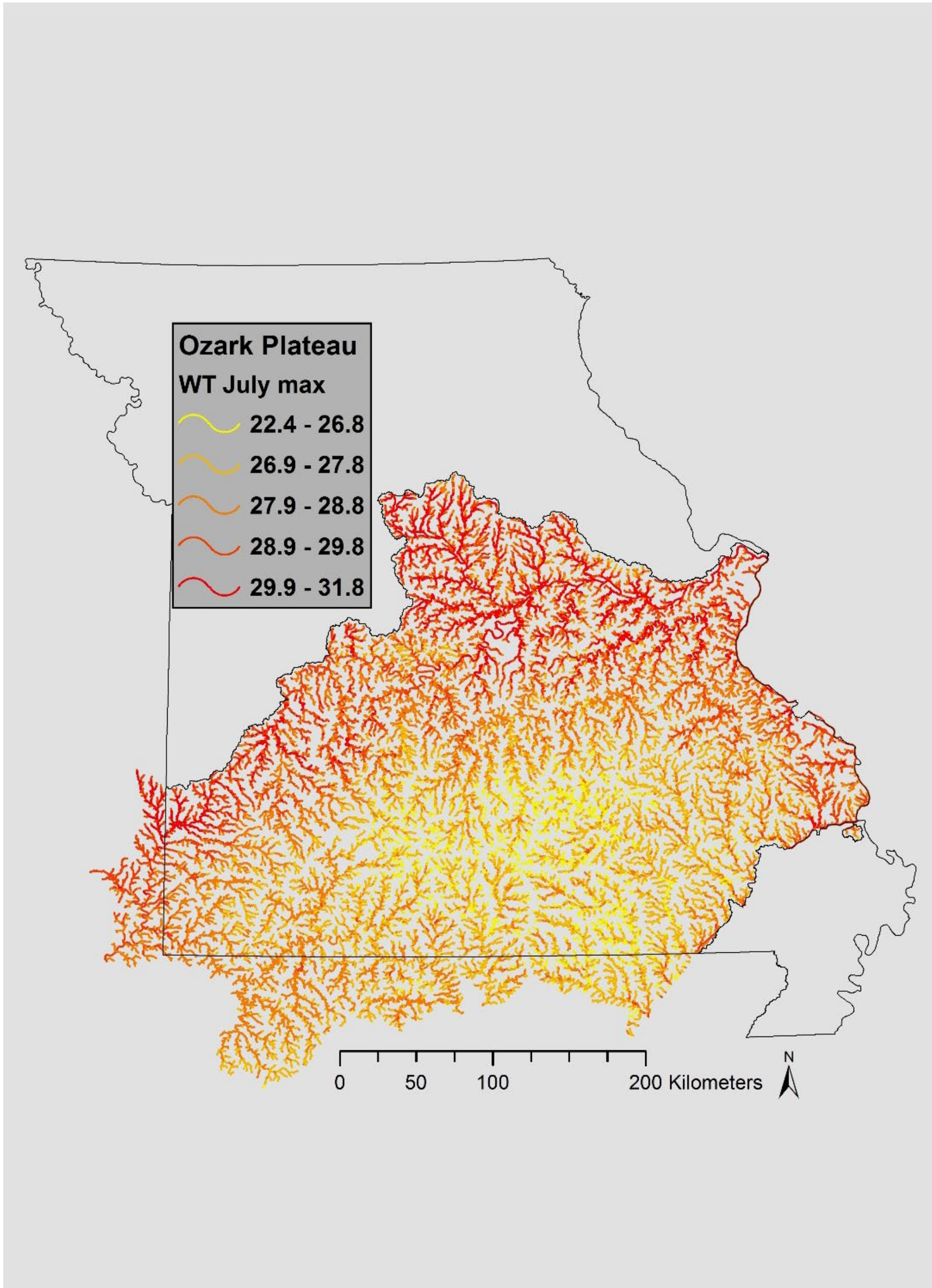


Figure 6. Ozark Plateau: range (maximum – minimum) of July daily mean predicted stream temperature. Strahler order 1 streams are not displayed in this image so watersheds are highlighted.

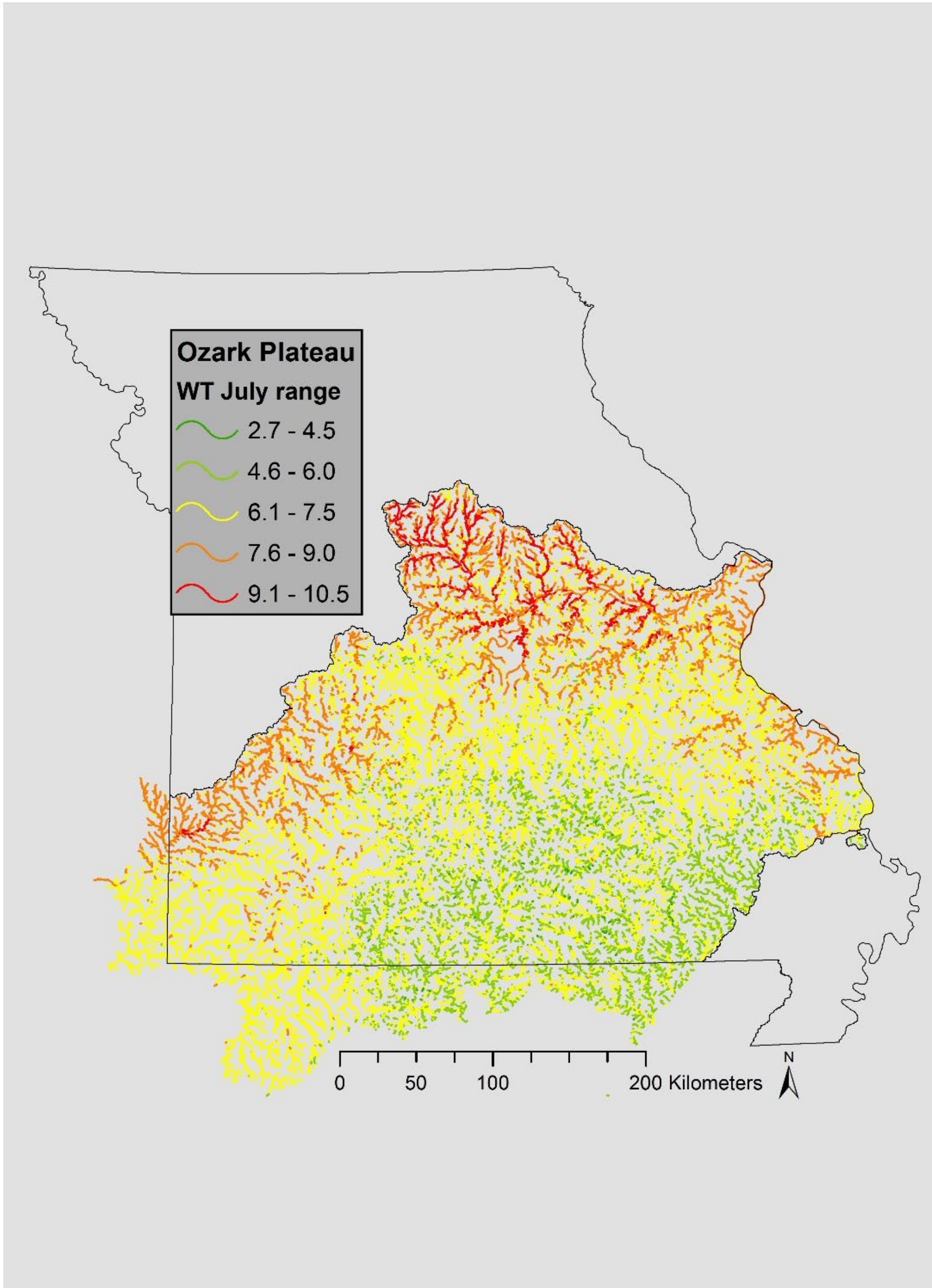


Figure 7. Current and Jack's Fork rivers. Annual mean daily predicted stream temperature.

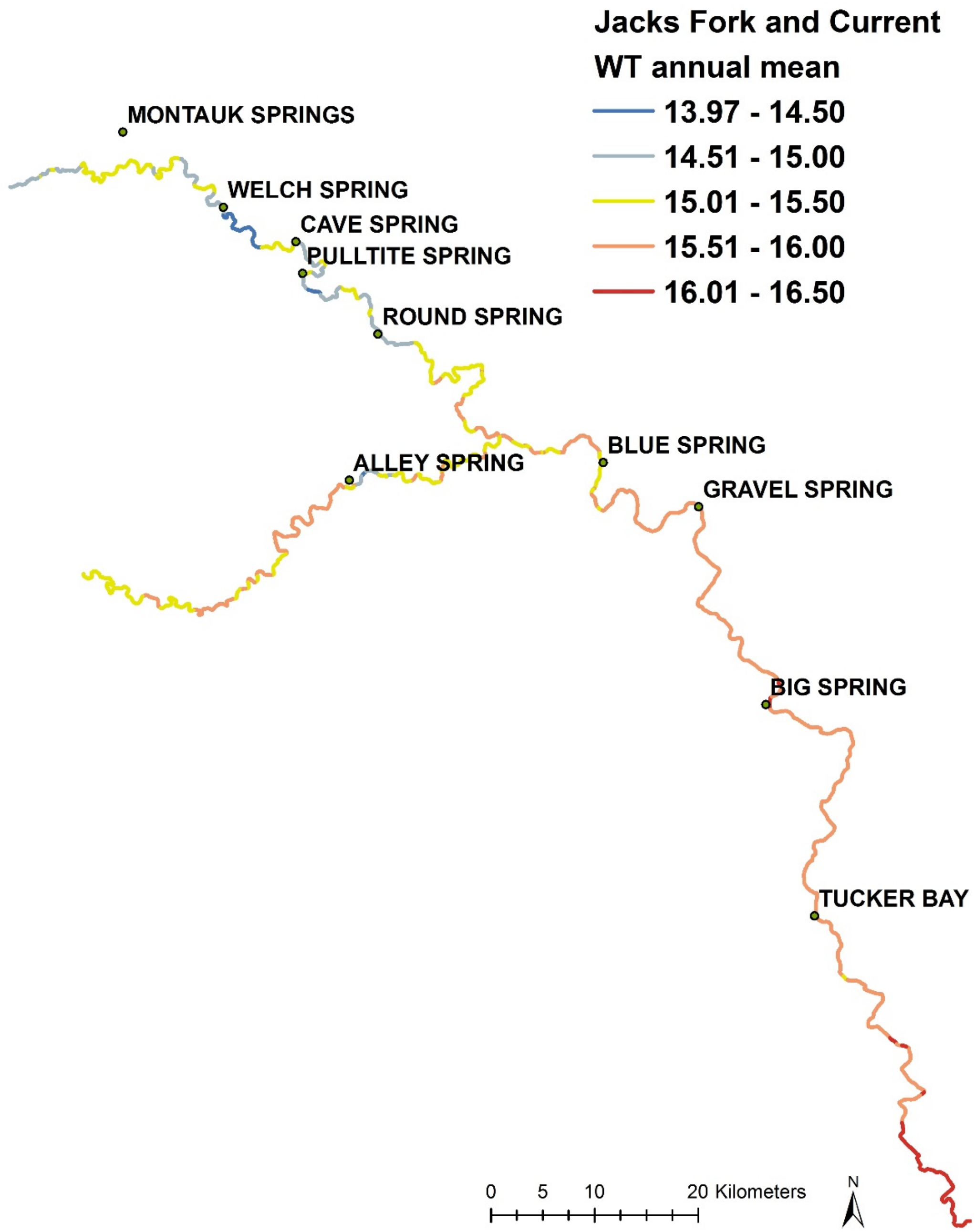

Jacks Fork and Current
WT annual mean
13.97 - 14.50
14.51 - 15.00
15.01 - 15.50
15.51 - 16.00
16.01 - 16.50
MONTAUK SPRINGS
WELCH SPRING
CAVE SPRING
PULLTITE SPRING
ROUND SPRING
BLUE SPRING
ALLEY SPRING
GRAVEL SPRING
BIG SPRING
TUCKER BAY
0
5
10
20 Kilometers
N

Figure 8. Eleven Point River. Annual mean daily predicted stream temperature.

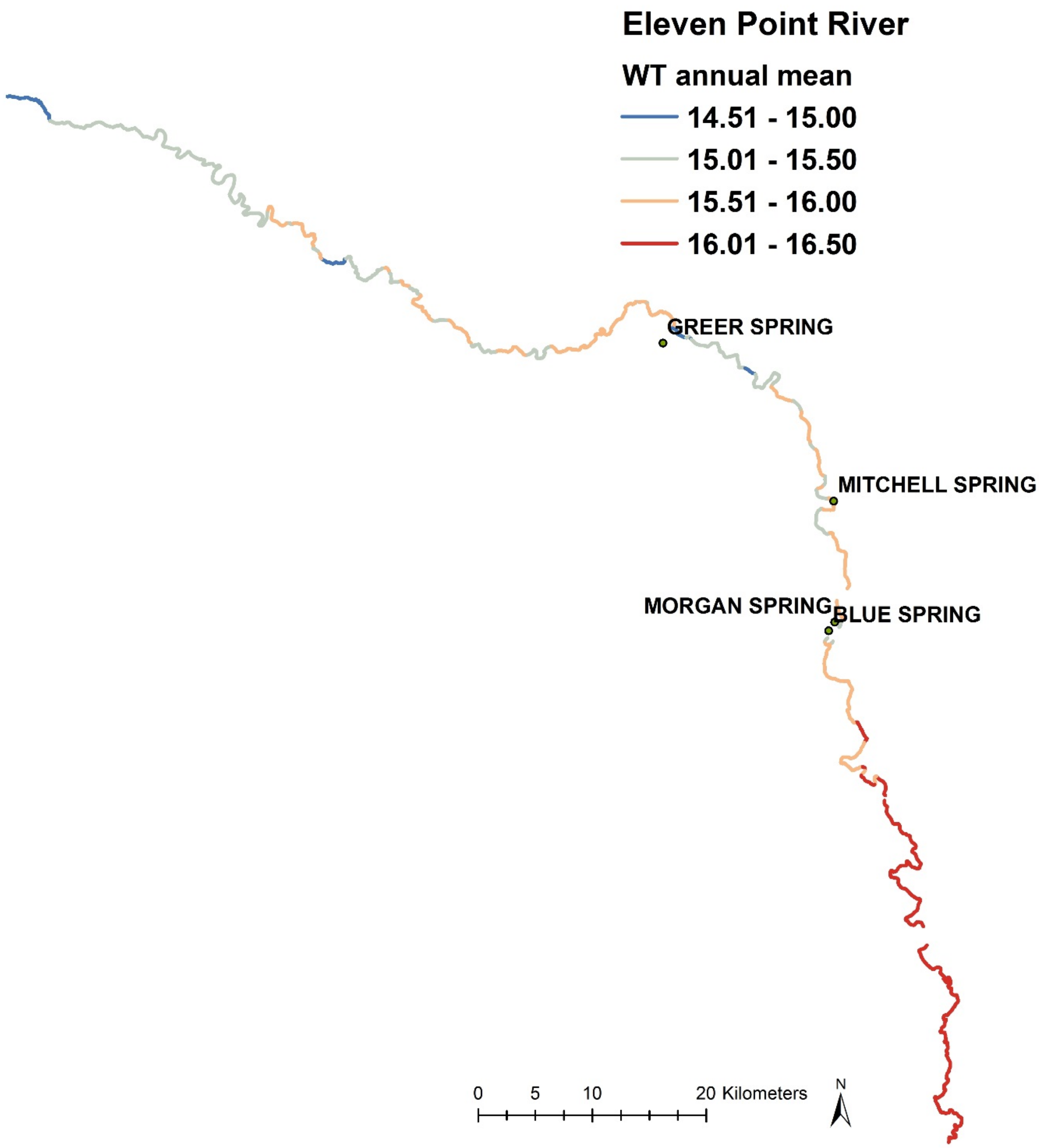


Figure 9. Grand River. Annual mean daily predicted stream temperature.

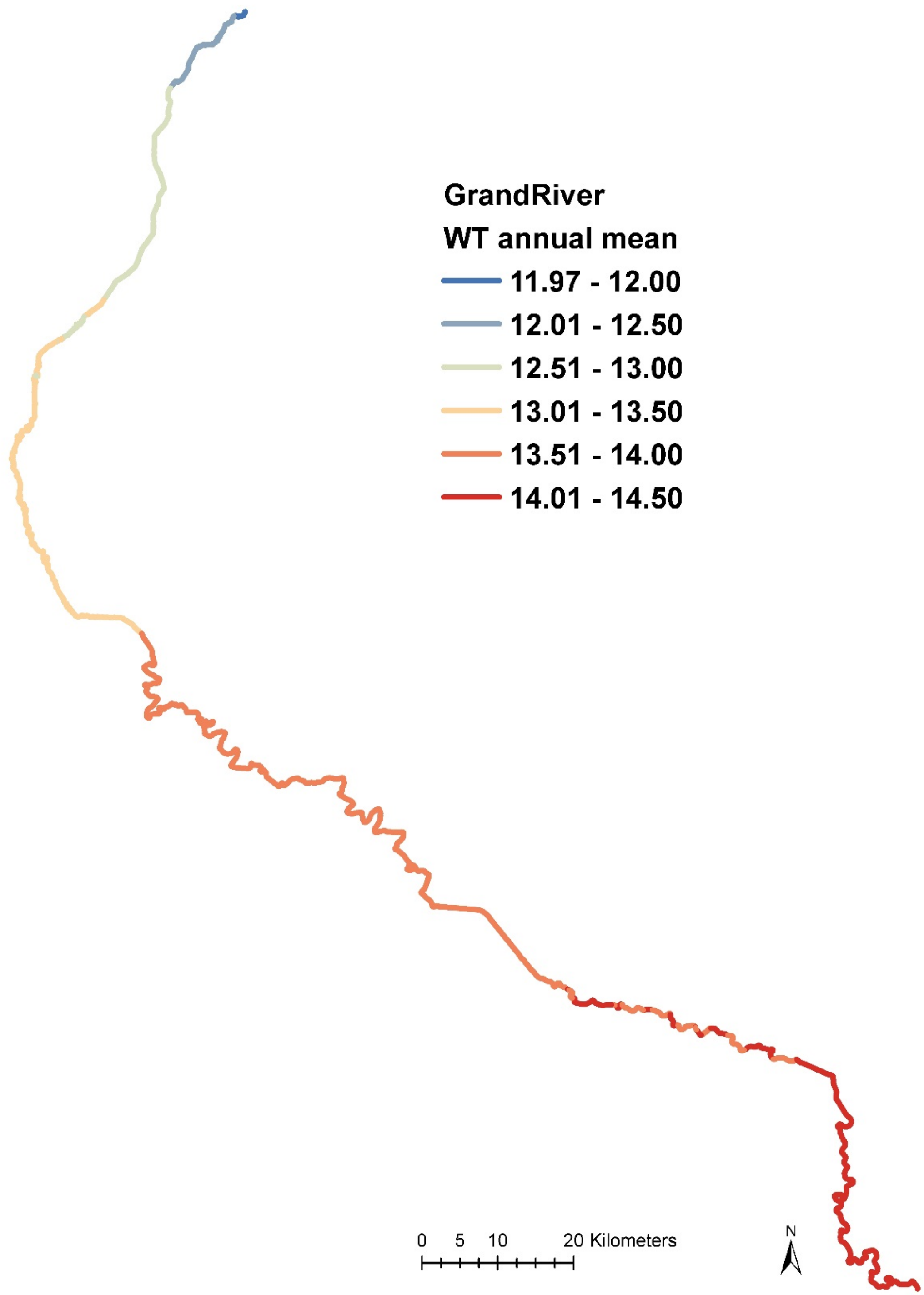
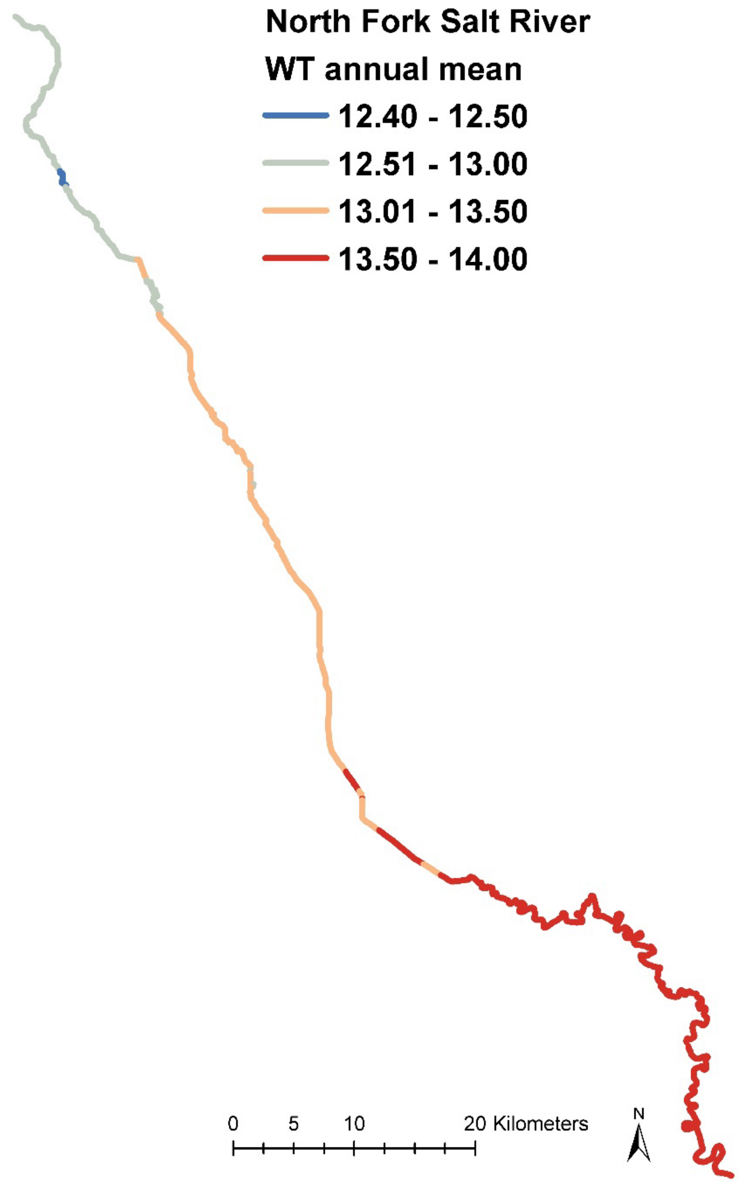


Figure 10. North Fork Salt River. Annual mean daily predicted stream temperature.

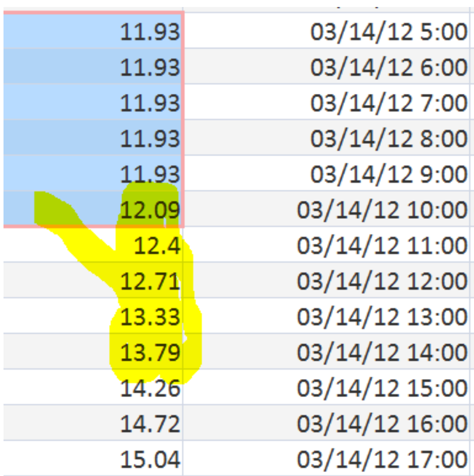


Appendix K: Plots of stream temperatures recorded for each site used to associate stream temperature with discharge. Each plot is labeled by: site number_point location_year. Header label: 1_A_2012 = site 1, A = point location of logger, 2012 = year. X axis is date; Y-axis in temperature in degrees C. ** = some data excluded.

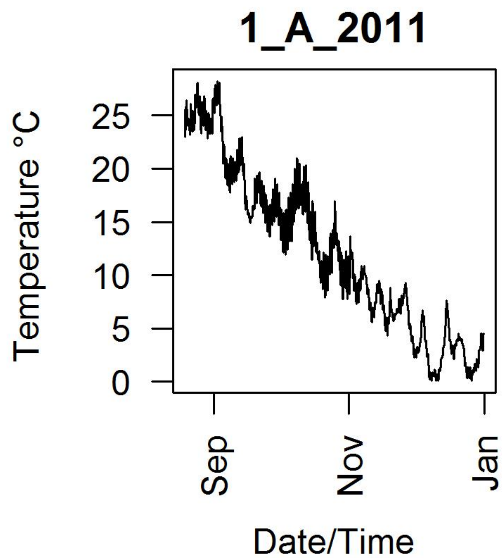
*Figure 1. Site 1, Point A: Crooked River near Richmond; 2011 – 2012.***

Notes: the stream at this site was dammed to create a pool after the loggers were set. Interpretation of data –rapid warming of stream in late March 2012 indicates when stream was dammed or maybe logger was exposed; rapid drop in April 2012 – logger no longer exposed?; 30C = 86F; June – Aug temps quite warm – indicative of being in a pool? SEQ Figure * ARABIC

Decision: did not use records post- 13 Mar 2012 which was the point when temperature began to jump by ~0.4°C in hourly records after having been relatively stable; previously water temps did rise mid-morning but only for a 1.5°C total increase.



11.93	03/14/12 5:00
11.93	03/14/12 6:00
11.93	03/14/12 7:00
11.93	03/14/12 8:00
11.93	03/14/12 9:00
12.09	03/14/12 10:00
12.4	03/14/12 11:00
12.71	03/14/12 12:00
13.33	03/14/12 13:00
13.79	03/14/12 14:00
14.26	03/14/12 15:00
14.72	03/14/12 16:00
15.04	03/14/12 17:00



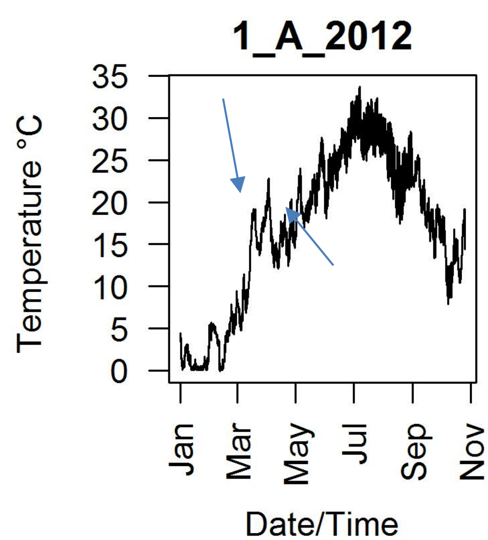
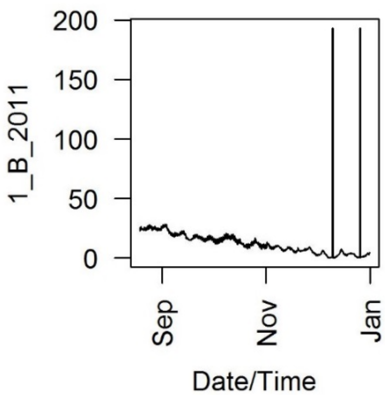


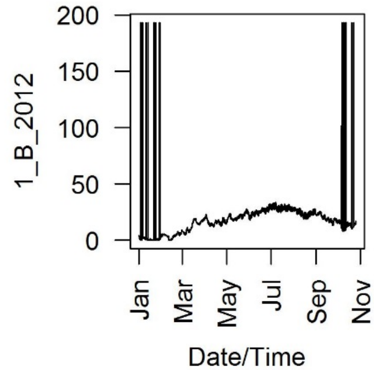
*Figure 2. Site 1, Point B: Crooked River near Richmond, 2011 – 2012.***

Notes: temperature readings of 193.35°C? This is happening with several loggers. Searched online to learn if this is a default number indicating something wrong with logger. No answers found. Logger ID: 48563; associated temperatures hovering at 0°C.

<u>Original data</u>

Decision: deleted records with temperature >193.3°C and adjacent records.



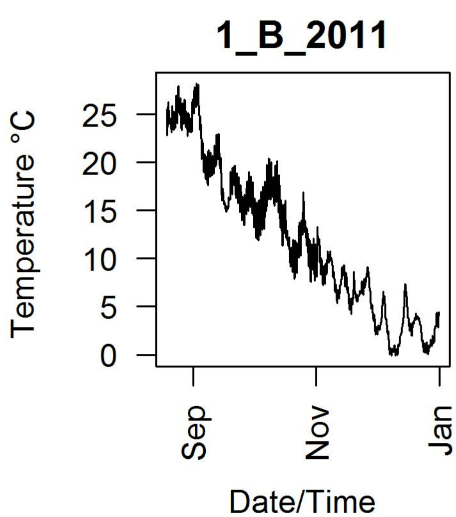


193.35	12/10/11 9:00
193.35	12/26/11 3:00
193.35	12/26/11 2:00
193.35	12/26/11 5:00
193.35	12/26/11 6:00
193.35	12/26/11 7:00
193.35	12/26/11 4:00
193.35	12/10/11 8:00
193.35	12/10/11 3:00
193.35	12/10/11 4:00
193.35	12/10/11 5:00
193.35	12/10/11 6:00
193.35	12/10/11 7:00
193.35	12/26/11 8:00
193.35	12/26/11 9:00
193.3	12/10/11 2:00
28.26	09/02/11 16:00

<u>Modified data</u>

The stream at this site was dammed to create a pool sometime after the loggers were set. Interpretation of data –rapid warming of stream in late March 2012 indicates when stream was dammed or maybe logger was exposed; rapid drop in April 2012 – logger no longer exposed?; 30C = 86F; June – Aug temps quite warm – indicative of being in a pool?

Decision: as with site A, didn't use records post-13 Mar 13 2012 which was the point when temperature began to jump by ~0.4C in hourly records after having been relatively stable; previously water temps did rise mid-morning but only for a 1.5C total increase.



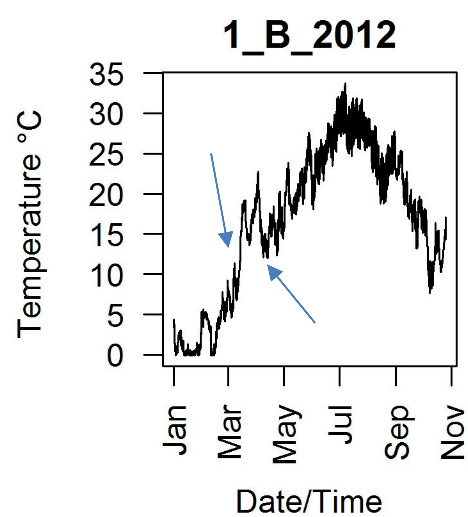
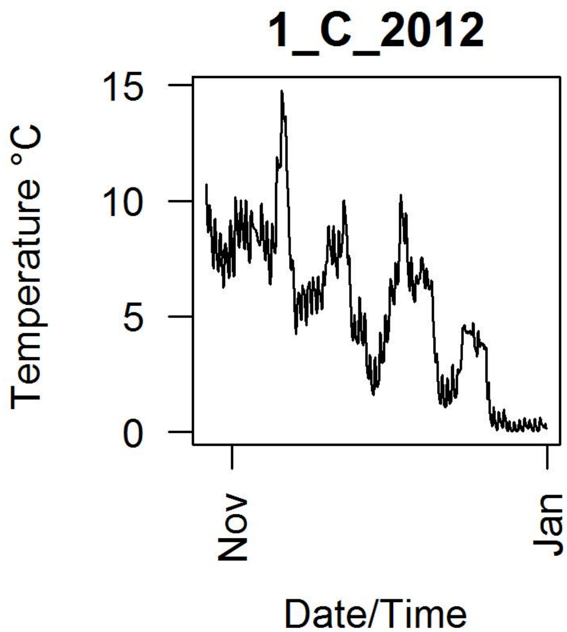


Figure 3. Site 1, Point C: Crooked River near Richmond, 2012 – 2013.
Decision: used all records.



The rapid increase in temperature followed by a corresponding rapid decrease is apparent in most logger data from throughout MO from the first week in May 2013. This resulted from a rainfall/snow event (http://climate.missouri.edu/news/arc/jun2013.php) that occurred during this time.

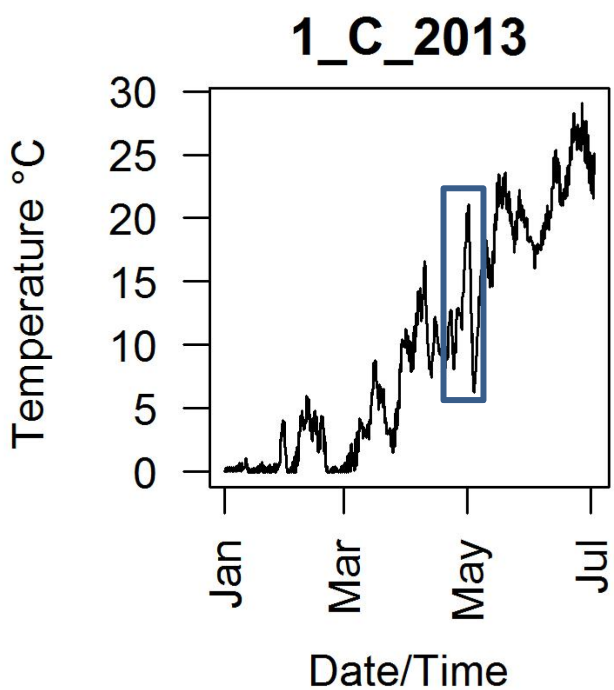
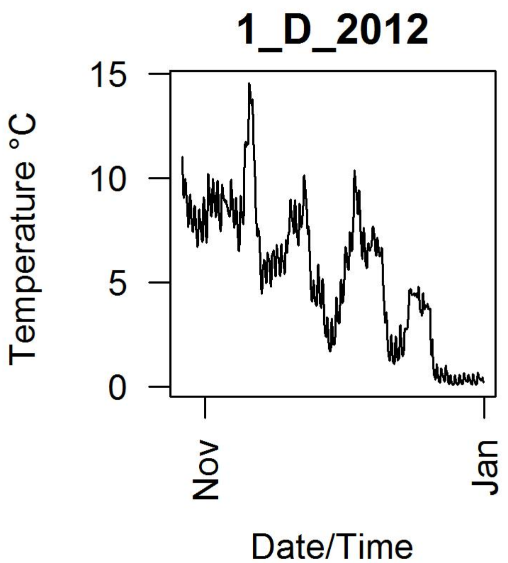


Figure 4. Site 1, Point D: Crooked River near Richmond, 2012 – 2013.
Decision: used all records.



The rapid increase in temperature followed by a corresponding rapid decrease is apparent in most logger data from throughout MO from the first week in May 2013. This resulted from a rainfall/snow event (http://climate.missouri.edu/news/arc/jun2013.php) that occurred during this time.

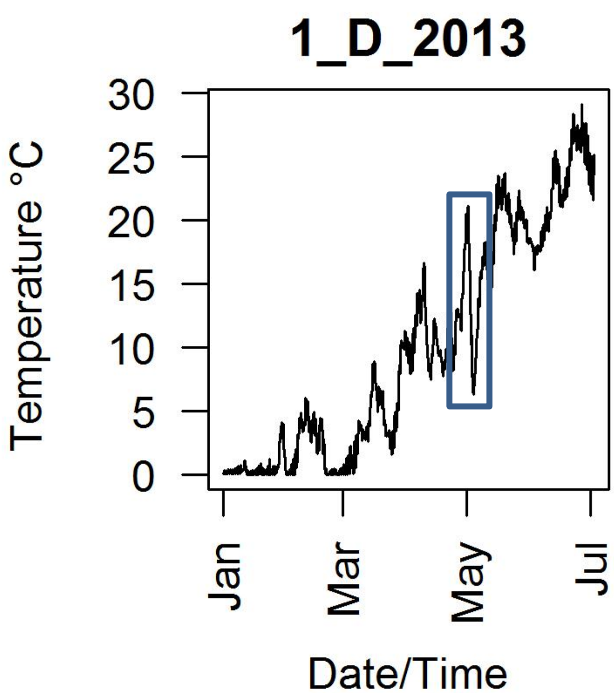


Figure 5. Site 2, Point A: Locust Creek near Linneus, 2012.
Decision: Not sure why temperature increased in Oct. Similar trend at Site 1 which is in same region. Temperature spikes at other times; at retrieval on 25 Oct 2012, the logger was in water and not buried. Used all records.

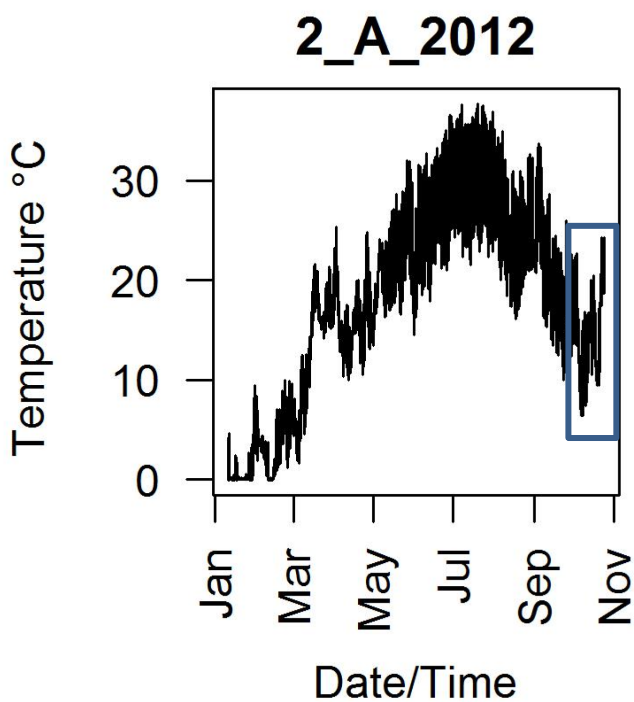
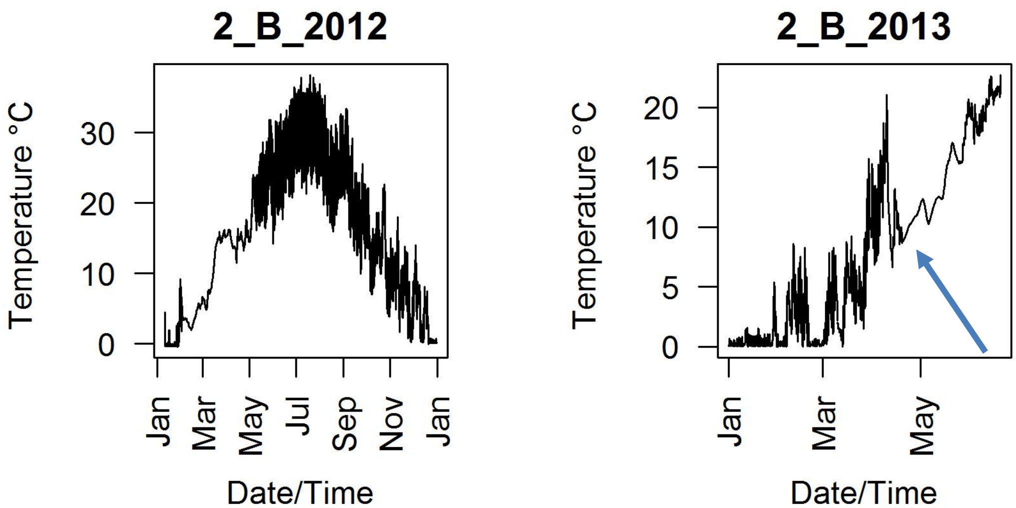
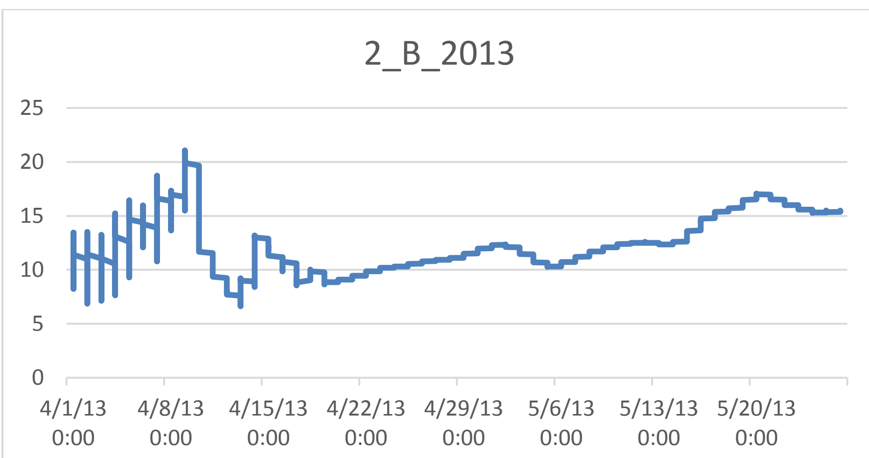


*Figure 6. Site 2, Point B: Locust Creek near Linneus, 2012 – 2013.***

Decision: When retrieved in 2013 the logger was buried. Did not use data after 10 April 2013. The February to May period in 2012 looks very much like the logger may have been buried. Point A data for this period was very different. Did not use data from 3 Feb 2012 – 4 May 2012.





˚C

Figure 7. Site 2 Point C: Locust Creek near Linneus, 2013 – 2014.
Decision: used all records.

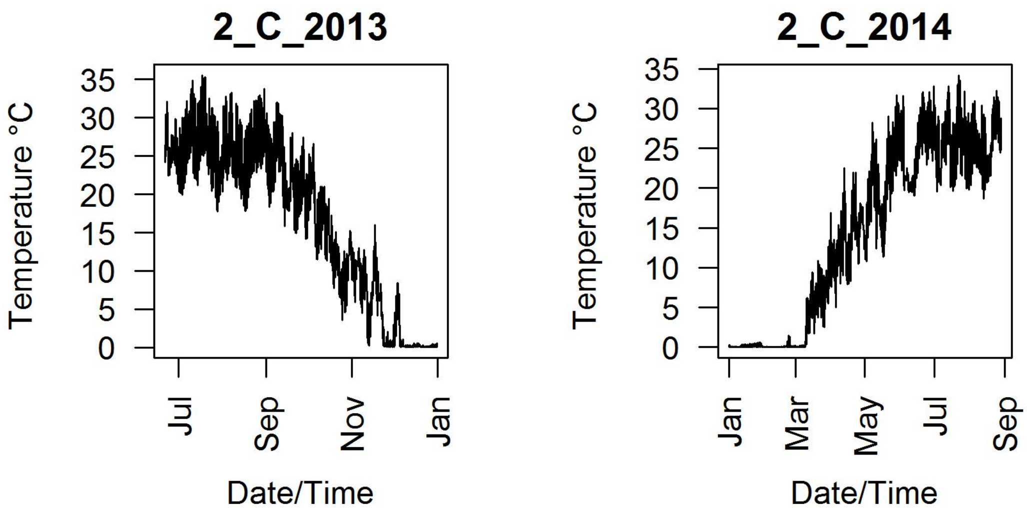


Figure 8. Site 2 Point D: Locust Creek near Linneus, 2013 – 2014.
Decision: used all records.

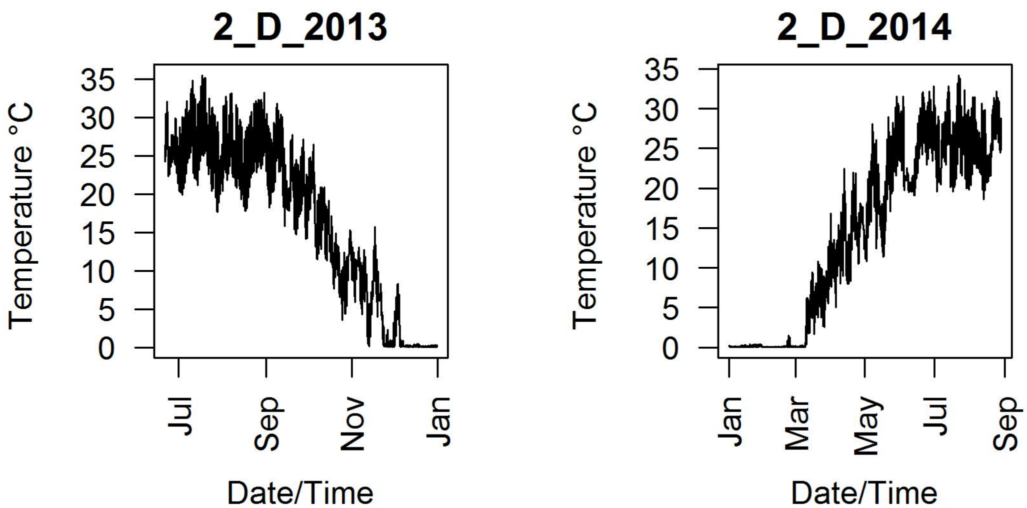


Figure 9. Site 3, Point A: Grand River near Sumner, 2012 – 2013.
Decision: used all records.

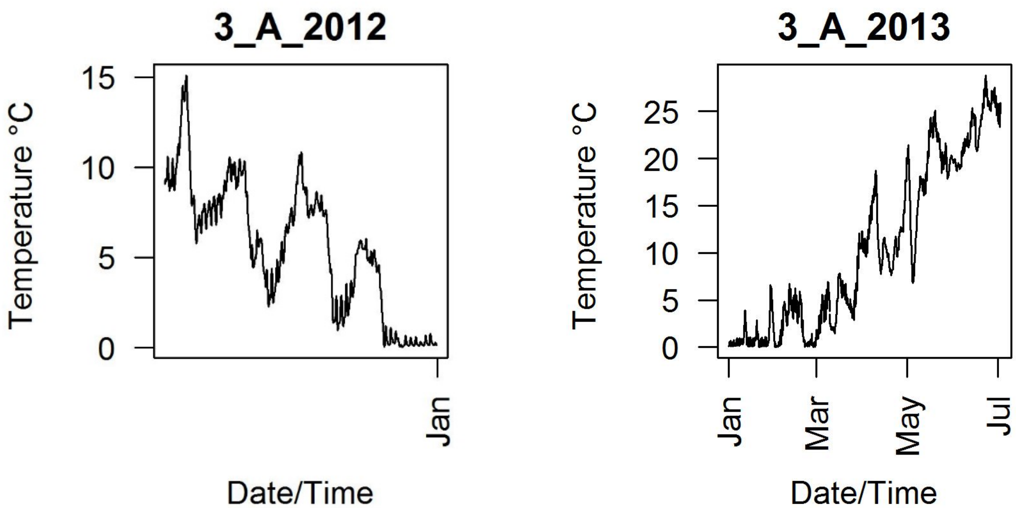


Figure 10. Site 3, Point B: Grand River near Sumner, 2012 – 2013.
Decision: used all records.

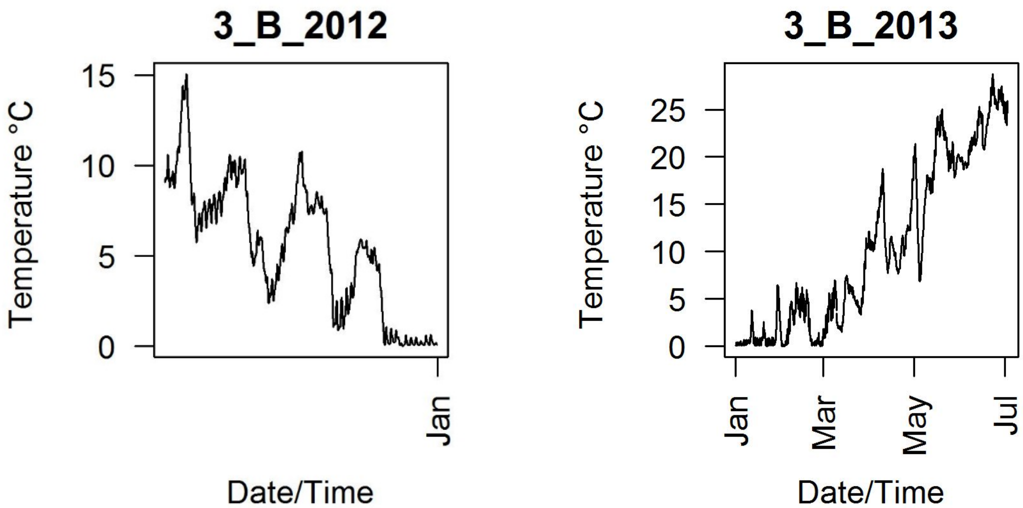
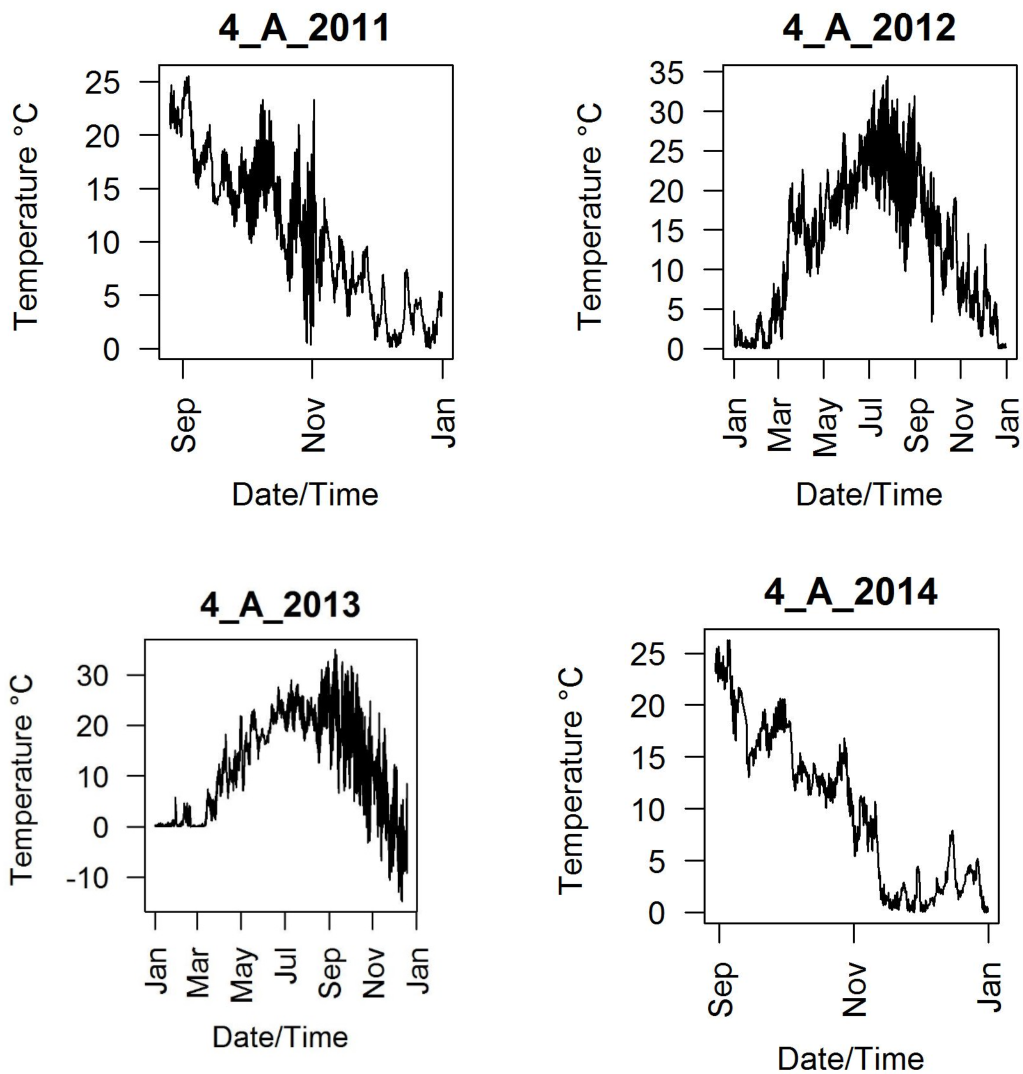
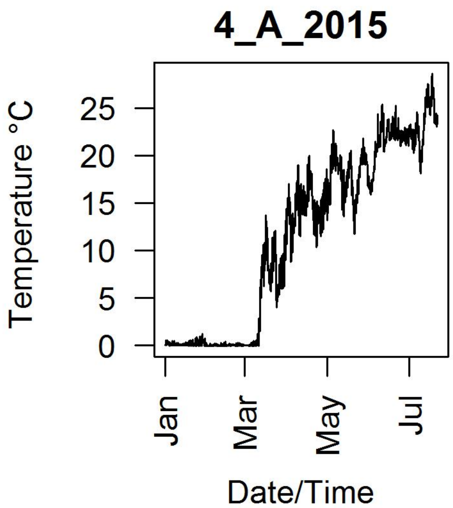


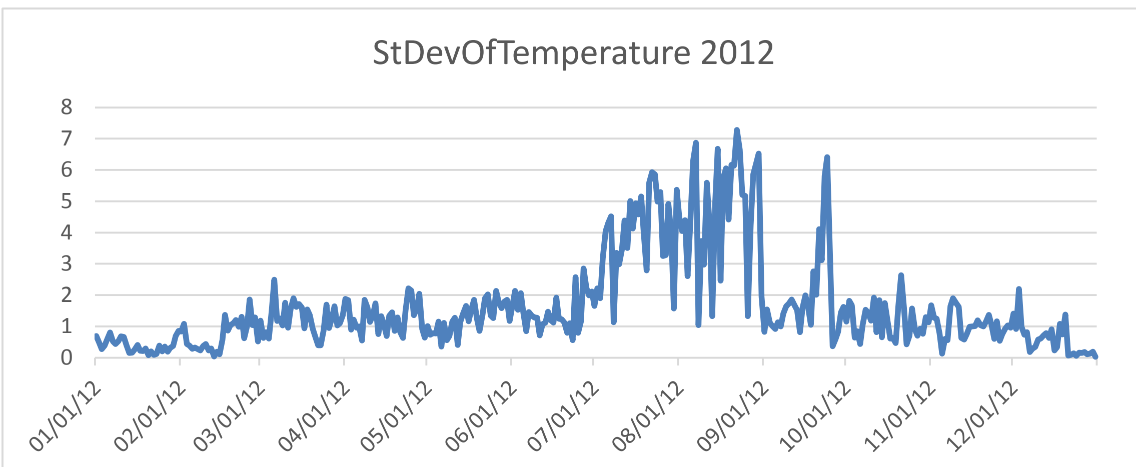
*Figure 11. Site 4 Point A: Long Branch Creek near Atlanta; 2011 – 2015.***

Notes: In 2012, daily variation increased between July 4 – Sept 20 which may indicate the logger was exposed. In December 2013, the site was dry when retrieved logger. Daily variation increased in mid-Aug 2013. Records drop well below 0˚C in winter months which makes sense because logger was exposed.

Decision: for 2012 did not use records from July 4 – Sept 20. For 2013 did not use records post-15 Aug. Used remaining records.




4_A_2015
Temperature °C
25
20
15
10
5
0
Jan
Mar
May
Jul
Date/Time


StDevOfTemperature 2012
8
7
6
5
4
3
2
1
0
01/01/12
02/01/12
03/01/12
04/01/12
05/01/12
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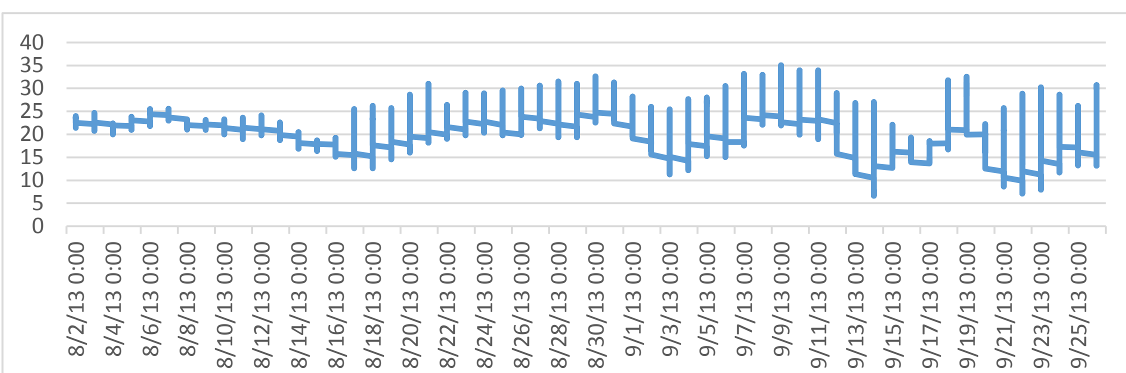
10/01/12
11/01/12
12/01/12

2013


40
35
30
25
20
15
10
5
0
8/2/13 0:00
8/4/13 0:00
8/6/13 0:00
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8/10/13 0:00
8/12/13 0:00
8/14/13 0:00
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8/22/13 0:00
8/24/13 0:00
8/26/13 0:00
8/28/13 0:00
8/30/13 0:00
9/1/13 0:00
9/3/13 0:00
9/5/13 0:00
9/7/13 0:00
9/9/13 0:00
9/11/13 0:00
9/13/13 0:00
9/15/13 0:00
9/17/13 0:00
9/19/13 0:00
9/21/13 0:00
9/23/13 0:00
9/25/13 0:00

Figure 12. Site 4, Point B: Long Branch Creek near Atlanta, 2011 – 2013.

Notes: In 2012, daily variation increased between July 4 – Sept 20 which may indicate the logger was exposed. The same pattern occurred at Site A during same period.

Decision: for 2012 did not use records from July 4 – Sept 20. Used remaining records.

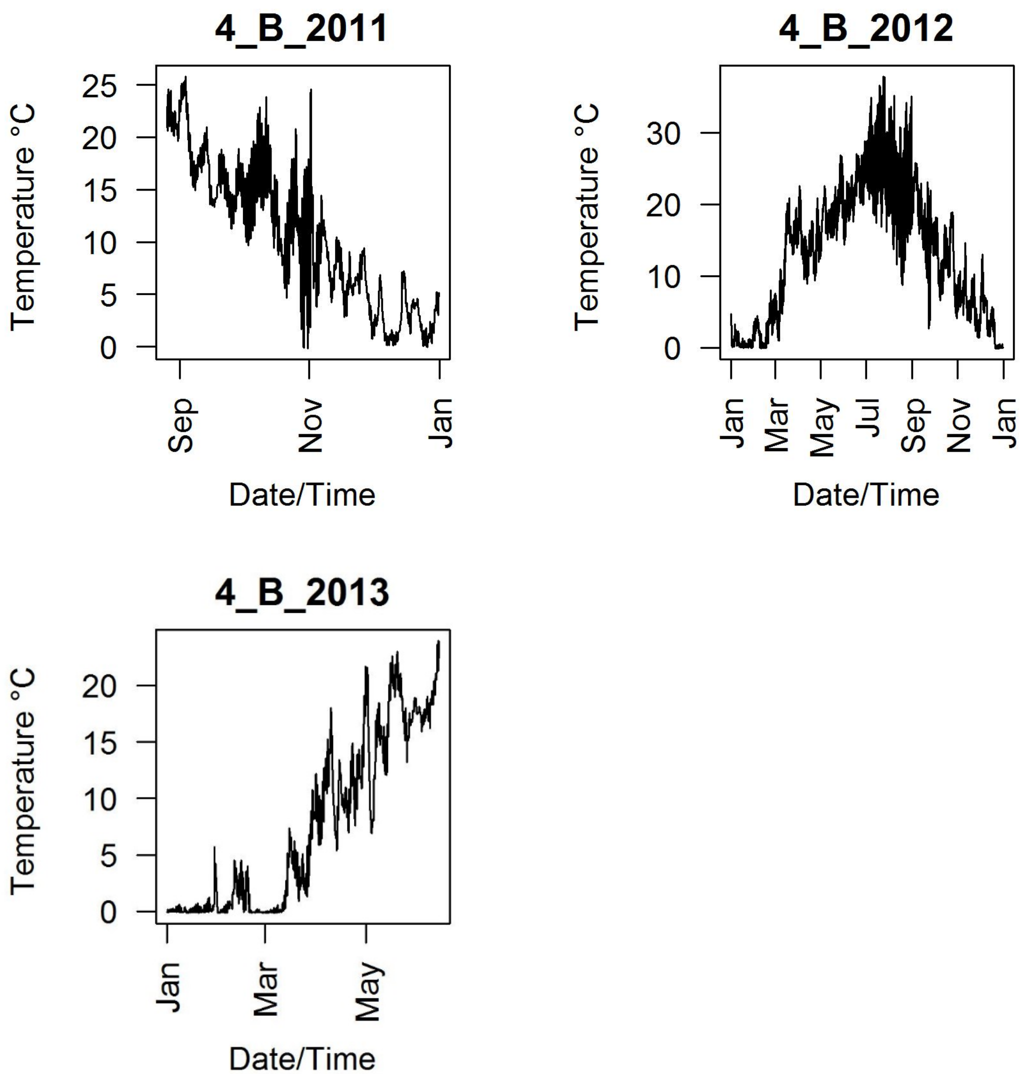
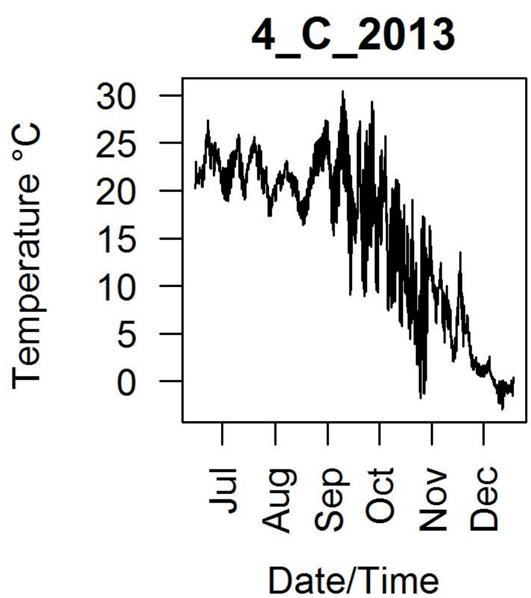


*Figure 13. Site 4, Point C: Long Branch Creek near Atlanta, 2013.***

Notes: Site was dry in Dec 2013 when retrieved logger. Pattern of daily temperature fluctuation increased in mid-Aug 2013.

Decision: do not use records post- 15 Aug 2013 for site C.



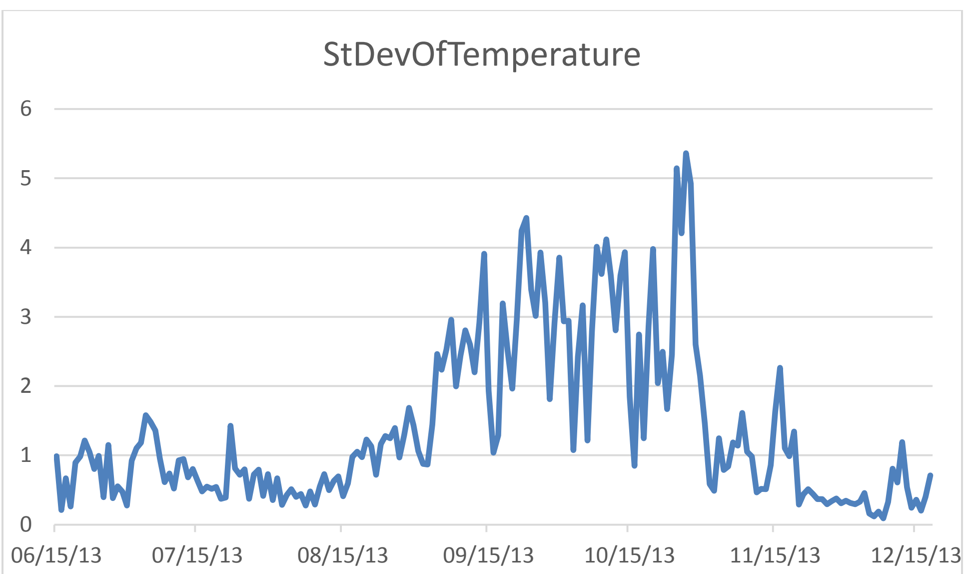


Figure 14. Site 5, Point A: South Fork Dry Sac River near Springfield, 2012 – 2015.
Odd high/low spikes at points A & B on the same days; 9/15/2012 and 9/21/2013

Decision: used all records.

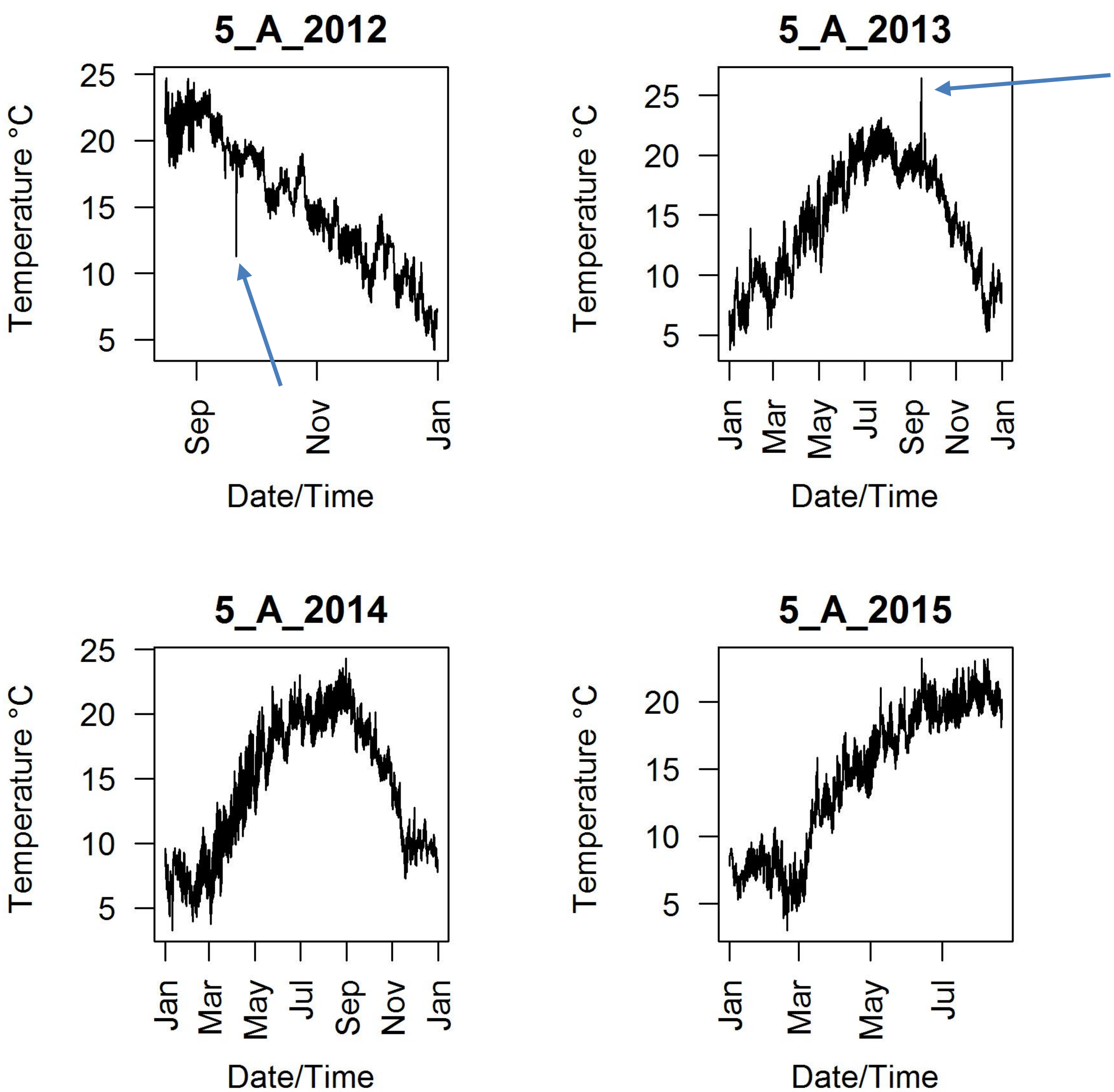


Figure 15. Site 5, Point B: South Fork Dry Sac River near Springfield, 2012 – 2015.

Odd high/low spikes at points A & B on the same days; 9/15/2012 and 9/21/2013

Decision: used all records.

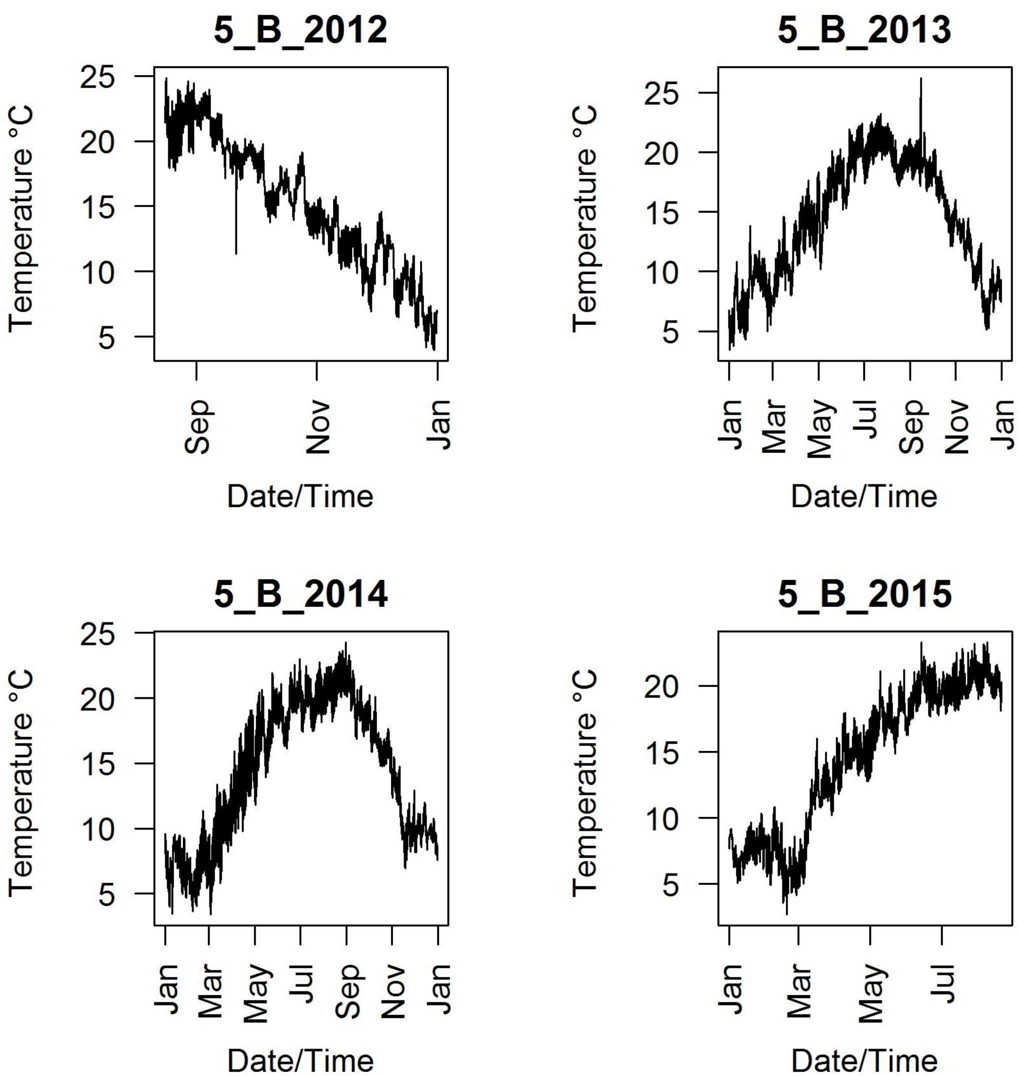


Figure 16. Site 6, Point A: Little Sac River near Morrisville, 2012 – 2015.
Logger was retrieved in Sept 2013 in good condition. In 2013, both A and B loggers show similar drop in temperature and less variation in late July; dampened variation continued up until retrieval.

Decision: used all records.

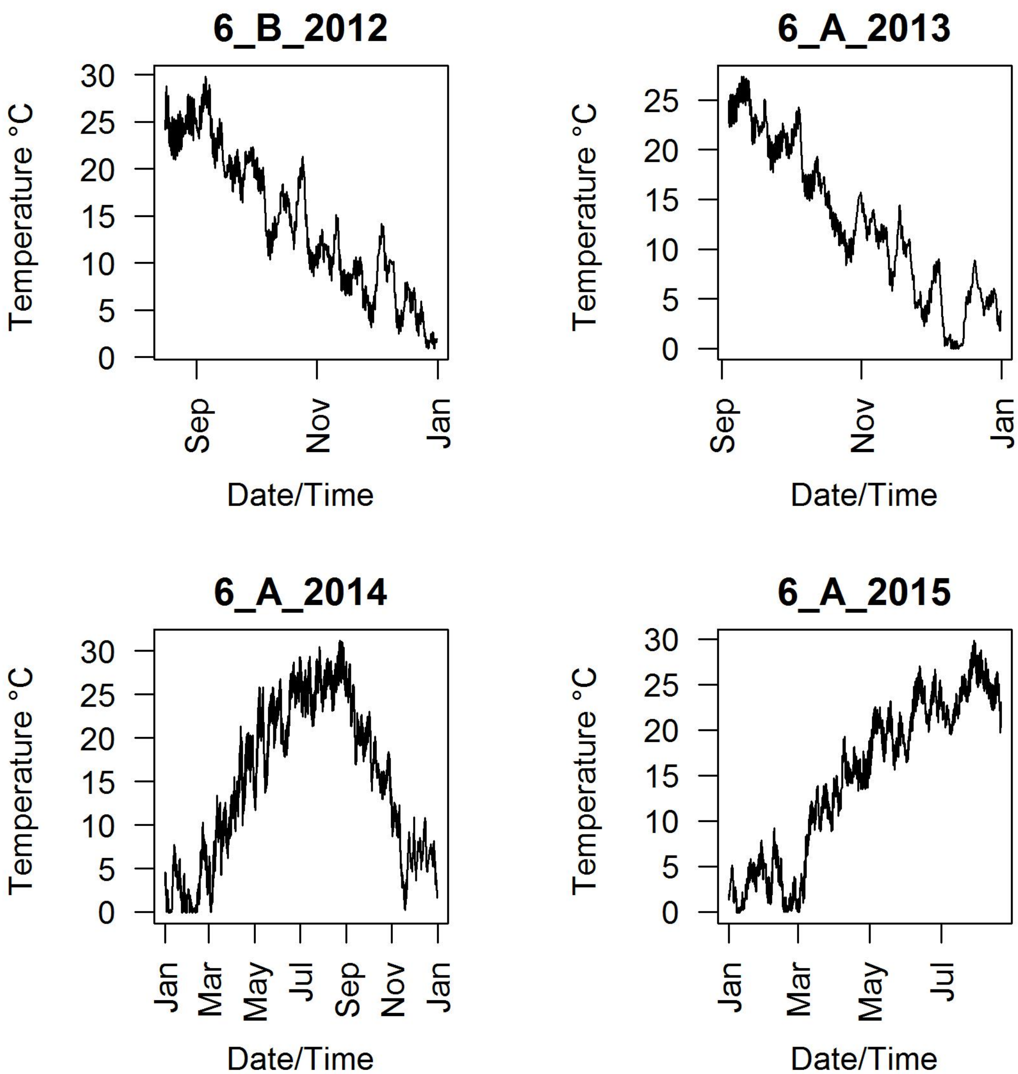


Figure 17. Site 6, Point B: Little Sac River near Morrisville, 2012 – 2015.
Decision: used all records.

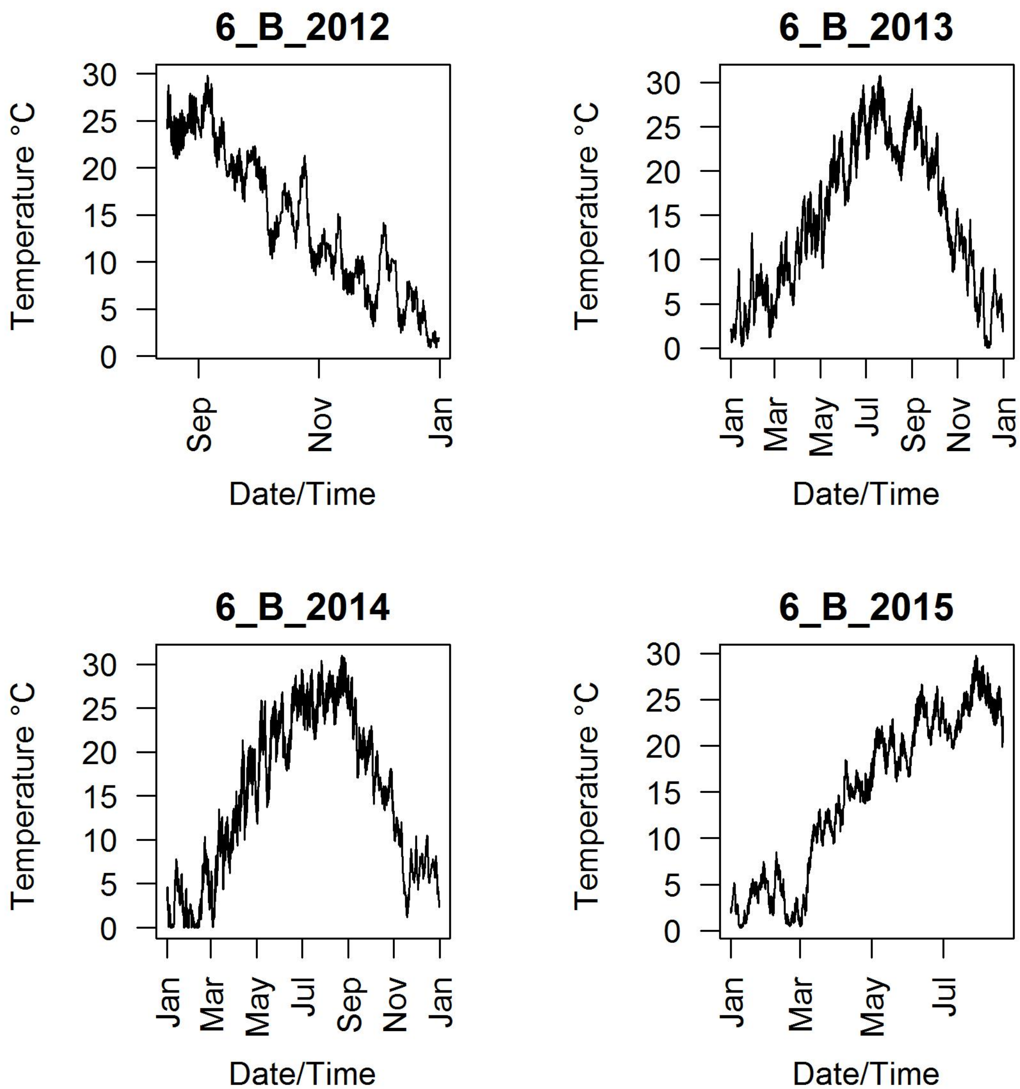


Figure 18. Site 7, Point A: Cedar Creek near Pleasant View, 2011 – 2012.
Decision: used all records.

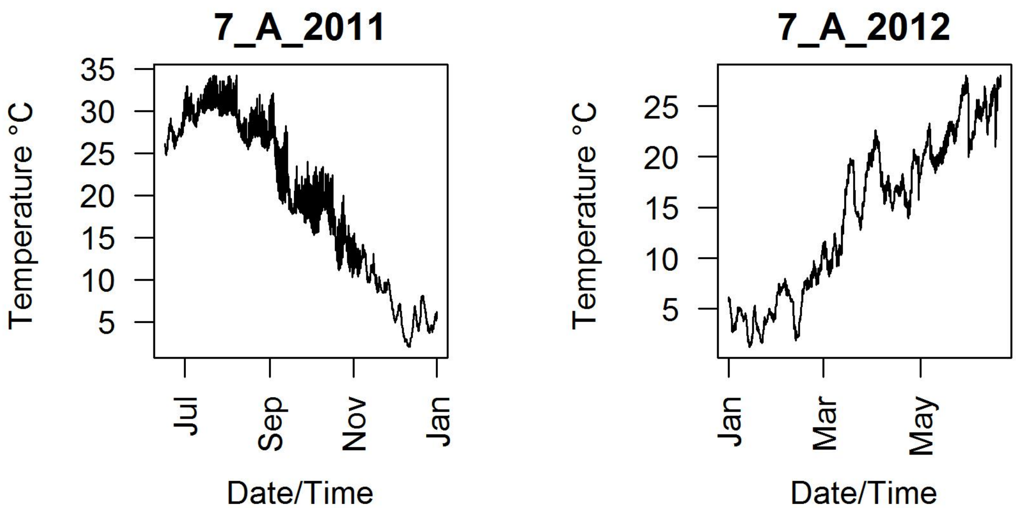


Figure 19. Site 7, Point D: Cedar Creek near Pleasant View, 2013 – 2015.
Decision: used all records.

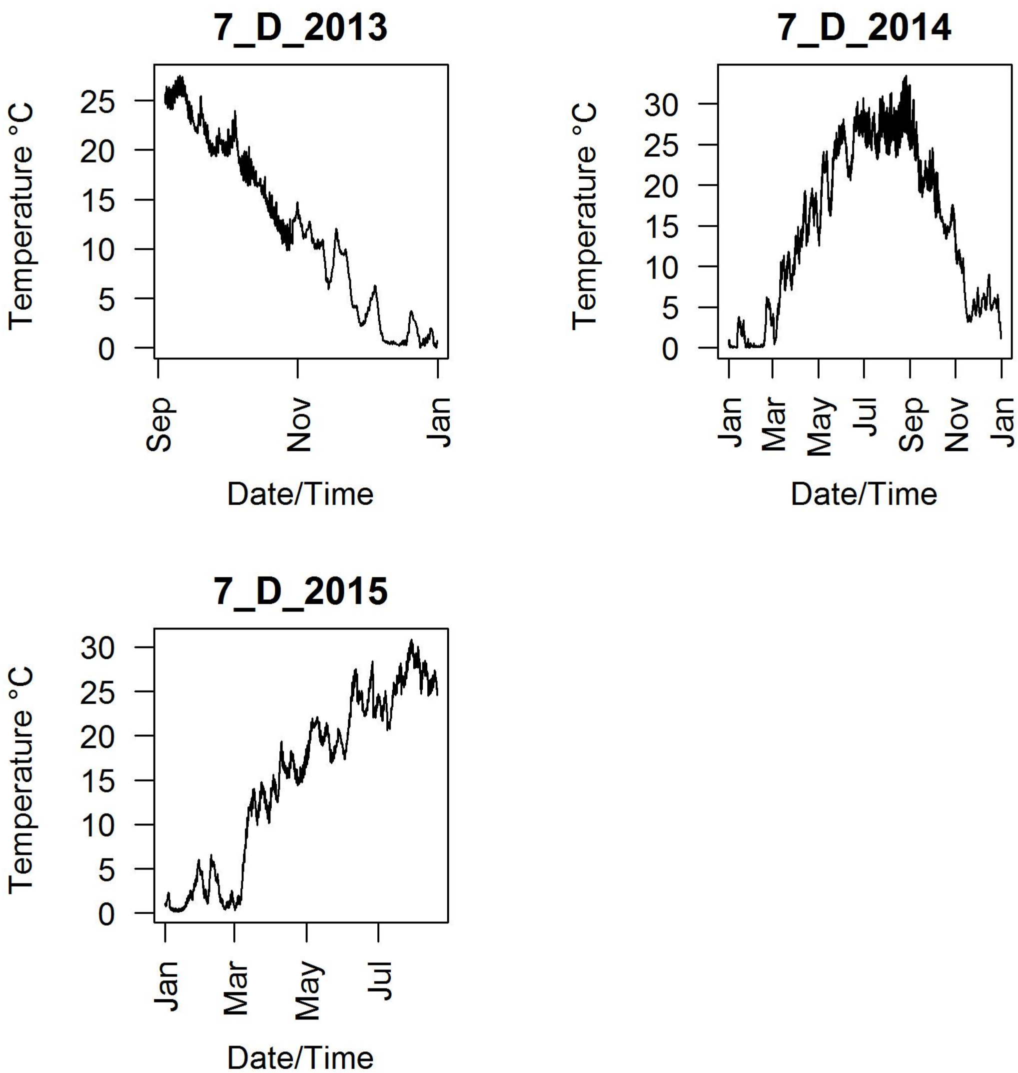
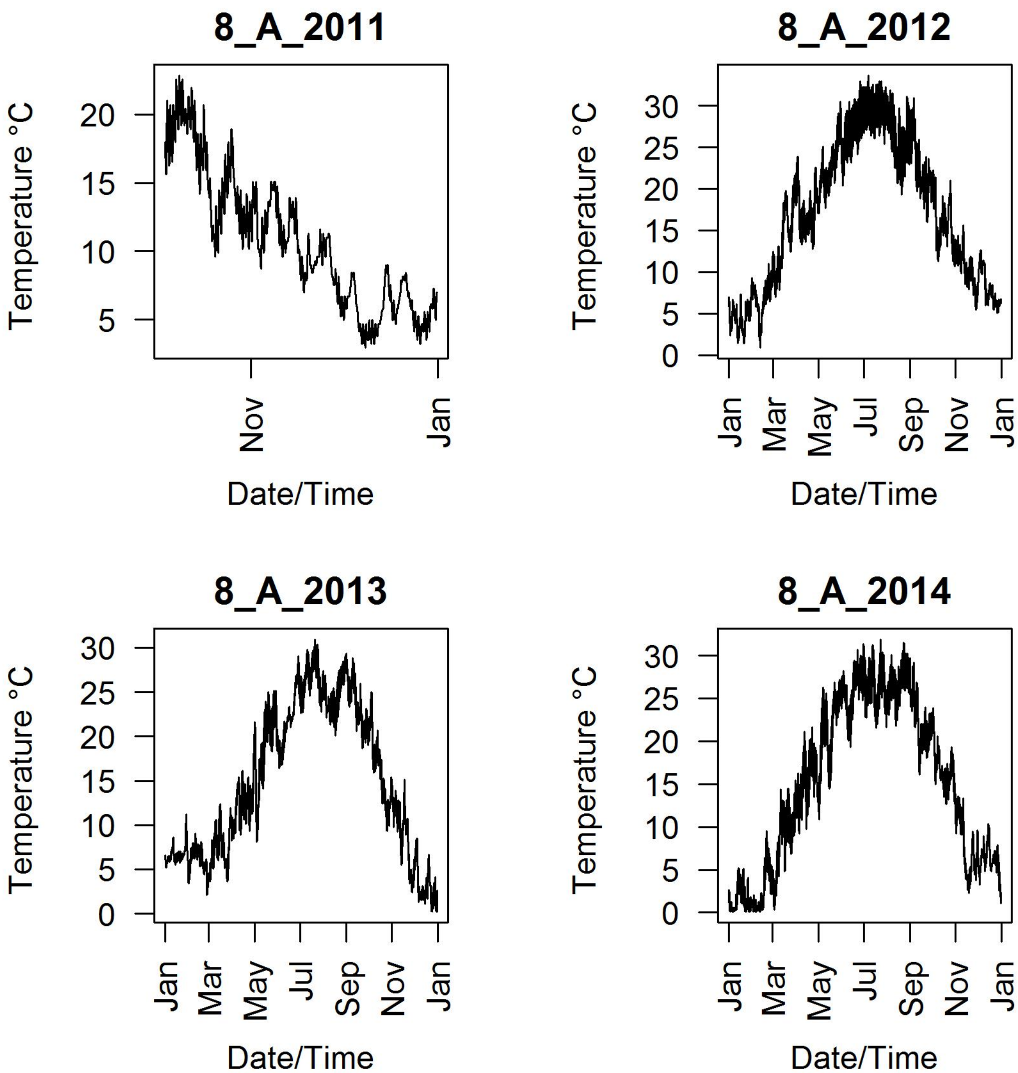


Figure 20. Site 8 Point A: Weaubleau Creek near Weaubleau; 2011 – 2015.
Decision: used all records.



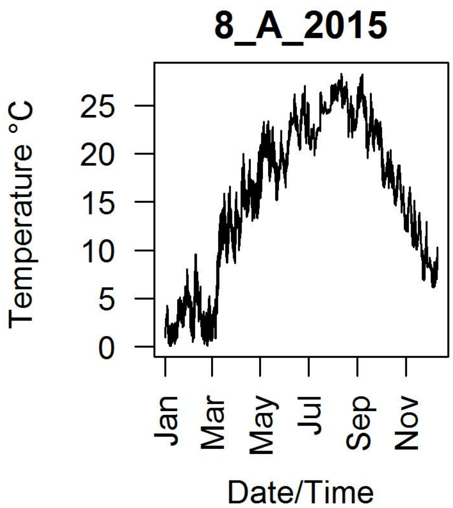
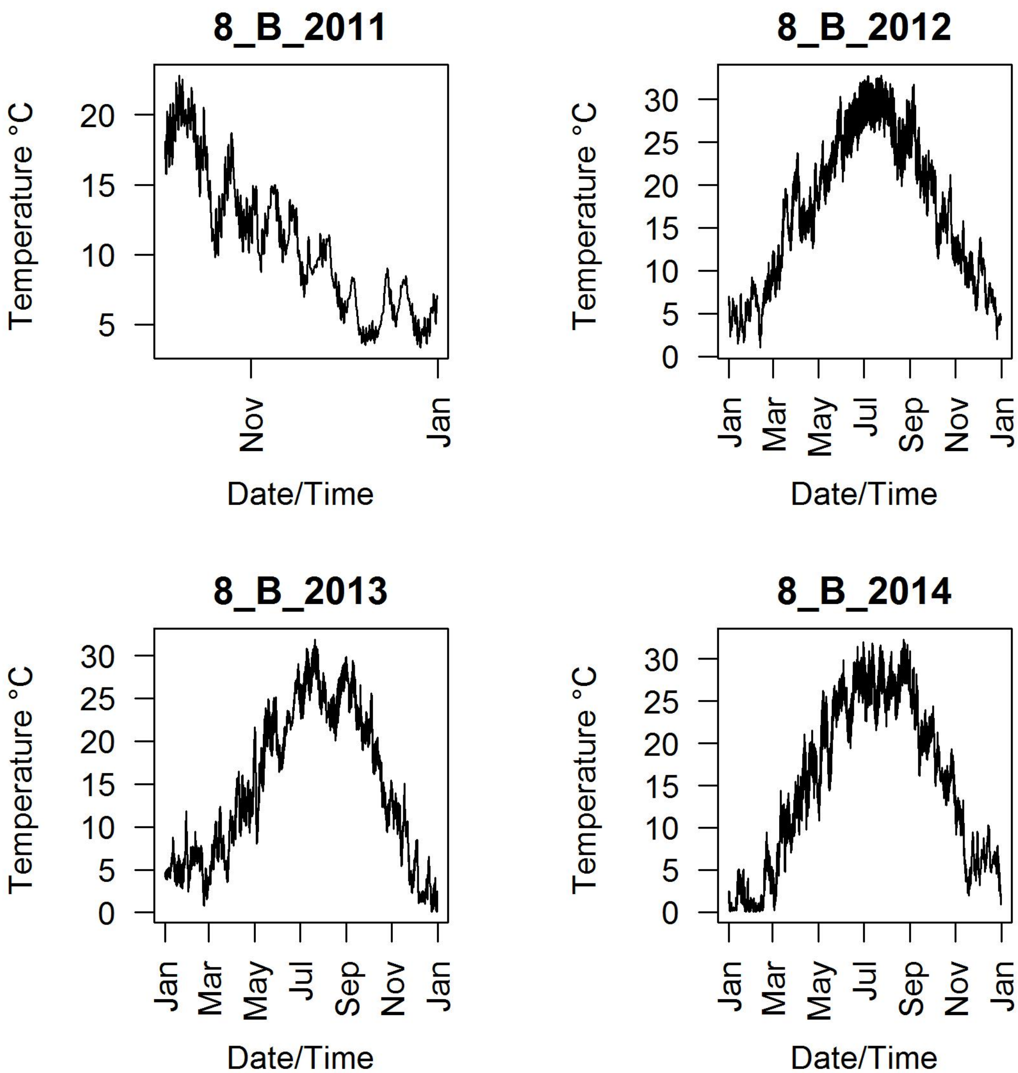

8_A_2015
Temperature °C
0
5
10
15
20
25
Jan
Mar
May
Jul
Sep
Nov
Date/Time

Figure 21. Site 8, Point B: Weaubleau Creek near Weaubleau, 2011 – 2015.

Decision: used all records.



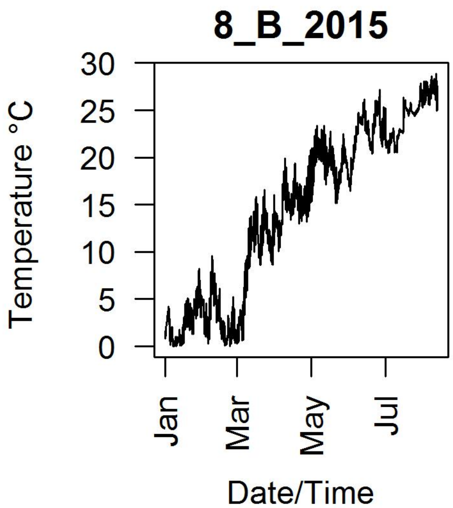
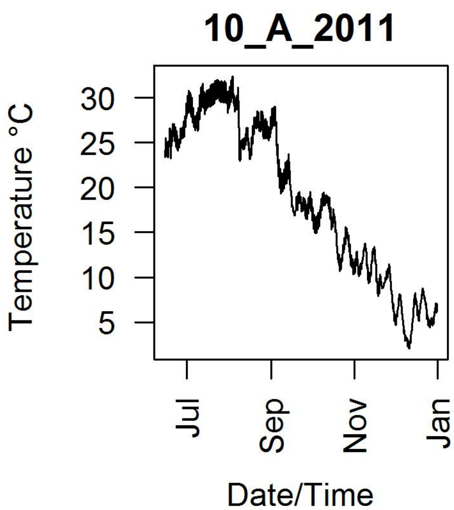
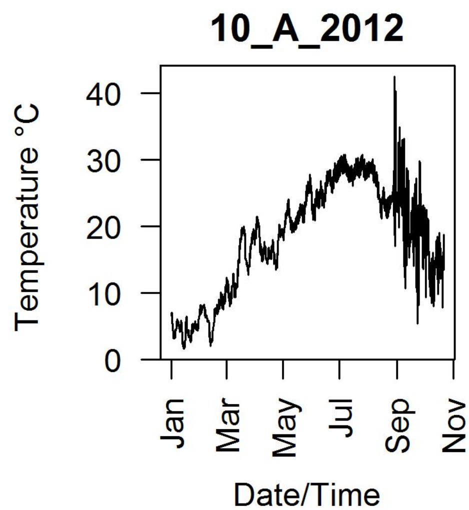

8_B_2015
Temperature °C
30
25
20
15
10
5
0
Jan
Mar
May
Jul
Date/Time

*Figure 22. Site 10, Point A: Niangua River at Windyville, 2011 – 2012***

Notes: No record of conditions when retrieved. On 29 Aug. 2012 temperature records spiked to >40 C most likely due to the logger being exposed.

Decision: did not use records after 28 Aug. 2012.





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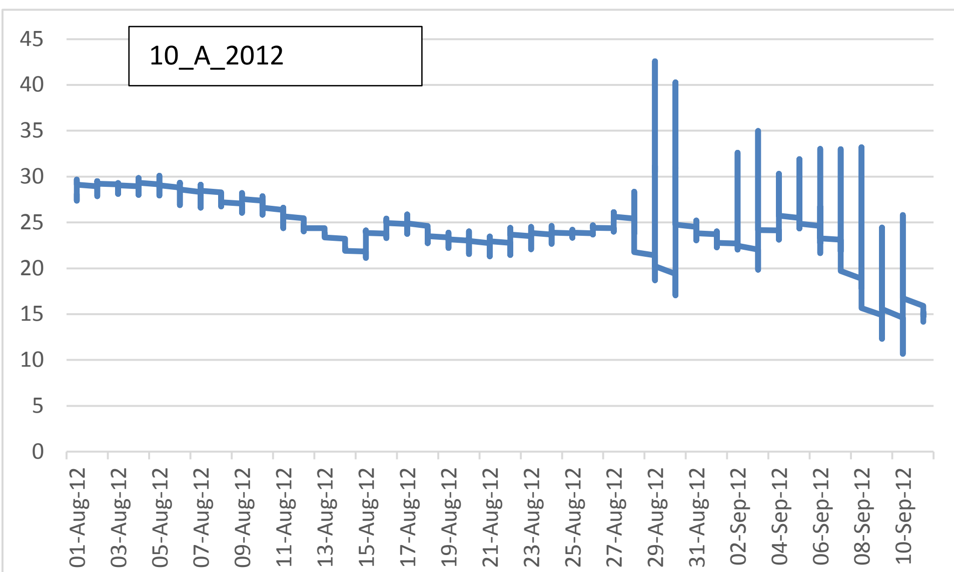
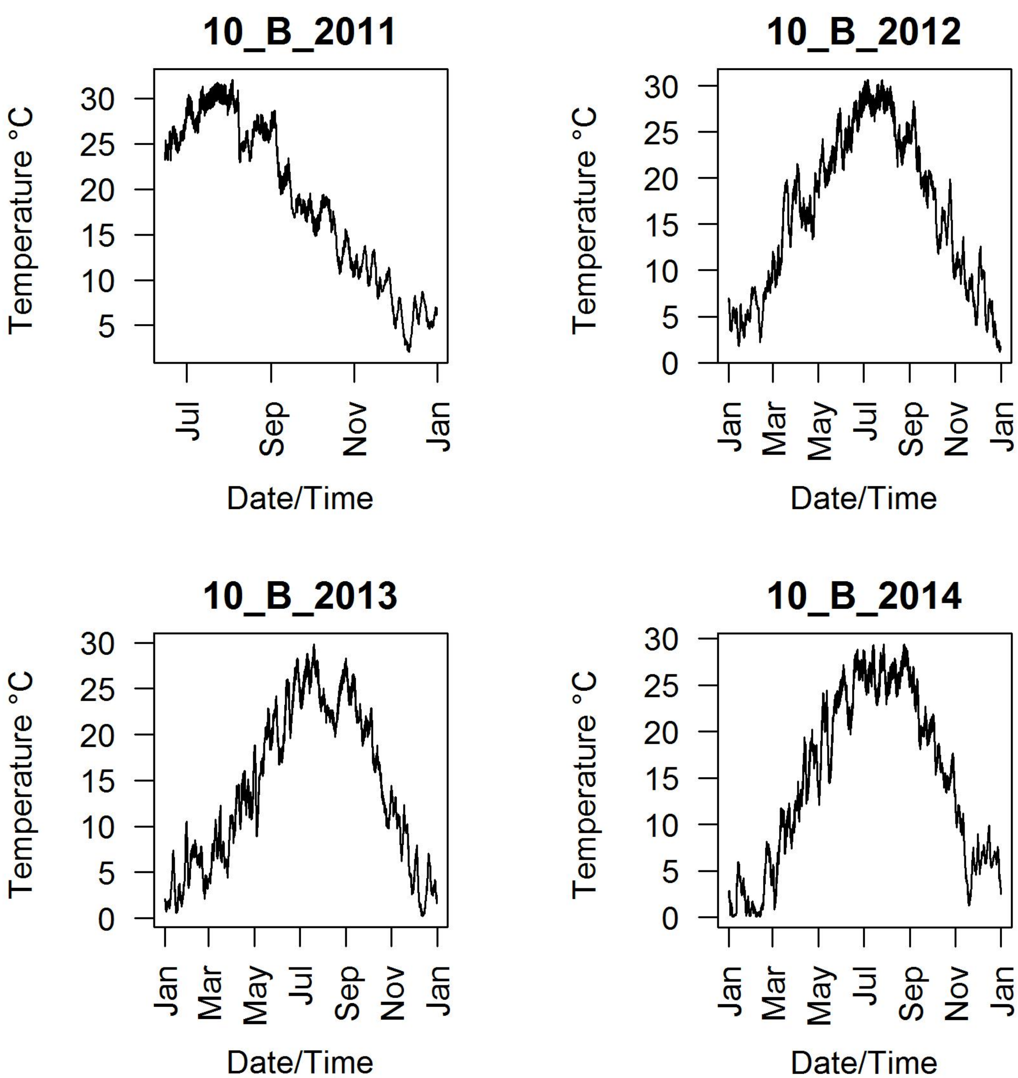


Figure 23. Site 10, Point B: Niangua River at Windyville, 2011 – 2015.
Decision: used all records.



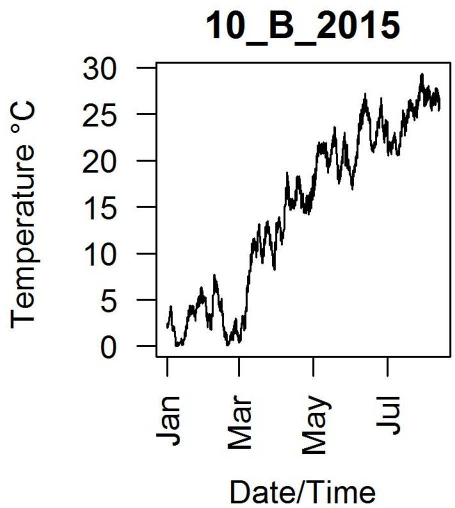

10_B_2015
Temperature °C
30
25
20
15
10
5
0
Jan
Mar
May
Jul
Date/Time

Figure 24. Site 10 Point C: Niangua River at Windyville; 2012 – 2014.
Decision: used all records.

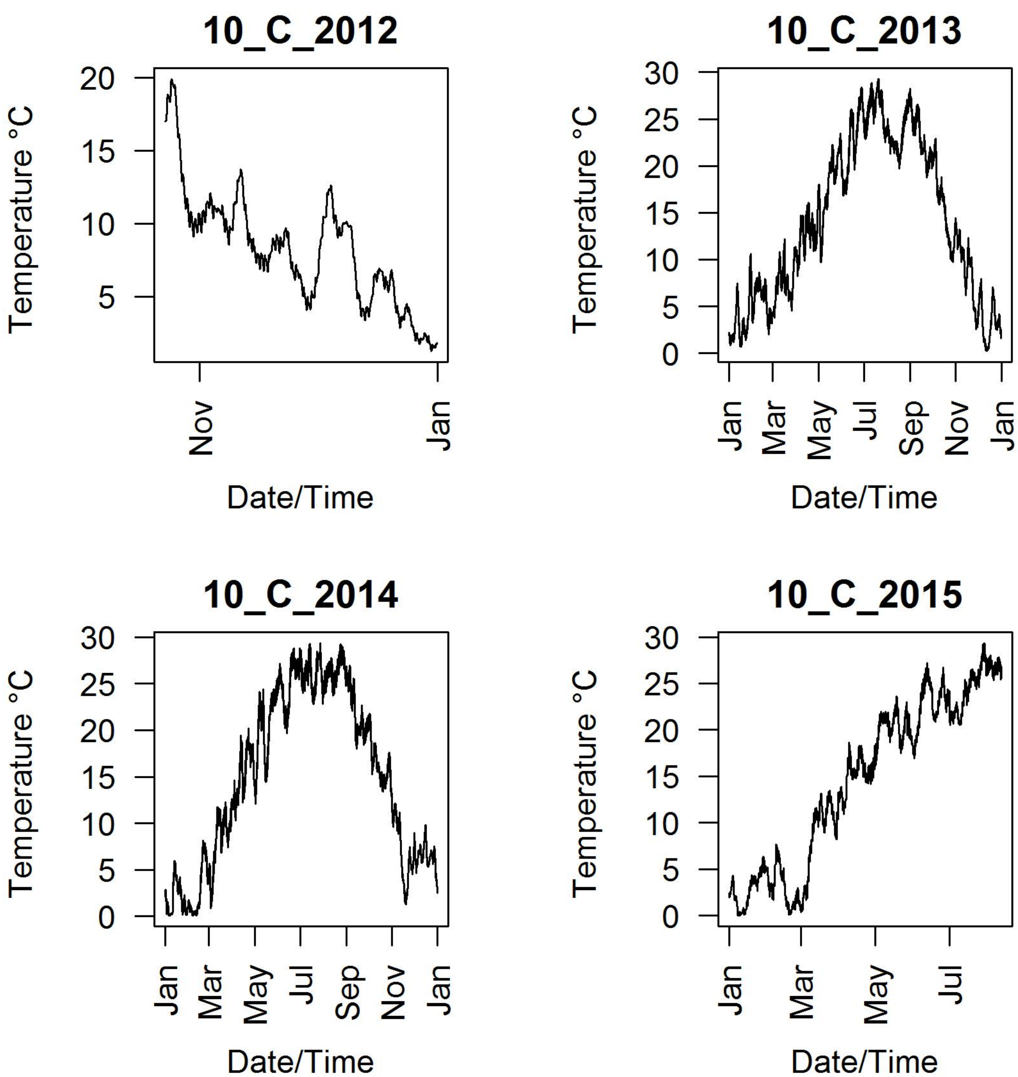
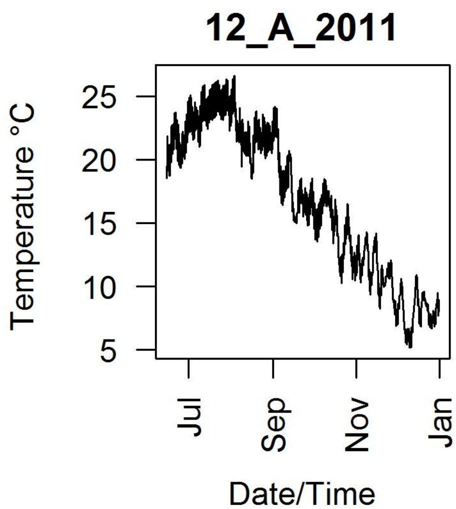
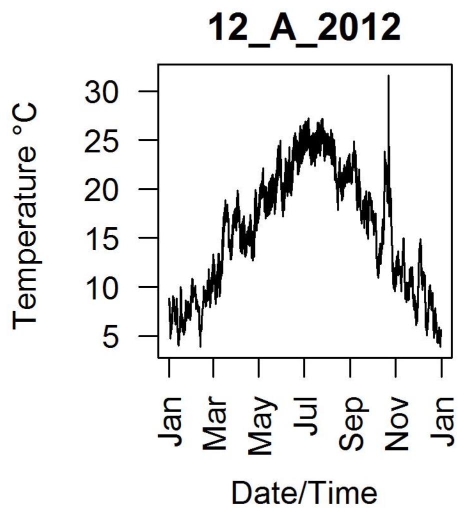


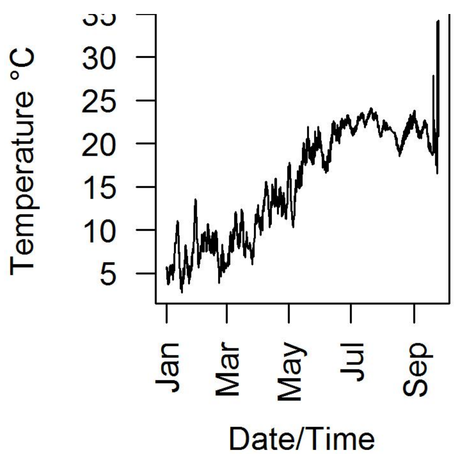
*Figure 25. Site 12, Point A: Niangua River ab Lake Niangua nr Macks Creek, 2011 – 2013***

Notes: A_2012: temperature spiked on 22 Oct 2012 – possibly from a rainfall event.

Decision: did not use data post 18 Sept 2013. Used all remaining records.







Retrieval notes from 2013 indicate that records after a major rainfall event in Aug may be suspect; logger was buried when retrieved. However, variability in daily temperature did not obviously dampen which could indicate burial; temperatures spiked on 19 Sept 2013 and reached highs that weren't seen on other years.

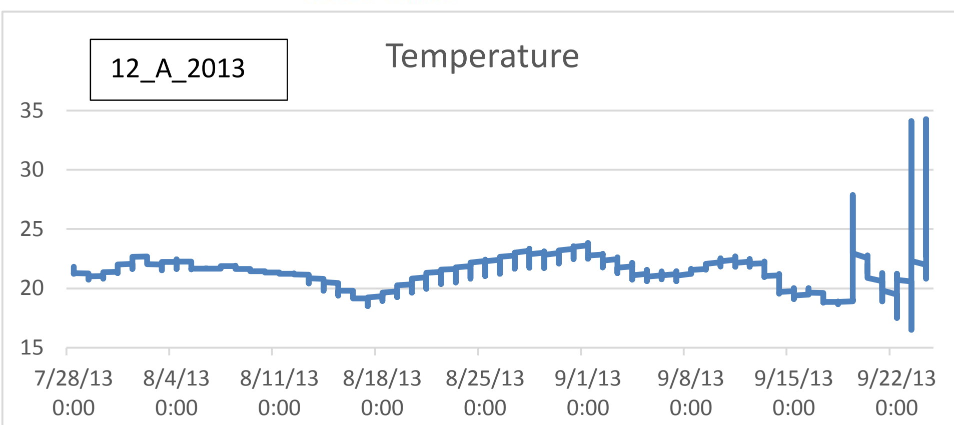


Figure 26. Site 12, Point B: Niangua River ab Lake Niangua nr Macks Creek, 2011 – 2012.
Decision: used all records.

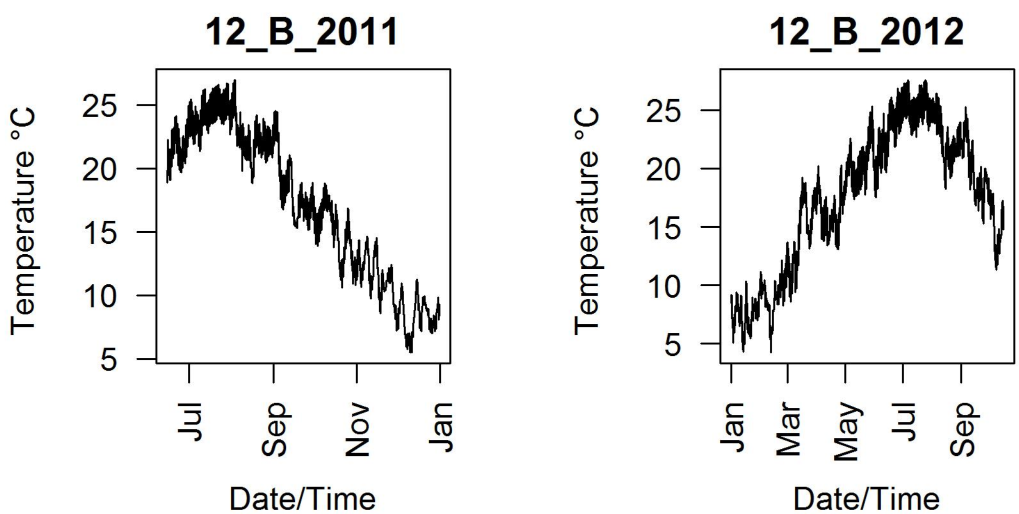


Figure 27. Site 12, Point C: Niangua River ab Lake Niangua nr Macks Creek, 2013 – 2014.
Decision: used all records.

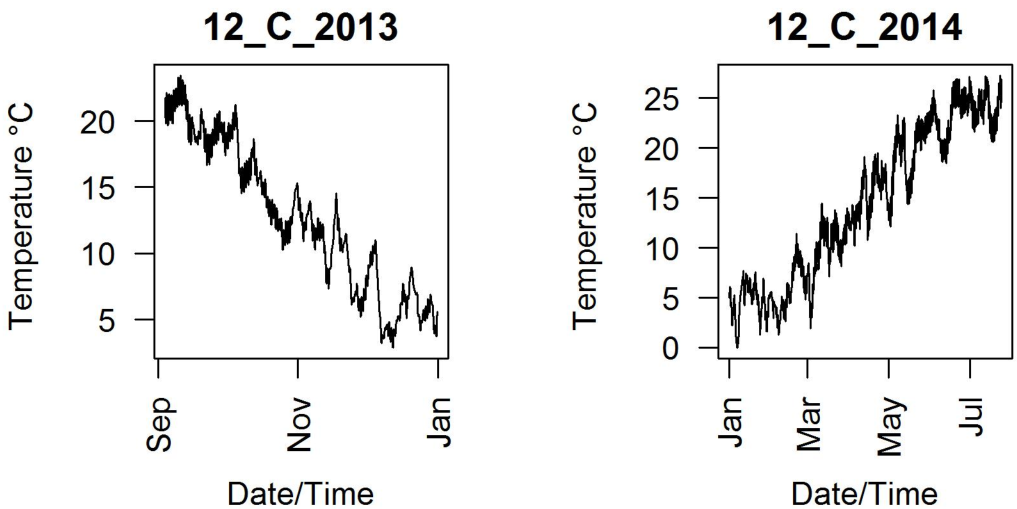
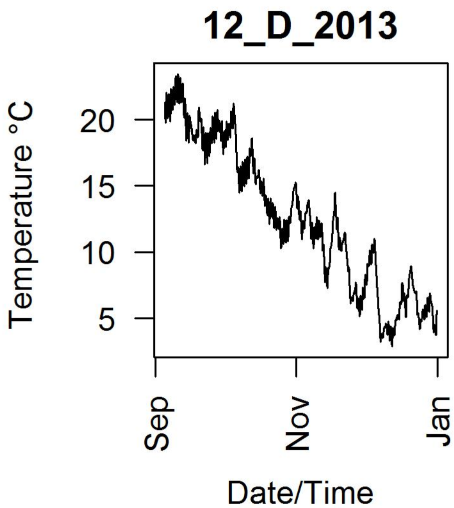
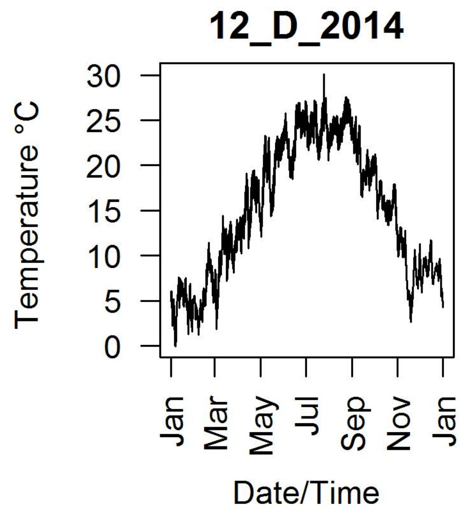


Figure 28. Site 12, Point D: Niangua River ab Lake Niangua nr Macks Creek, 2013 – 2015.
Decision: used all records.





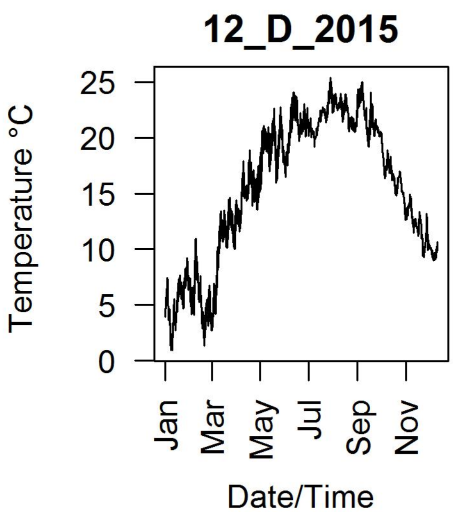


Figure 29. Site 12, Point E: Niangua River ab Lake Niangua nr Macks Creek, 2013 – 2014.
Decision: used all records.

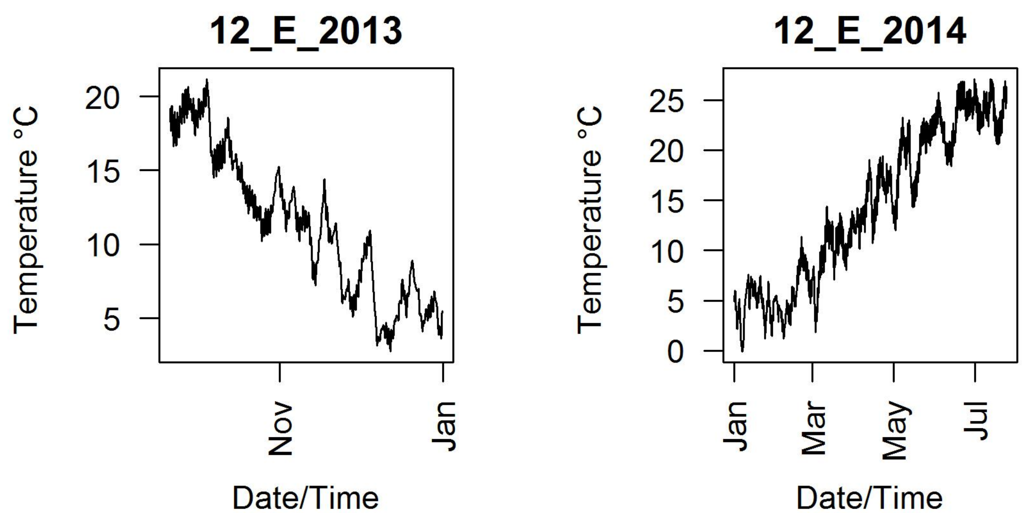


Figure 30. Site 13, Point A: Little Niangua River near Macks Creek, 2012 – 2013.
Decision: used all records.

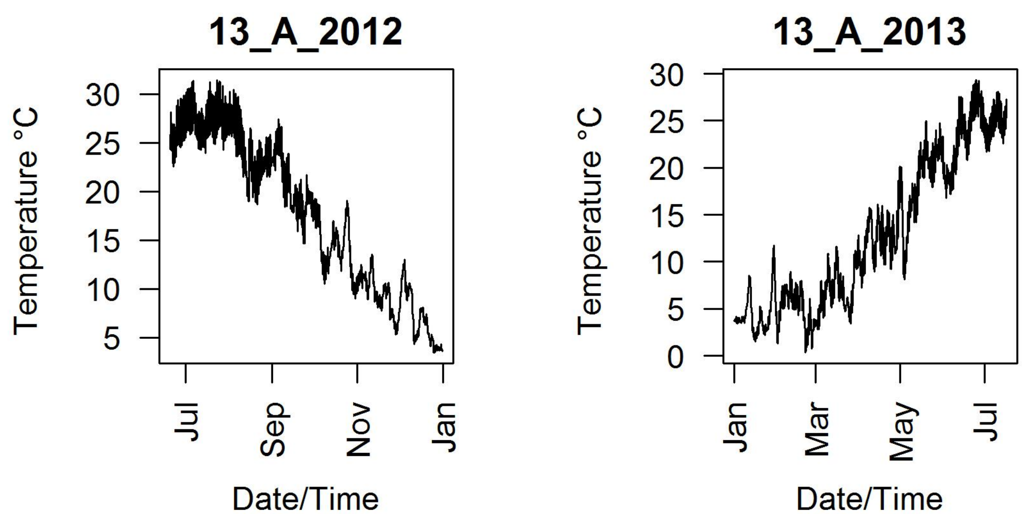


Figure 31. Site 13, Point B: Little Niangua River near Macks Creek, 2012 – 2013.

Notes: end was buried in 1” of sand when retrieved 17 July 2013. No obvious signal of being buried.

Decision: used all records.

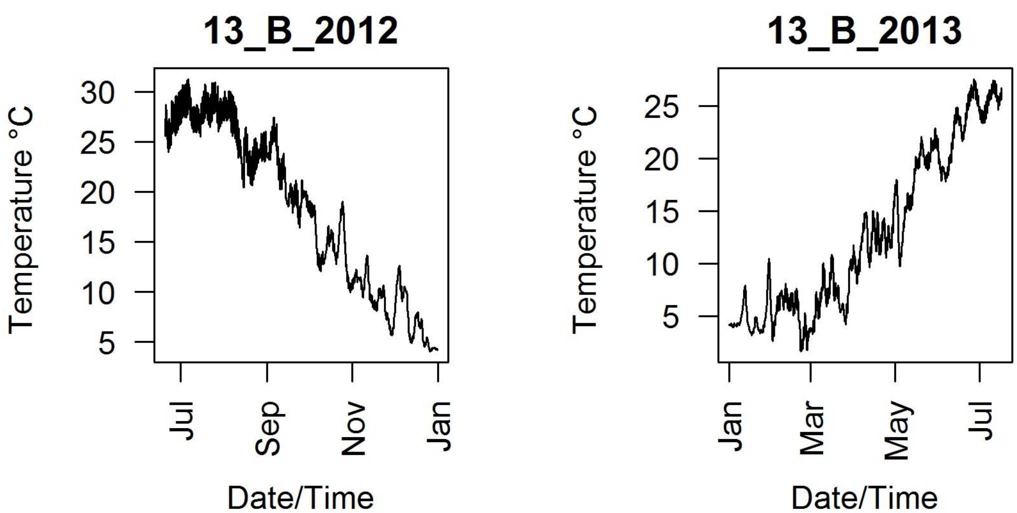


Figure 32. Site 13, Point C: Little Niangua River near Macks Creek, 2013 – 2014.
Decision: used all records.

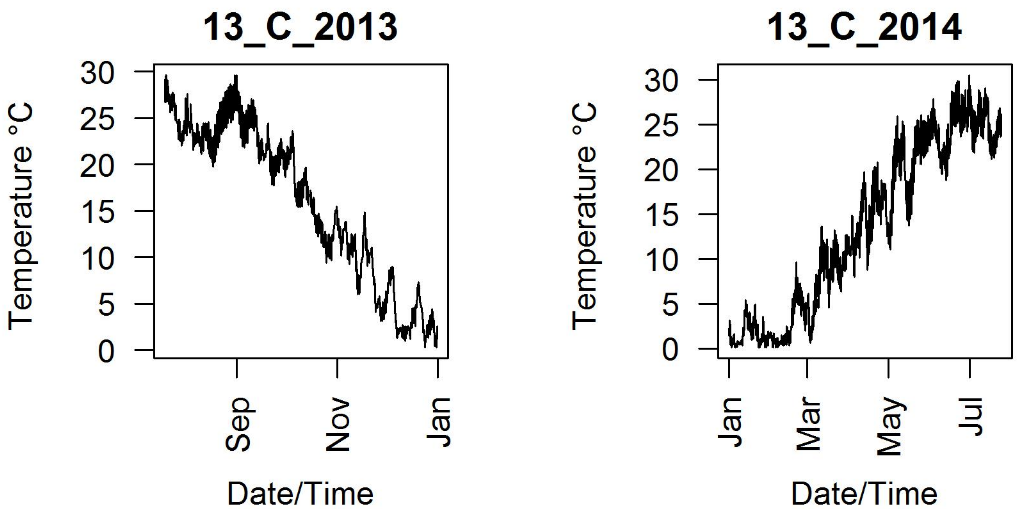


Figure 33. Site 13, Point D: Little Niangua River near Macks Creek, 2013 – 2014.
Decision: used all records.

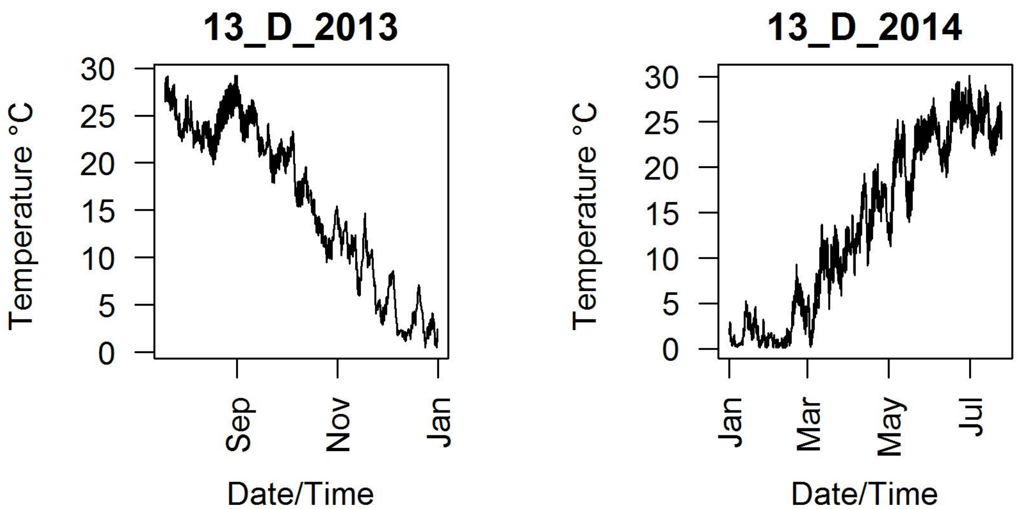
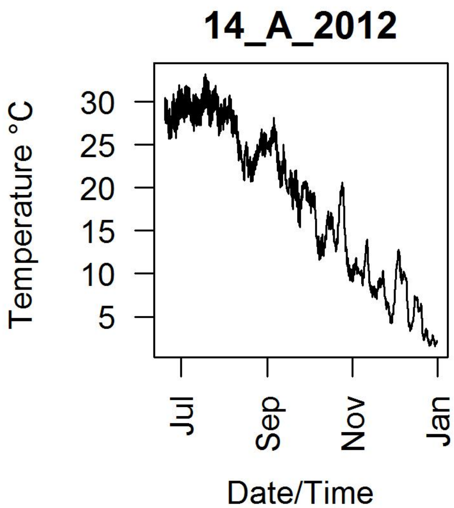
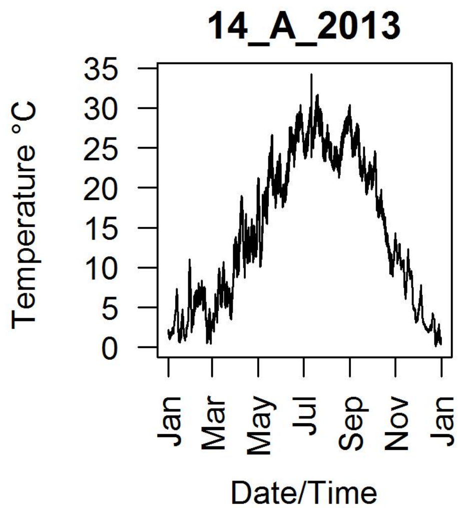


Figure 34. Site 14, Point A: Maries River at Westphalia, 2012 – 2014.
Decision: used all records.





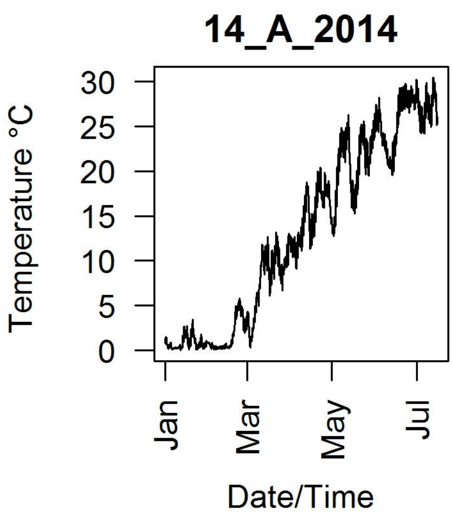
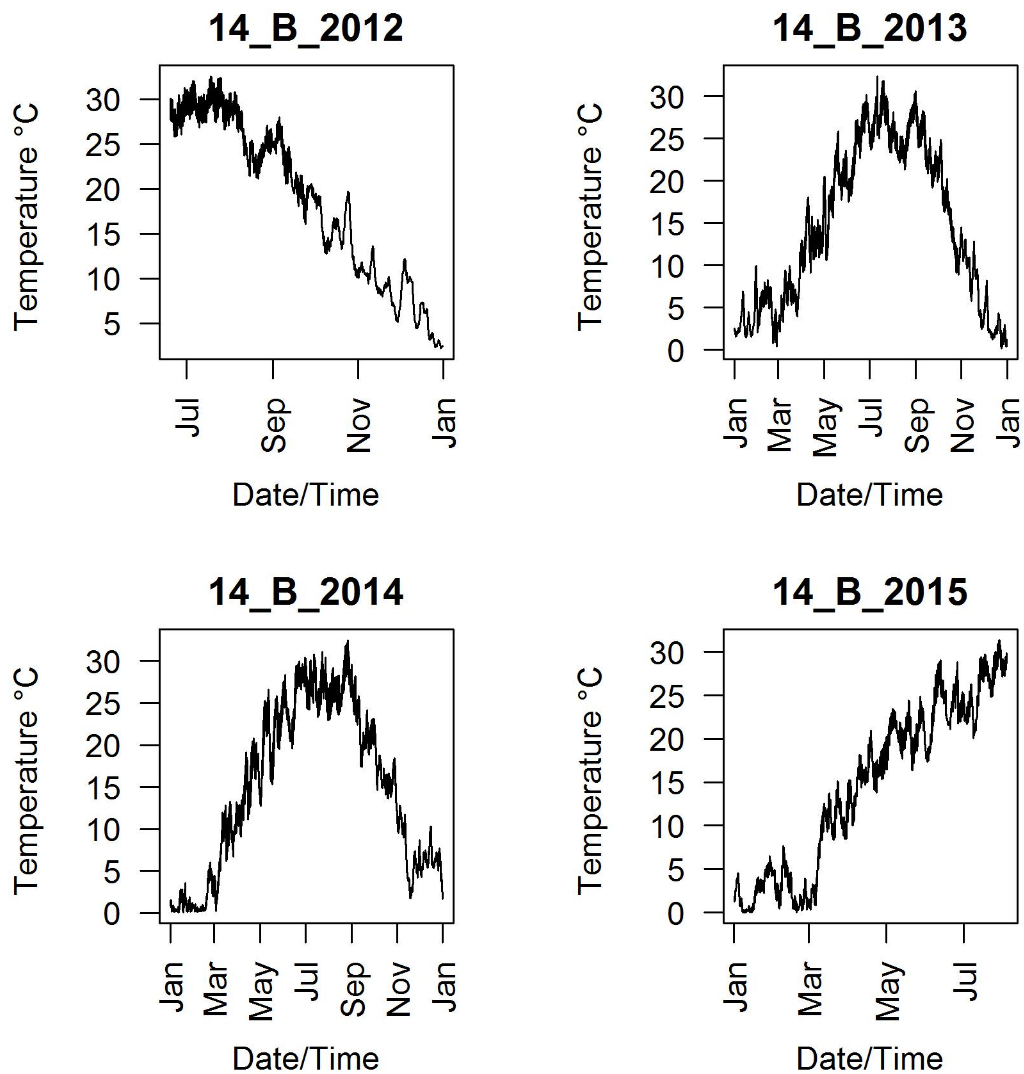
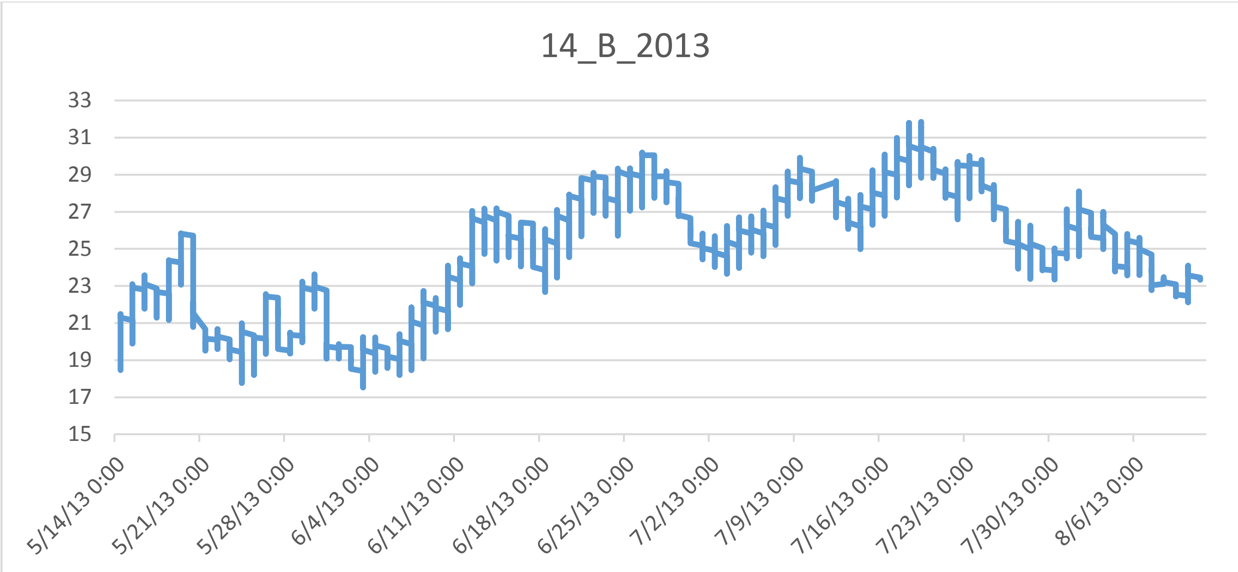


Figure 35. Site 14, Point B: Maries River at Westphalia, 2012 – 2015.

Notes: 11 July 2013, logger was partially buried when retrieved. Could not identify when logger was buried based on temperature signal.

Decision: used all records.





14_B_2013
33
31
29
27
25
23
21
19
17
15
5/14/13 0:00
5/21/13 0:00
5/28/13 0:00
6/4/13 0:00
6/11/13 0:00
6/18/13 0:00
6/25/13 0:00
7/2/13 0:00
7/9/13 0:00
7/16/13 0:00
7/23/13 0:00
7/30/13 0:00
8/6/13 0:00

Figure 36. Site 15, Point A: Gasconade River near Rich Fountain, 2011 – 2014.

16 July 2014: logger was buried when retrieved. Could not identify when logger was buried based on temperature signal or by comparison with data from site B.

Decision: used all records.

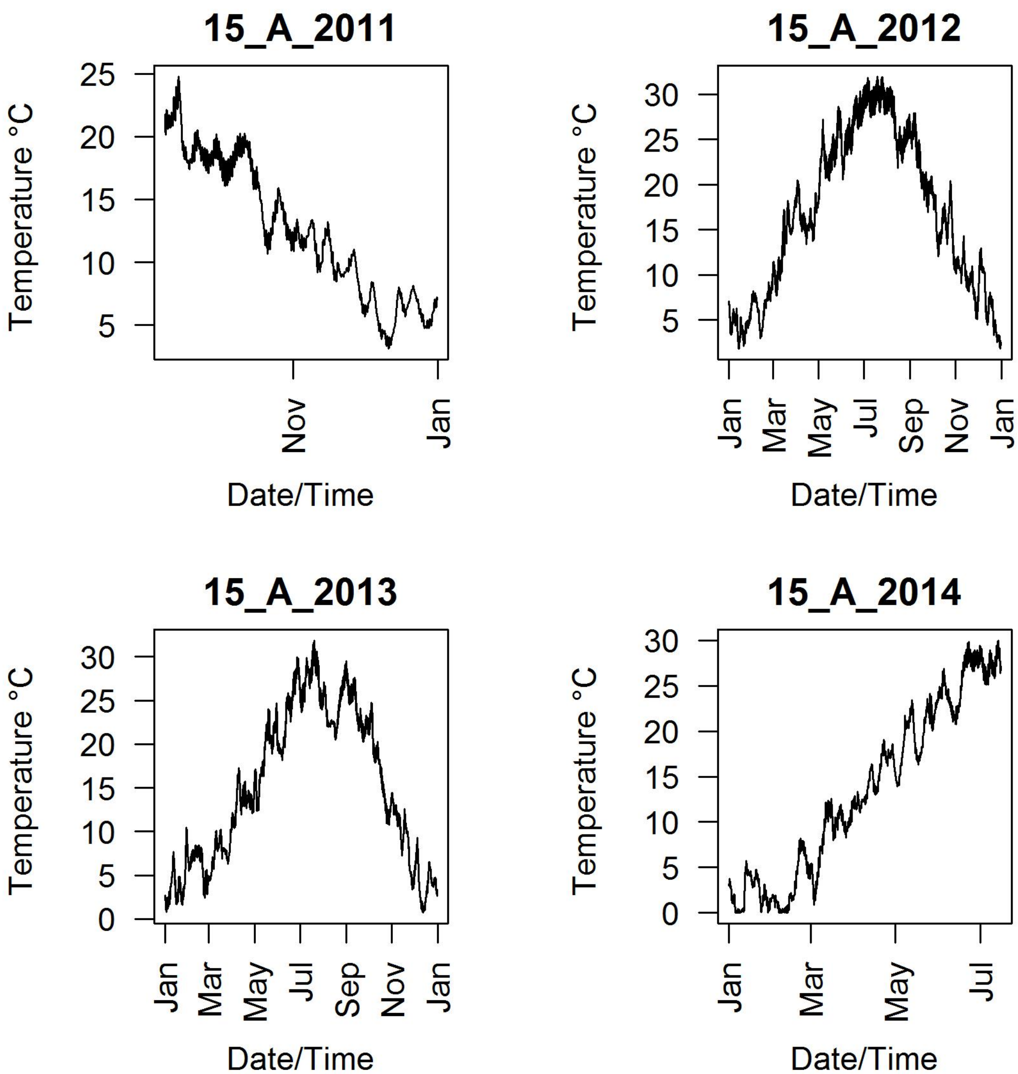


Figure 37. Site 15, Point B: Gasconade River near Rich Fountain, 2011 – 2014.
Decision: used all records.

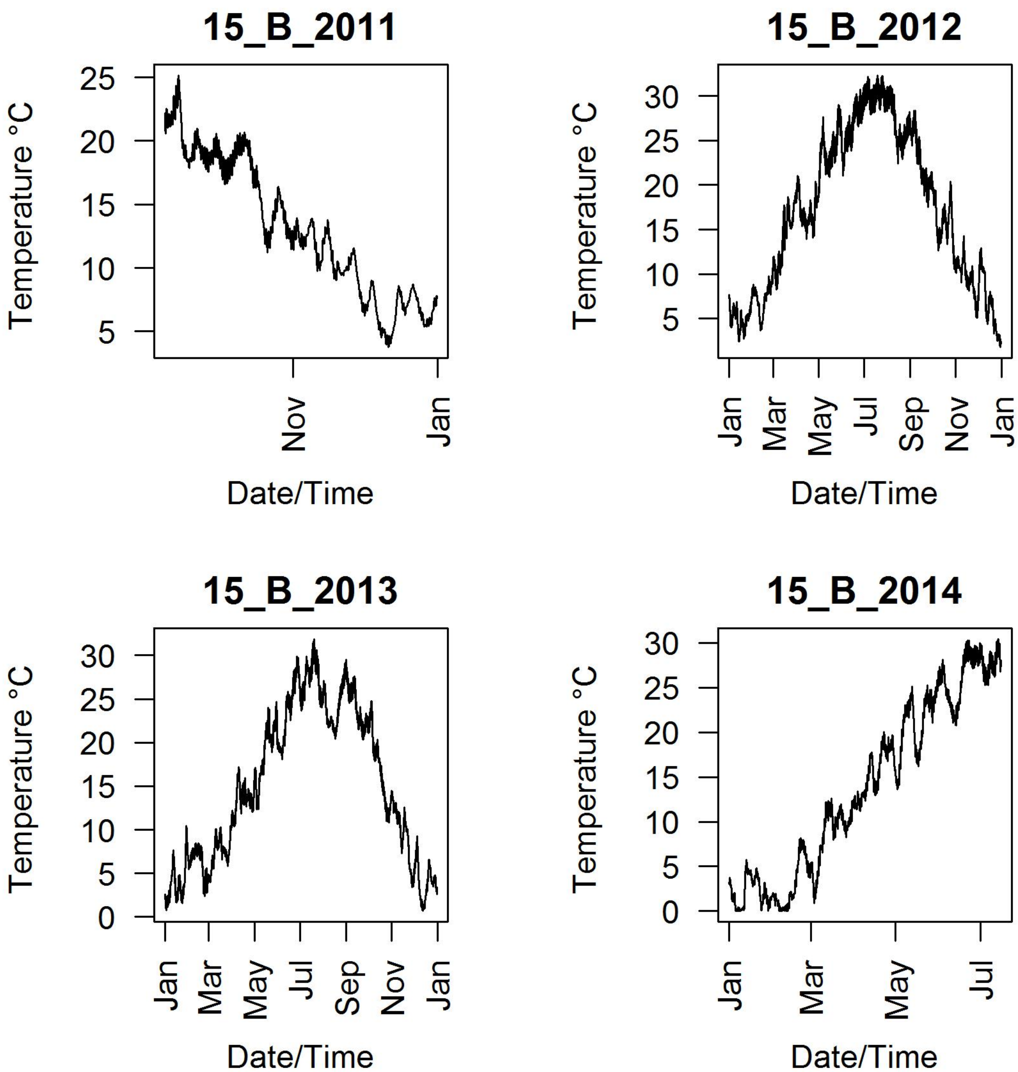
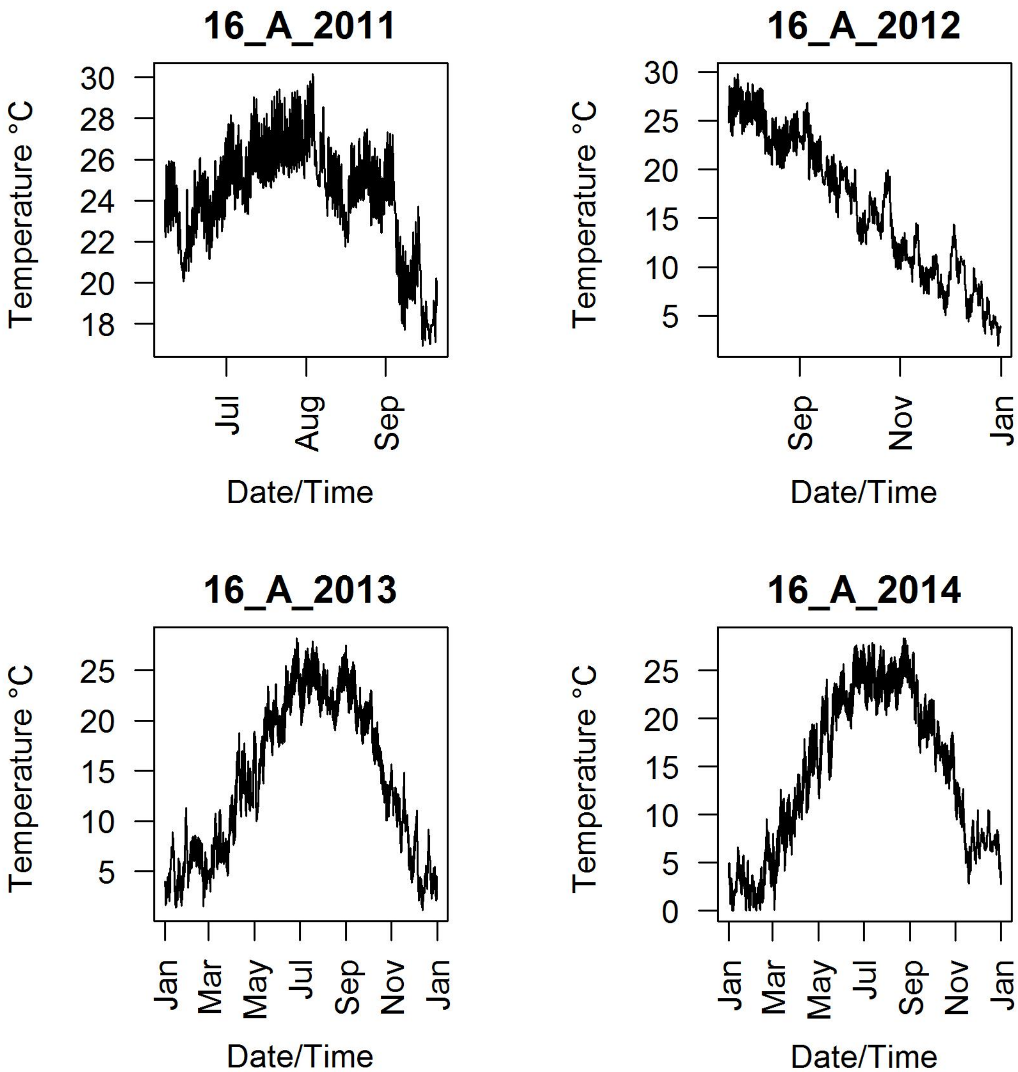
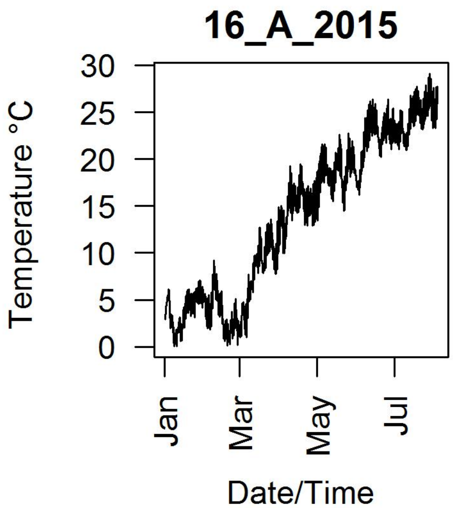


Figure 38. Site 16, Point A: Meramec River at Cook Station, 2011 – 2015.

Notes: Data missing for period of record from 9/21/2011 to 7/19/2012. On 8/24/2013 the logger was partially buried when retrieved. Could not identify when logger was buried based on temperature signal or by comparison with data from site B.

Decision: used all records.




16_A_2015
Temperature °C
30
25
20
15
10
5
0
Jan
Mar
May
Jul
Date/Time

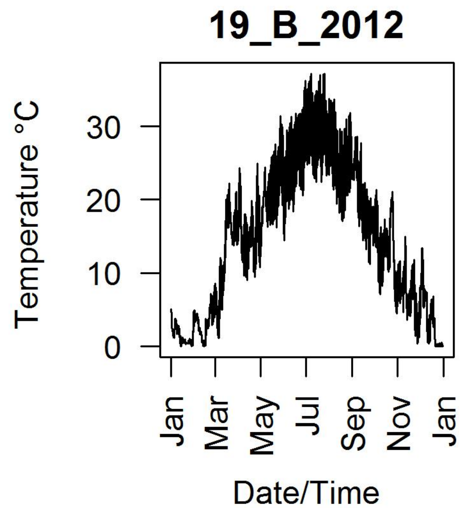

19_B_2012
Temperature °C
30
20
10
0
Jan
Mar
May
Jul
Sep
Nov
Jan
Date/Time

Figure 39. Site 16, Point B: Meramec River at Cook Station, 2011 – 2013.

Notes: 8/24/2013 - partially buried when retrieved; could not identify when logger was buried based on temperature signal or by comparison with data from site A.

Decision: used all records.

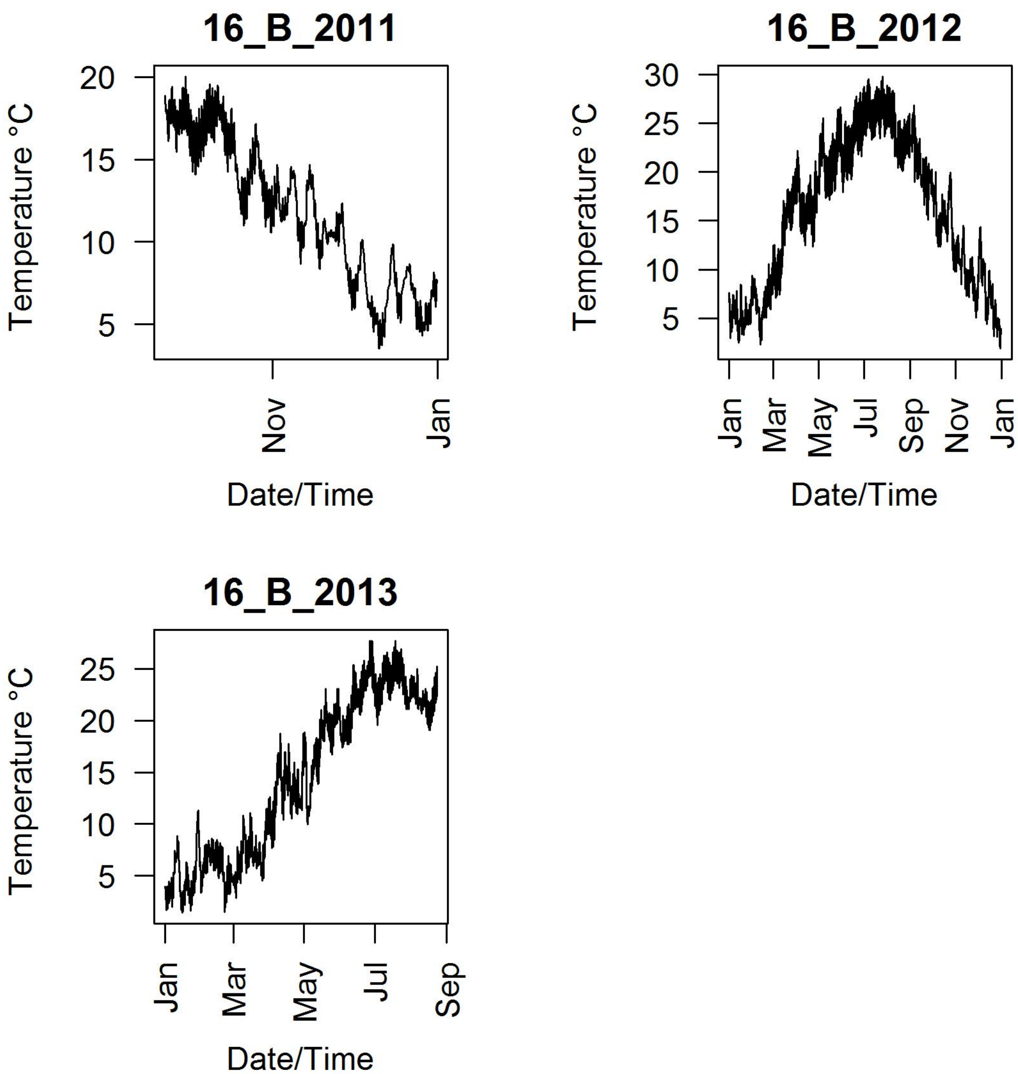


Figure 40. Site 16, Point C: Meramec River at Cook Station, 2013 – 2015.
Decision: used all records.

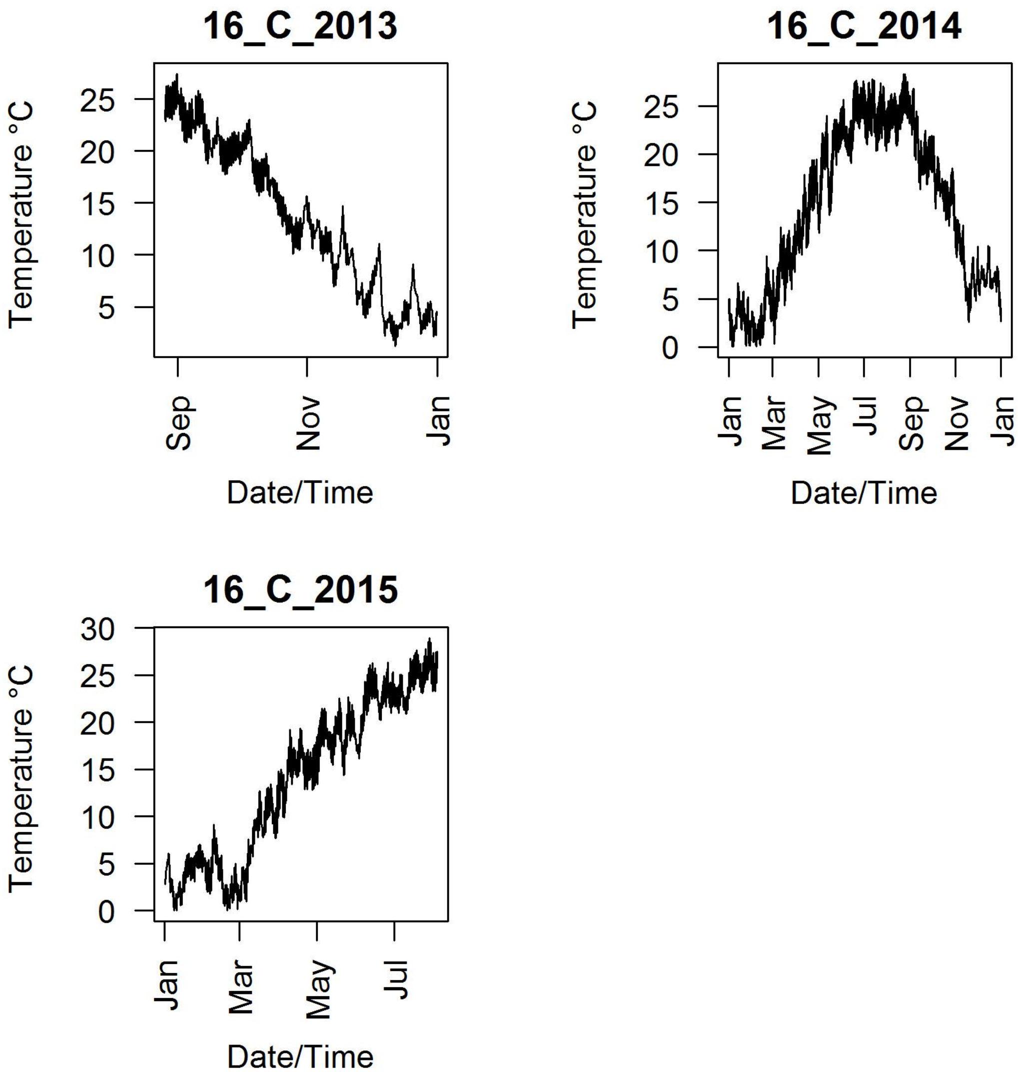
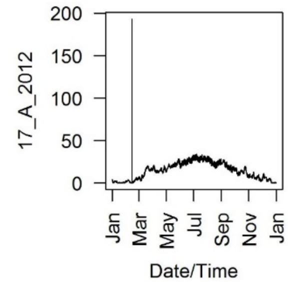
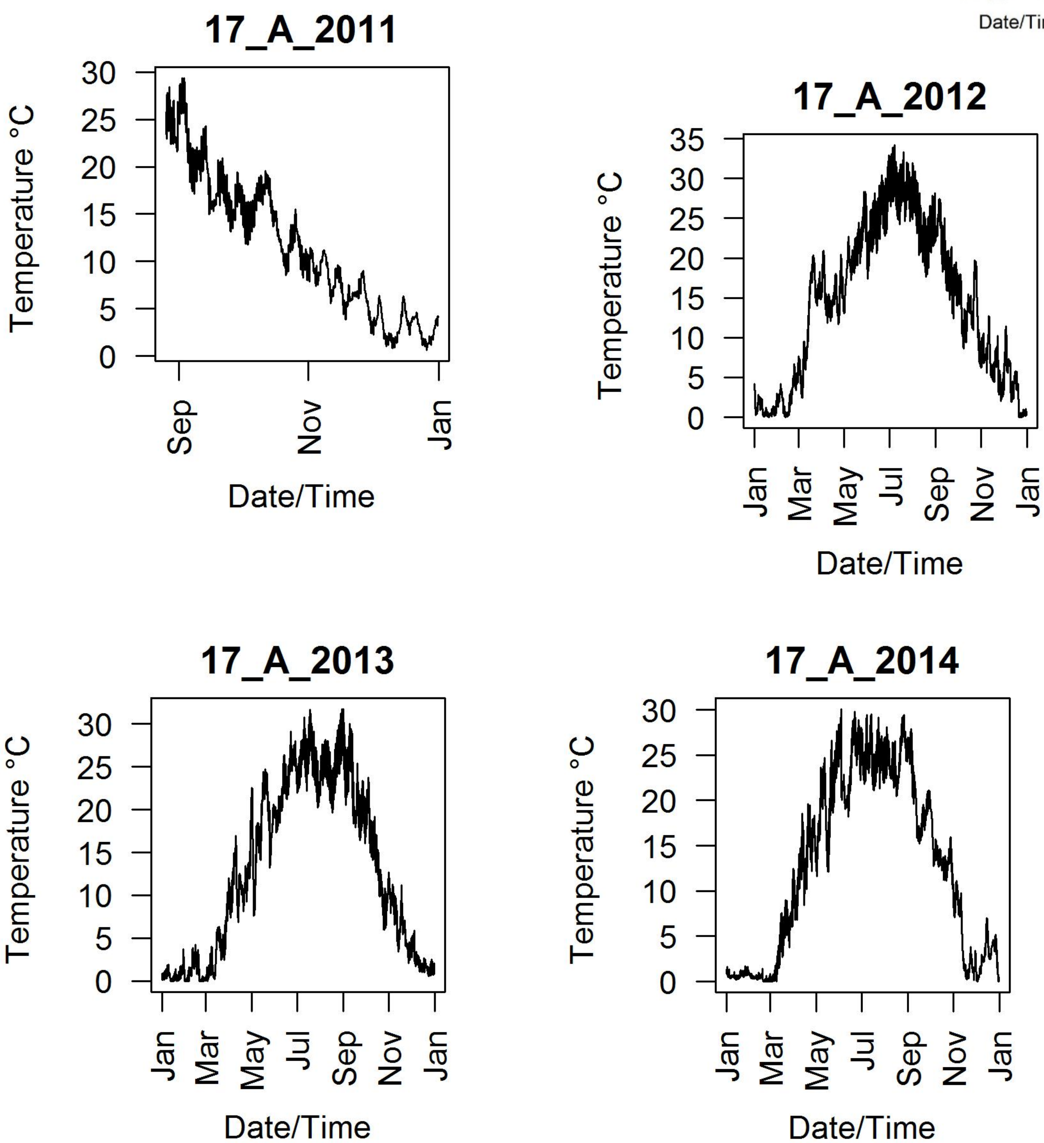


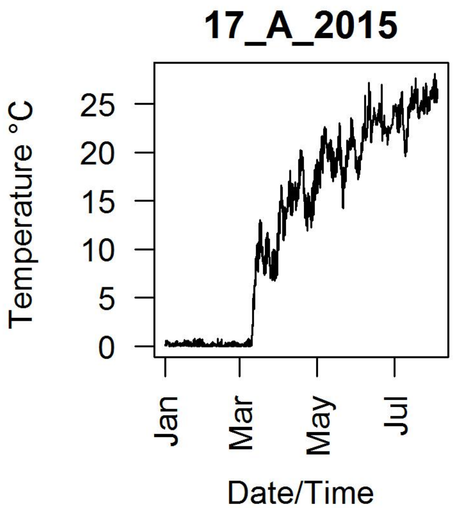
*Figure 41. Site 17, Point A: South Fabius River above Newark, 2011 – 2015***

Notes: extreme spike: 193.35; 02/13/12 23:00; temperatures hovering above zero; did not use recs with 193.35.

Decision: used remaining data.







17_A_2015
Temperature °C
25
20
15
10
5
0
Jan
Mar
May
Jul
Date/Time

Figure 42. Site 17 Point B: South Fabius River above Newark, 2011 – 2013
Decision: used all records.

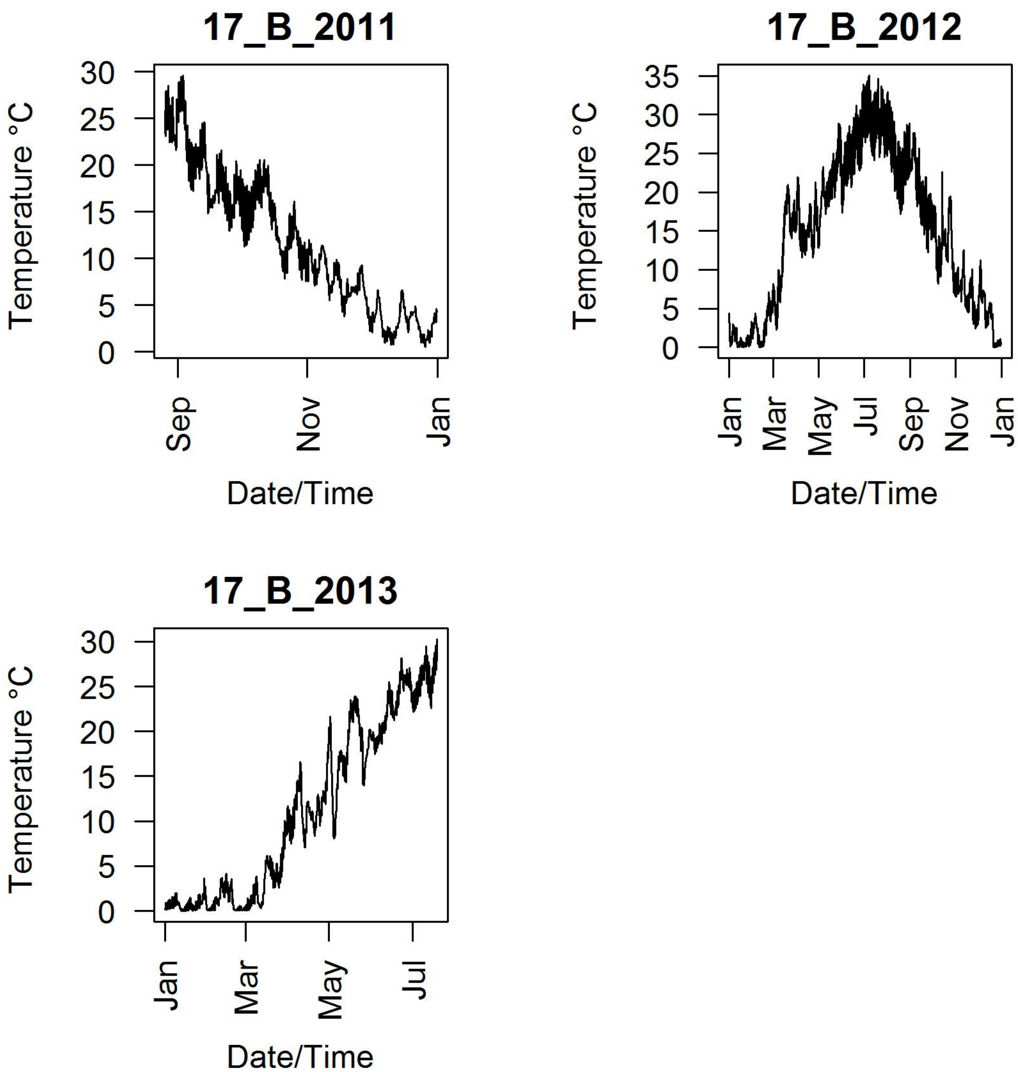


Figure 43. Site 17, Point C: South Fabius River above Newark, 2013 – 2015.
Decision: used all records.

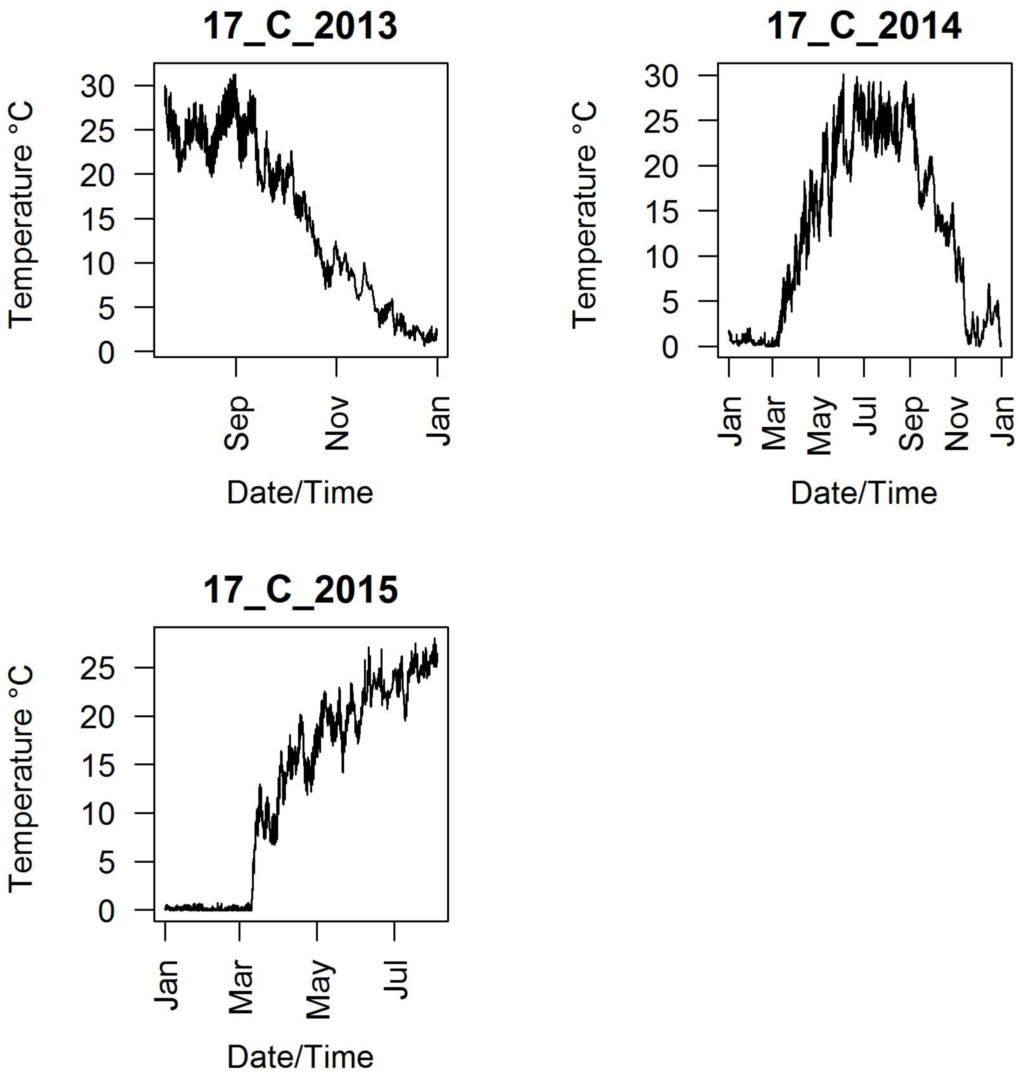
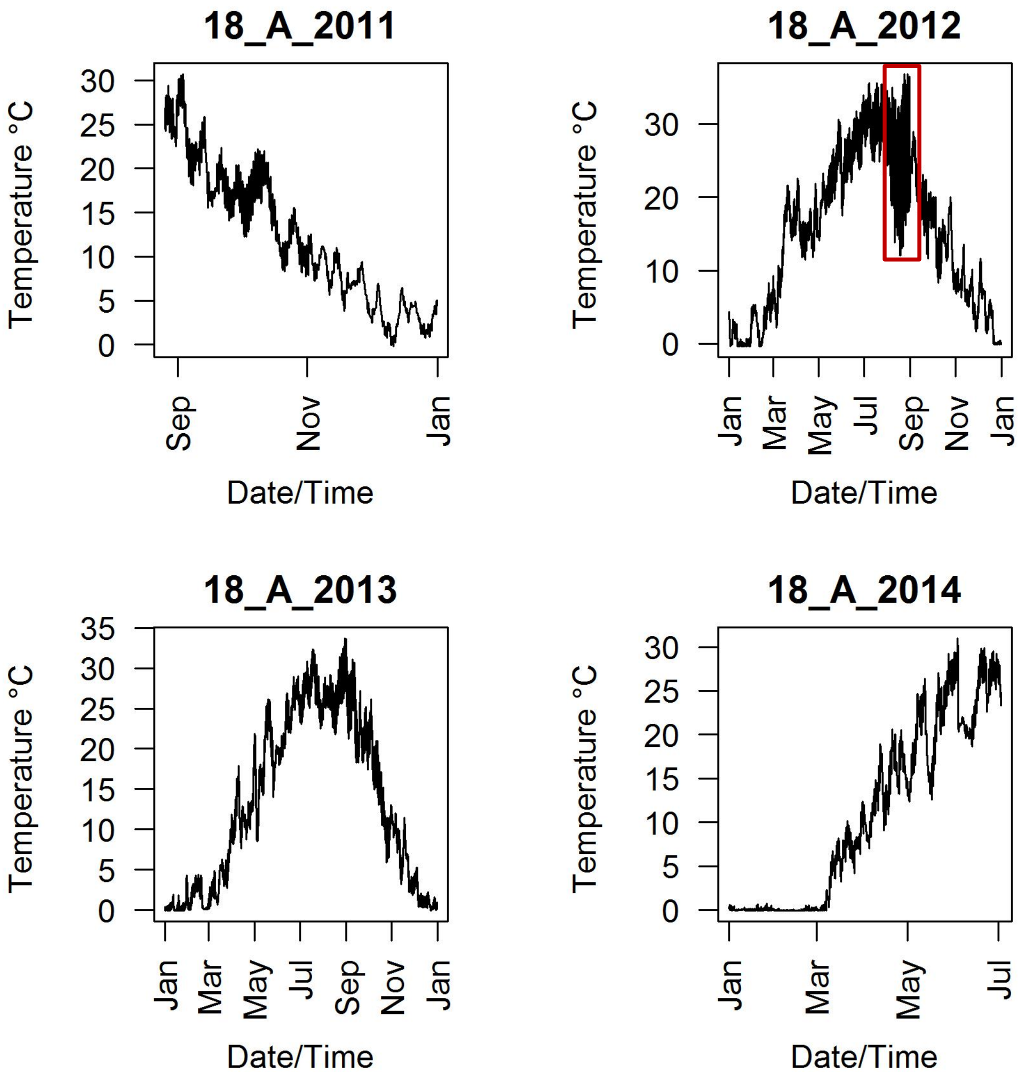


*Figure 44. Site 18, Point A: South Fabius River near Taylor, 2011 – 2015.***

Notes: July – Sept 2012: possible exposure to air? Fairly short period.

Decision: excluded records between 6 Aug and 1 Sept 2012. Used remaining records.



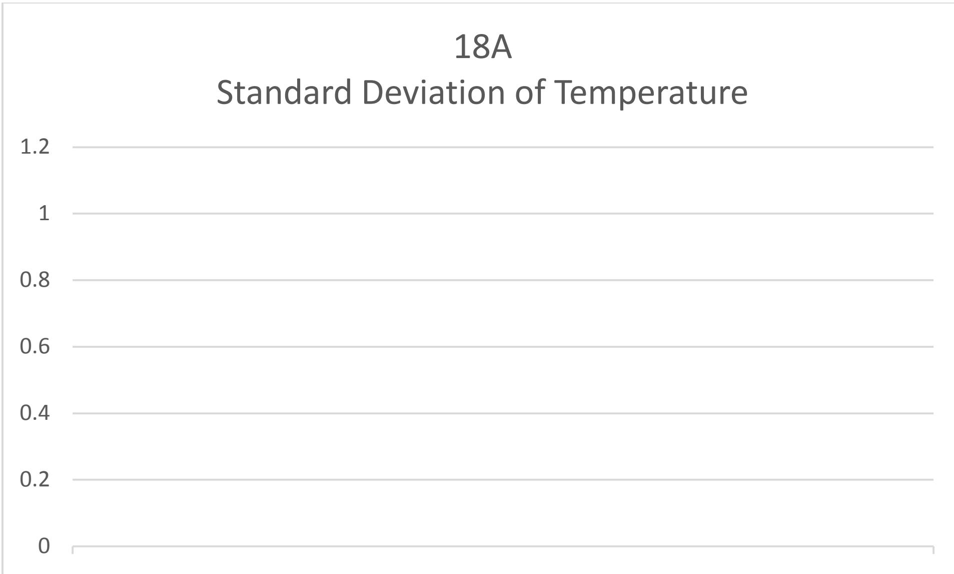

18A
Standard Deviation of Temperature
1.2
1
0.8
0.6
0.4
0.2
0

Figure 45. Site 18 Point B: South Fabius River near Taylor, 2011 – 2014.
Notes: 19 July 2013: recovered logger partially buried, no obvious signal of being buried.

Decision used all records.

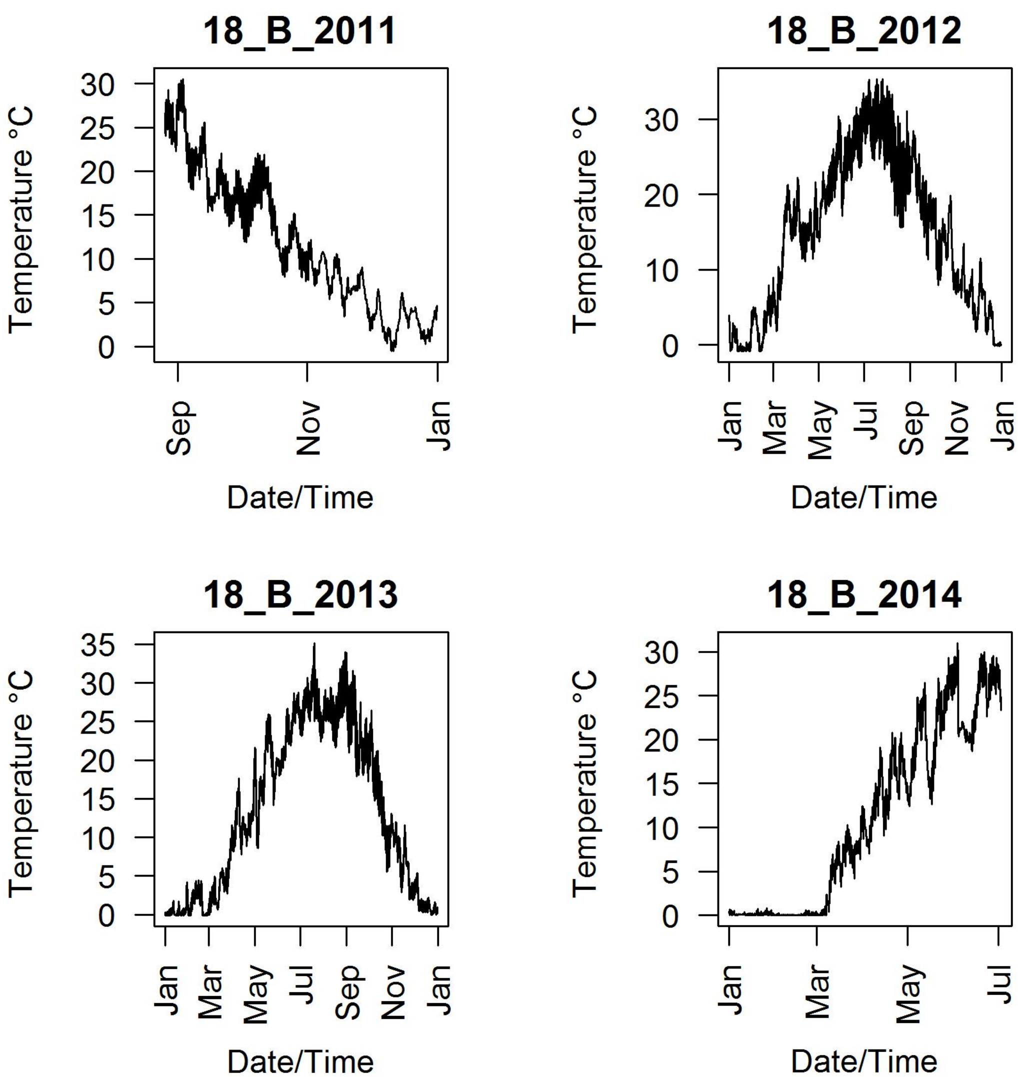


Figure 46. Site 19, Point A: North Fork Salt River at Hagers Grove, 2011 – 2013.
Decision: used all records.

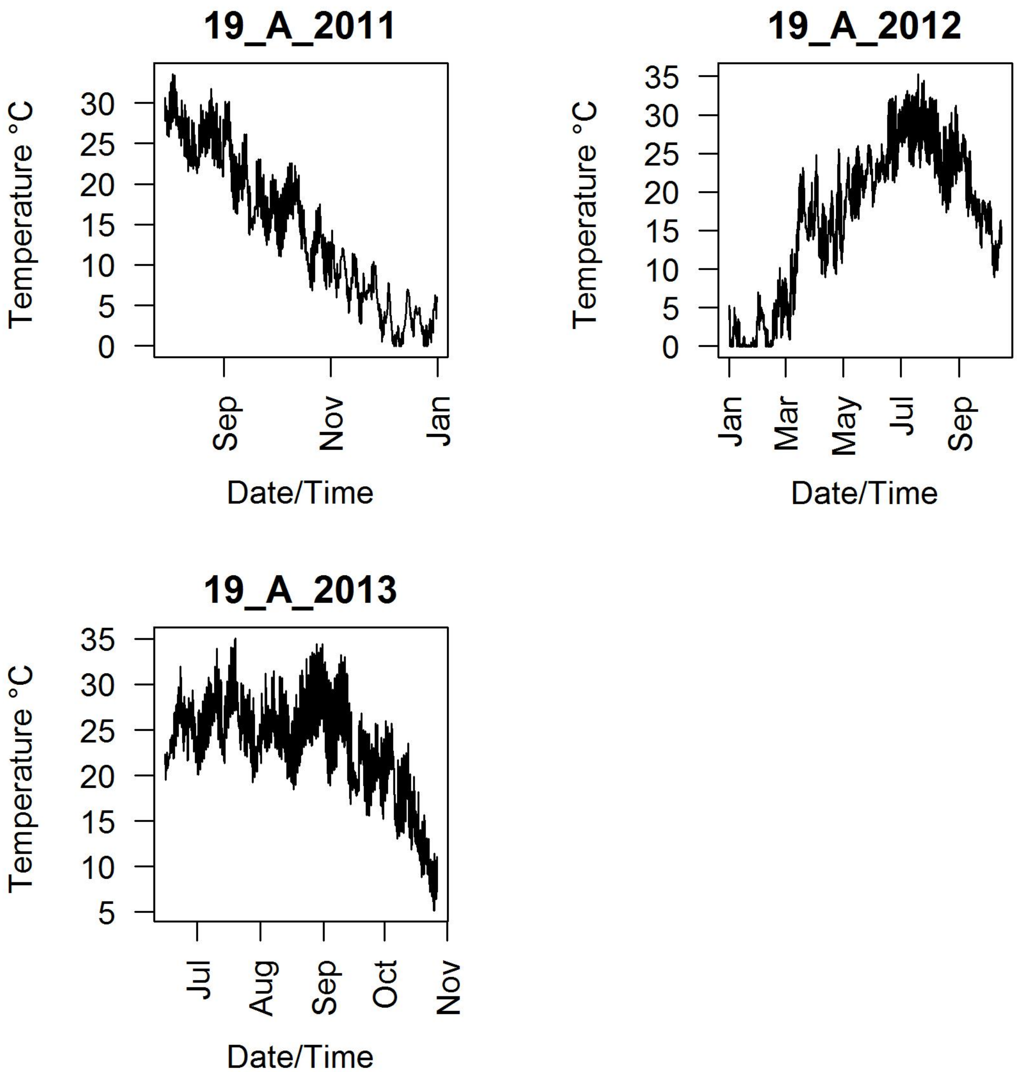


Figure 47. Site 19, Point B: North Fork Salt River at Hagers Grove, 2011 - 2013.CHECK RECORDS FOR 2013
Decision: used all records.

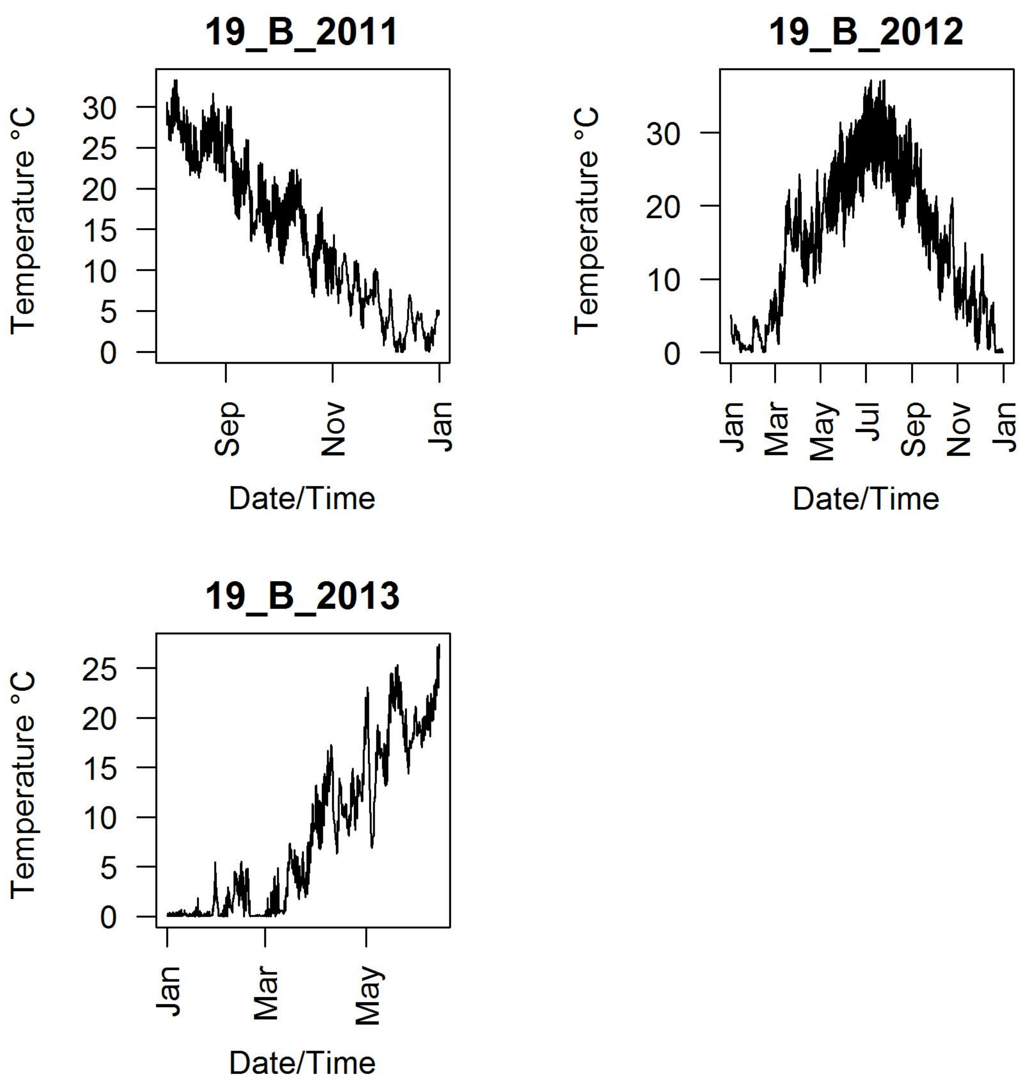
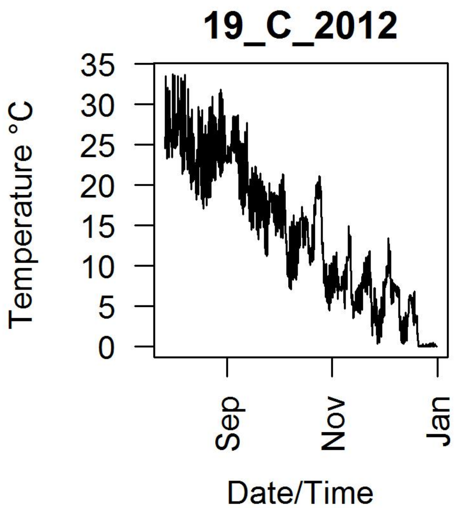


Figure 48. Site 19, Point C: North Fork Salt River at Hagers Grove, 2012 – 2013.
Decision: used all records.



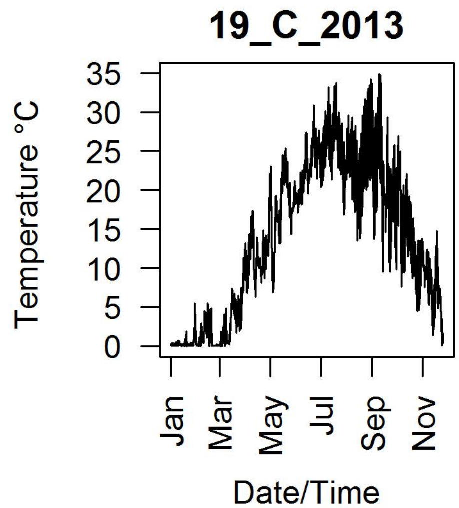


Figure 49. Site 20, Point A: North Fork Salt River near Shelbina, 2011 – 2014.
Decision: used all records.

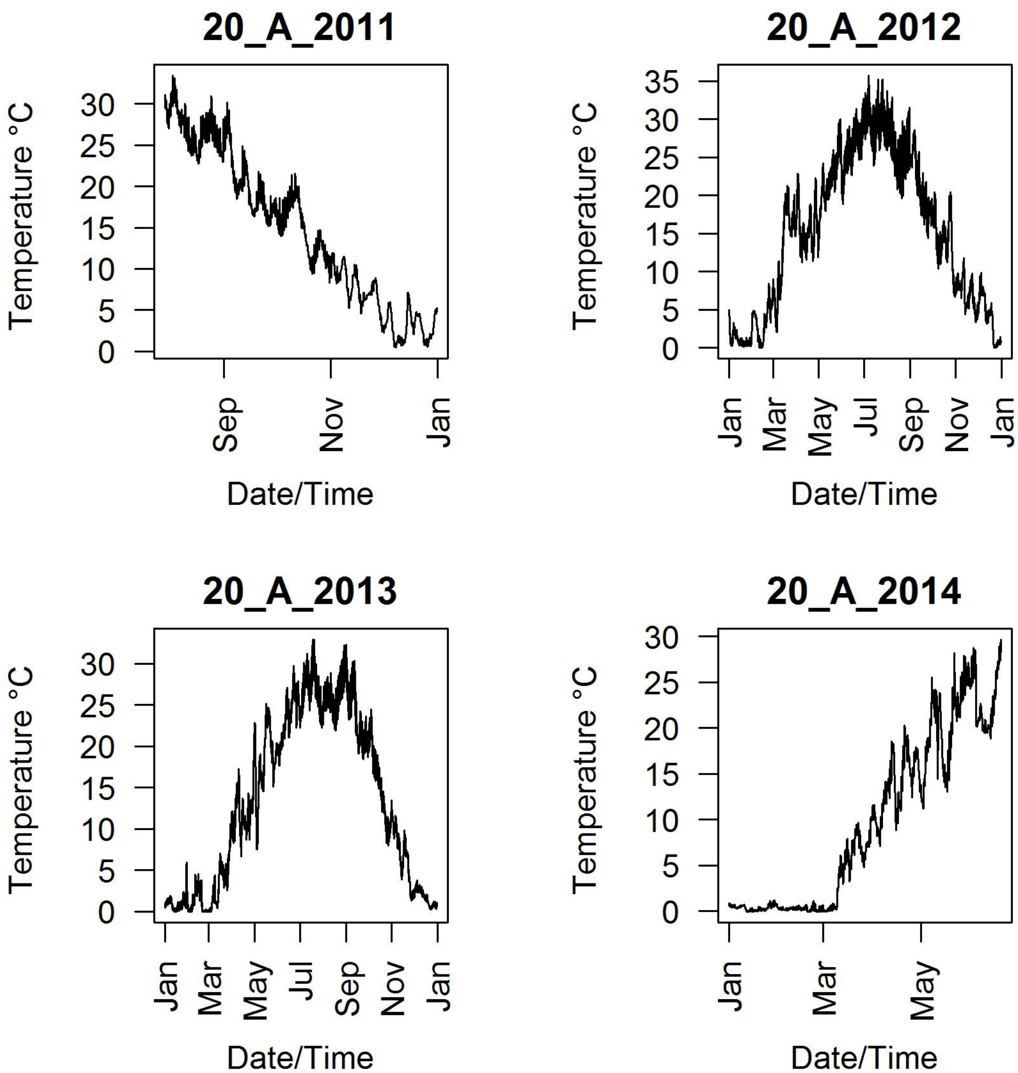
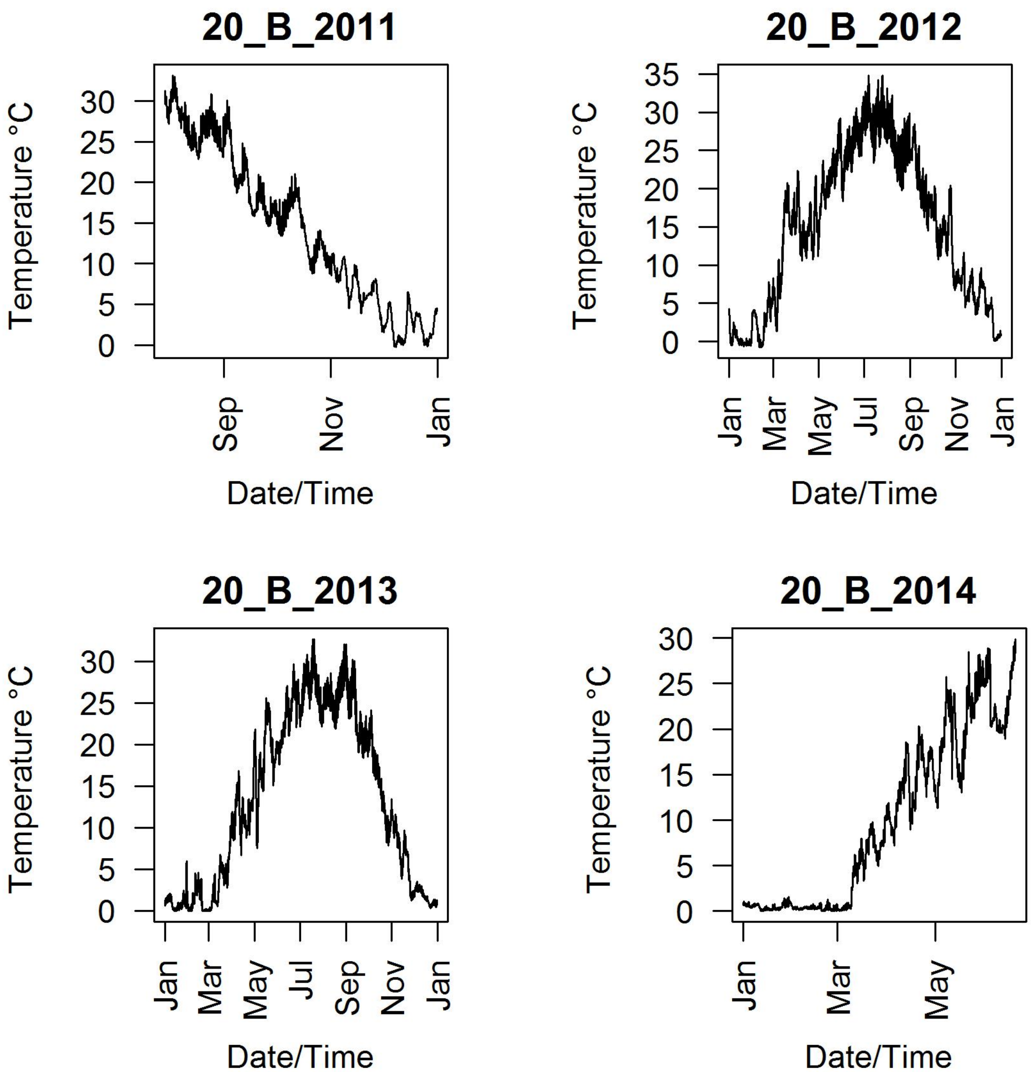


Figure 50. Site 20, Point B: North Fork Salt River near Shelbina, 2011 – 2014.
Decision: used all records.



:

*Figure 51. Site 21, Point A: Crooked Creek near Paris, 2011.***
Notes: 7/28/2011: logger was exposed when retrieved. Most of graph shows fairly extreme daily fluctuations which could indicate exposure.

Decision: did not use any of these data.

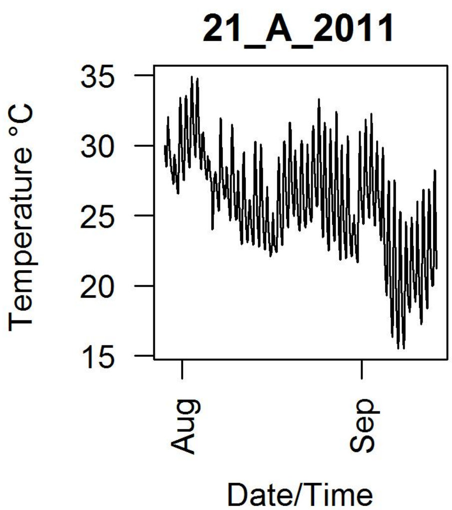
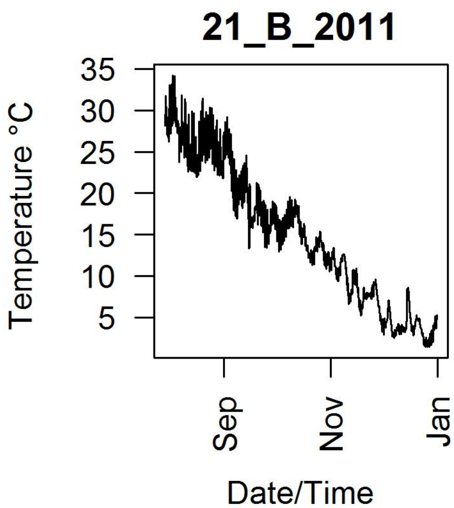
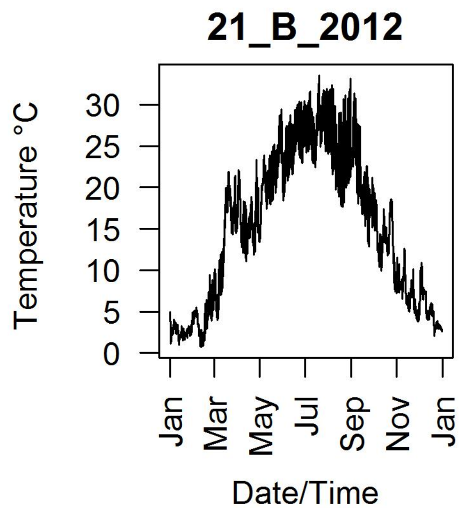


Figure 52. Site 21, Point B: Crooked Creek near Paris, 2011 – 2013.
Decision: used all records.





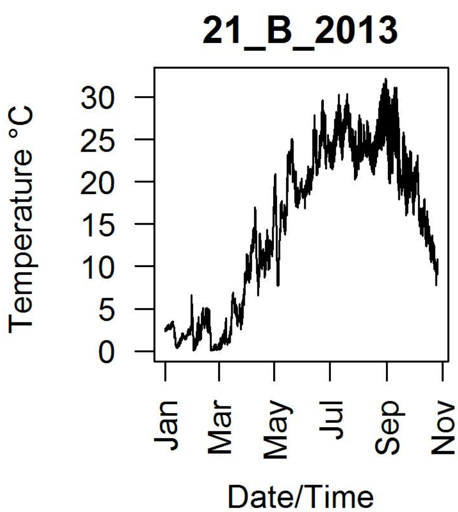


Figure 53. Site 21, Point C: Crooked Creek near Paris, 2011 – 2012.
Notes: Spring 2012 – extended rainfall events?

Decision: used all records.

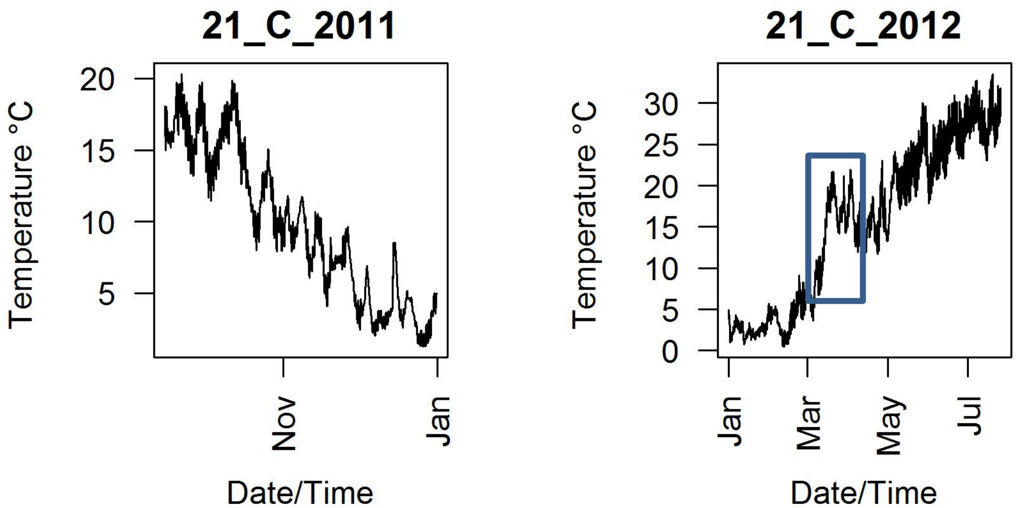


Figure 54. Site 21, Point D: Crooked Creek near Paris, 2014 – 2015.
Decision: used all records.

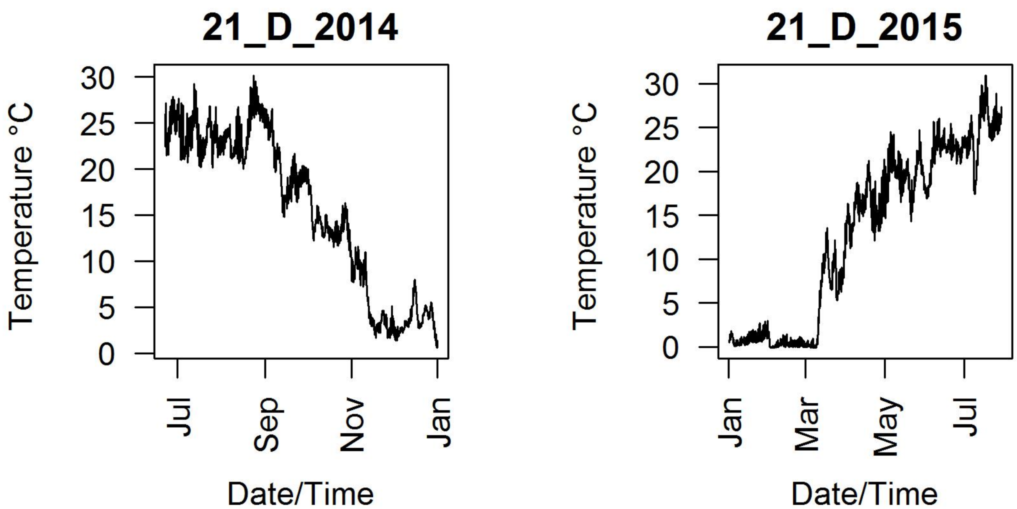


Figure 55. Site 21, Point E: Crooked Creek near Paris, 2013 – 2015.
Decision: used all records.

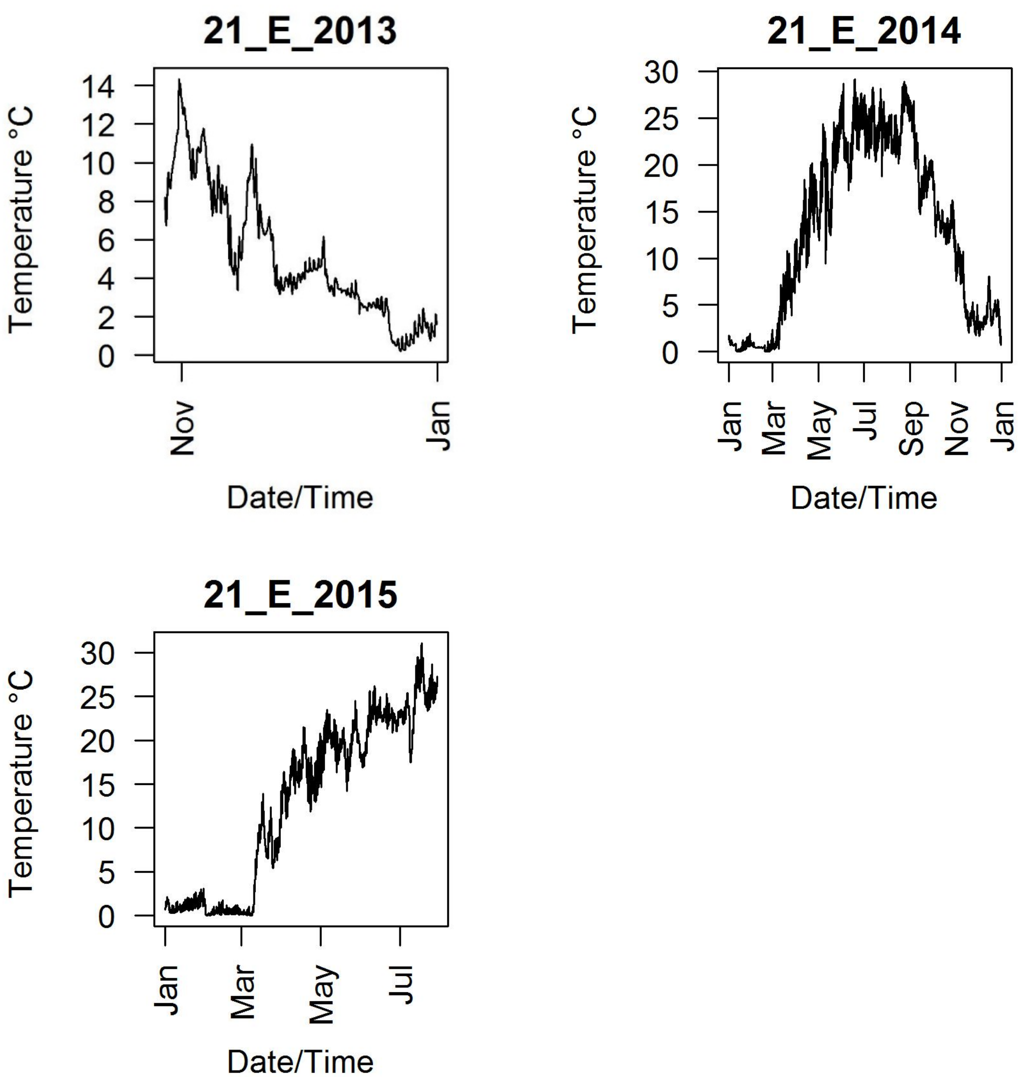
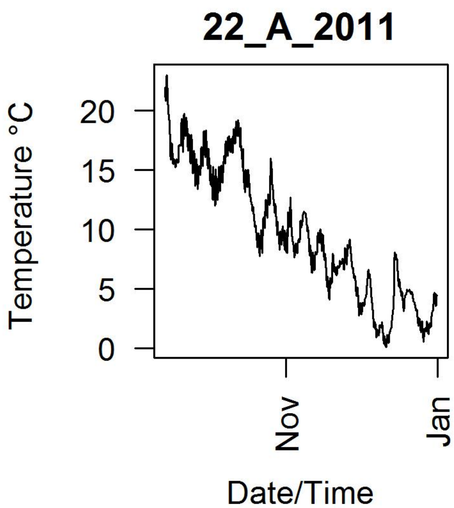


Figure 56. Site 22, Point A: Middle Fork Salt River near Holliday, 2011 – 2012.
Decision: used all data.



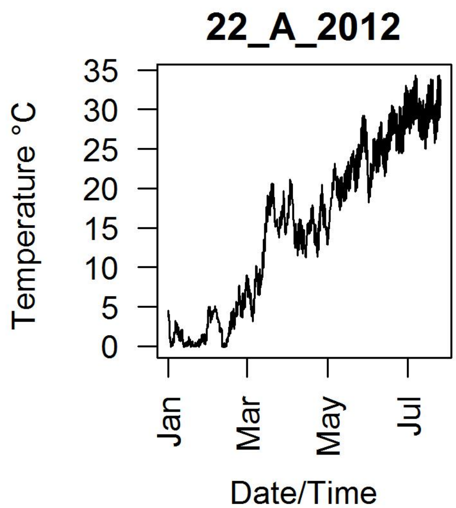


Figure 57. Site 22, Point B: Middle Fork Salt River near Holliday, 2011 – 2012.
Decision: used all data.

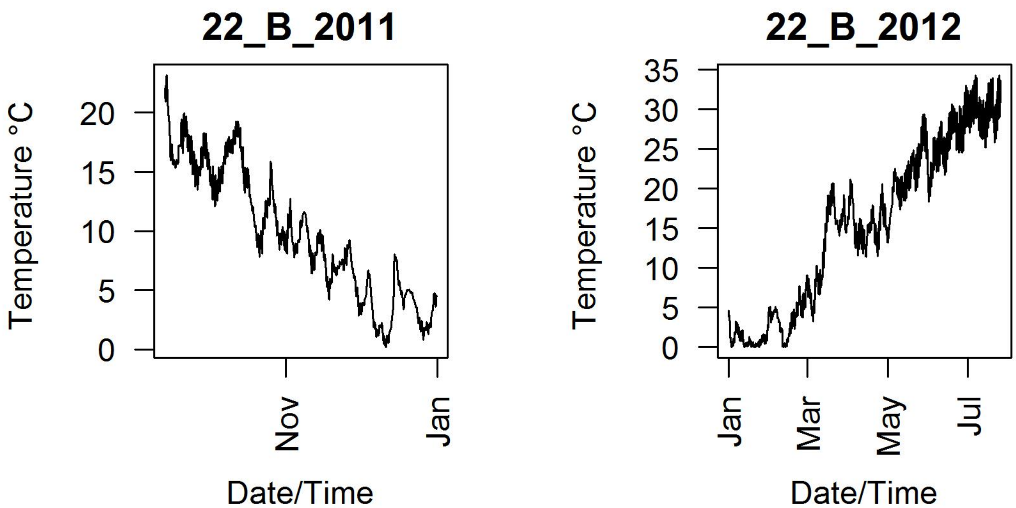


Figure 58. Site 22, Point D: Middle Fork Salt River near Holliday, 2013.
Decision: used all records.

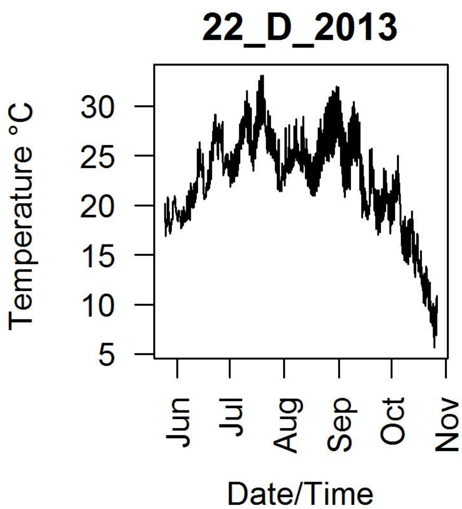


Figure 59. Site 22, Point E: Middle Fork Salt River near Holliday, 2013 – 2014.
Decision: Used all records.

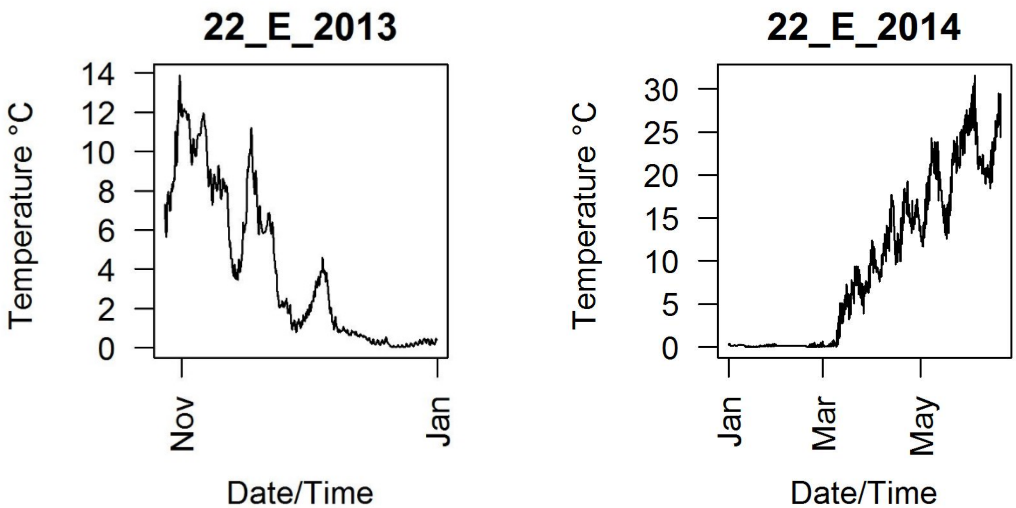


Figure 60. Site 22, Point F: Middle Fork Salt River near Holliday, 2014 – 2015.
Decision: Used all records.

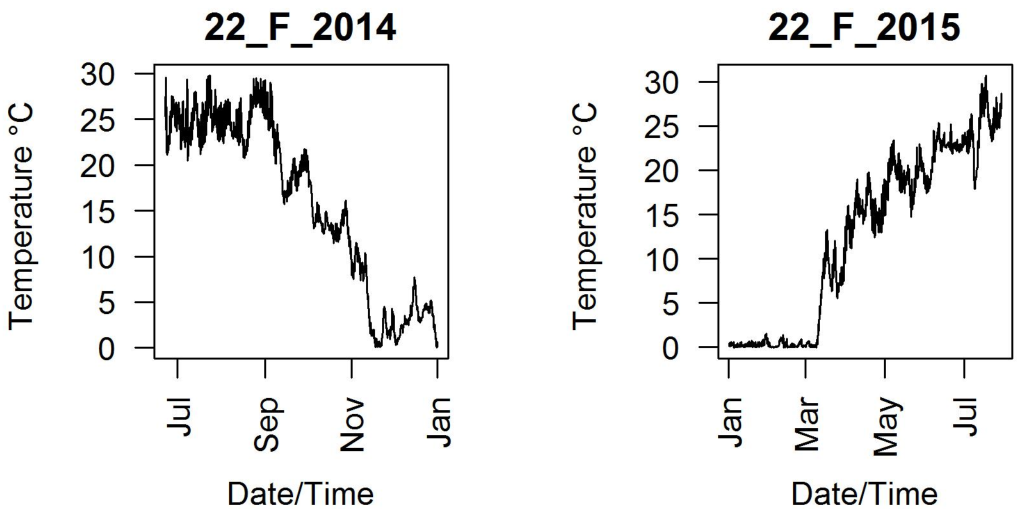


Figure 61. Site 22, Point G: Middle Fork Salt River near Holliday, 2014 – 2015.
Decision: used all records.

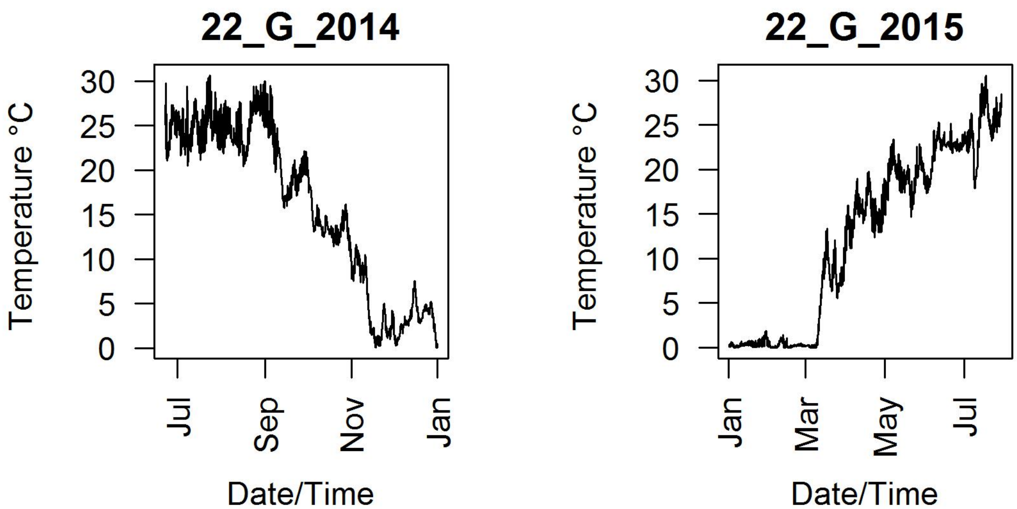
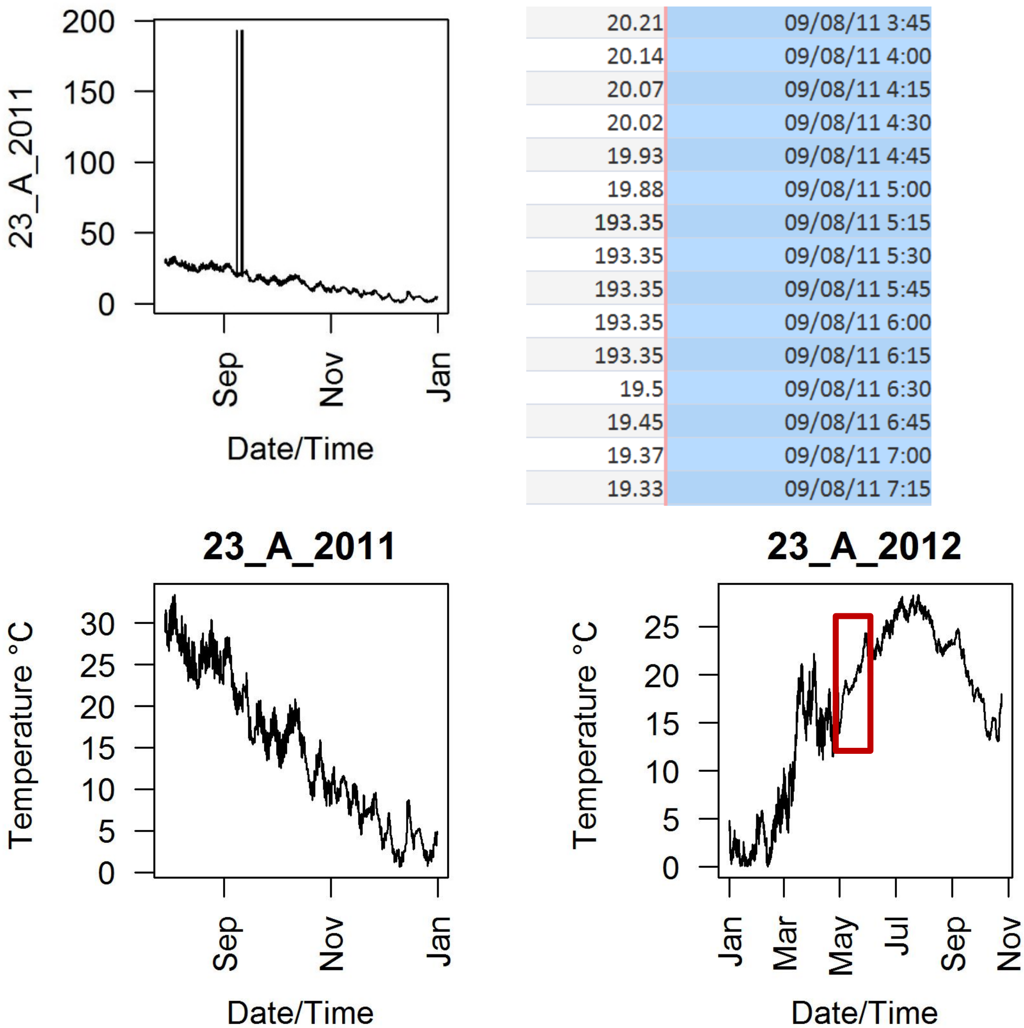


Figure 62. Site 23, Point A: Elk Fork Salt River near Madison, 2011 – 2012

Notes: Again the 193.35 records; not near zero degrees this time. Deleted the 193.35 recs.

Logger was buried when retrieved in 2012. Did not use records after 30 Apr 2012.

Decision: used remaining records.



20.21	09/08/11 3:45
20.14	09/08/11 4:00
20.07	09/08/11 4:15
20.02	09/08/11 4:30
19.93	09/08/11 4:45
19.88	09/08/11 5:00
193.35	09/08/11 5:15
193.35	09/08/11 5:30
193.35	09/08/11 5:45
193.35	09/08/11 6:00
193.35	09/08/11 6:15
19.5	09/08/11 6:30
19.45	09/08/11 6:45
19.37	09/08/11 7:00
19.33	09/08/11 7:15

*Figure 63. Site 23, Point B: Elk Fork Salt River near Madison, 2011 – 2012.***
Notes: Buried when retrieved.

Decision: did not use any of these records.

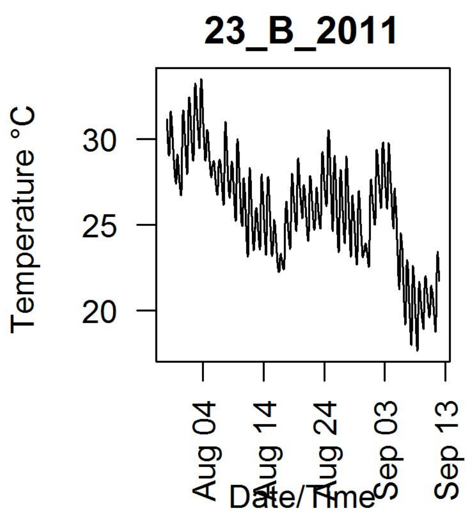
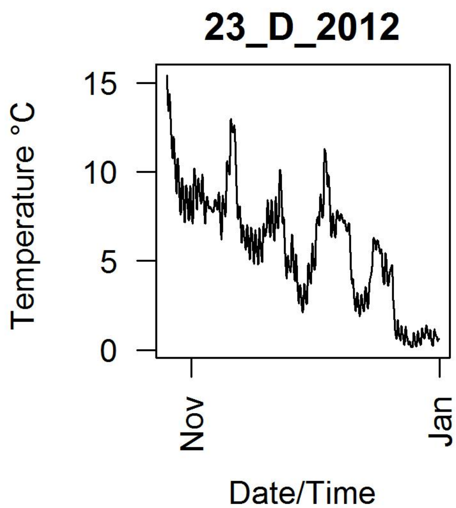


Figure 64. Site 23, Point D: Elk Fork Salt River near Madison, 2012 – 2013.
Decision: used all records.



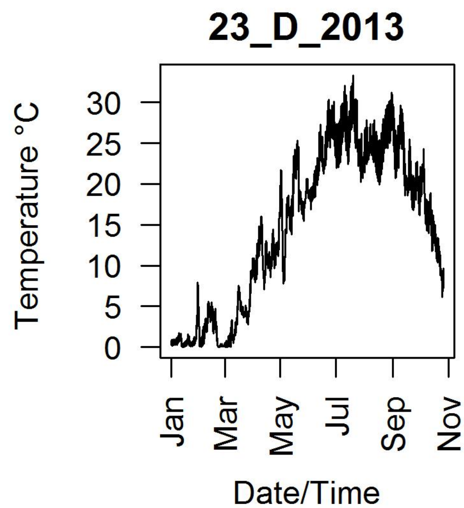


Figure 65. Site 23, Point E: Elk Fork Salt River near Madison, 2013 – 2015.
Decision: used all records.

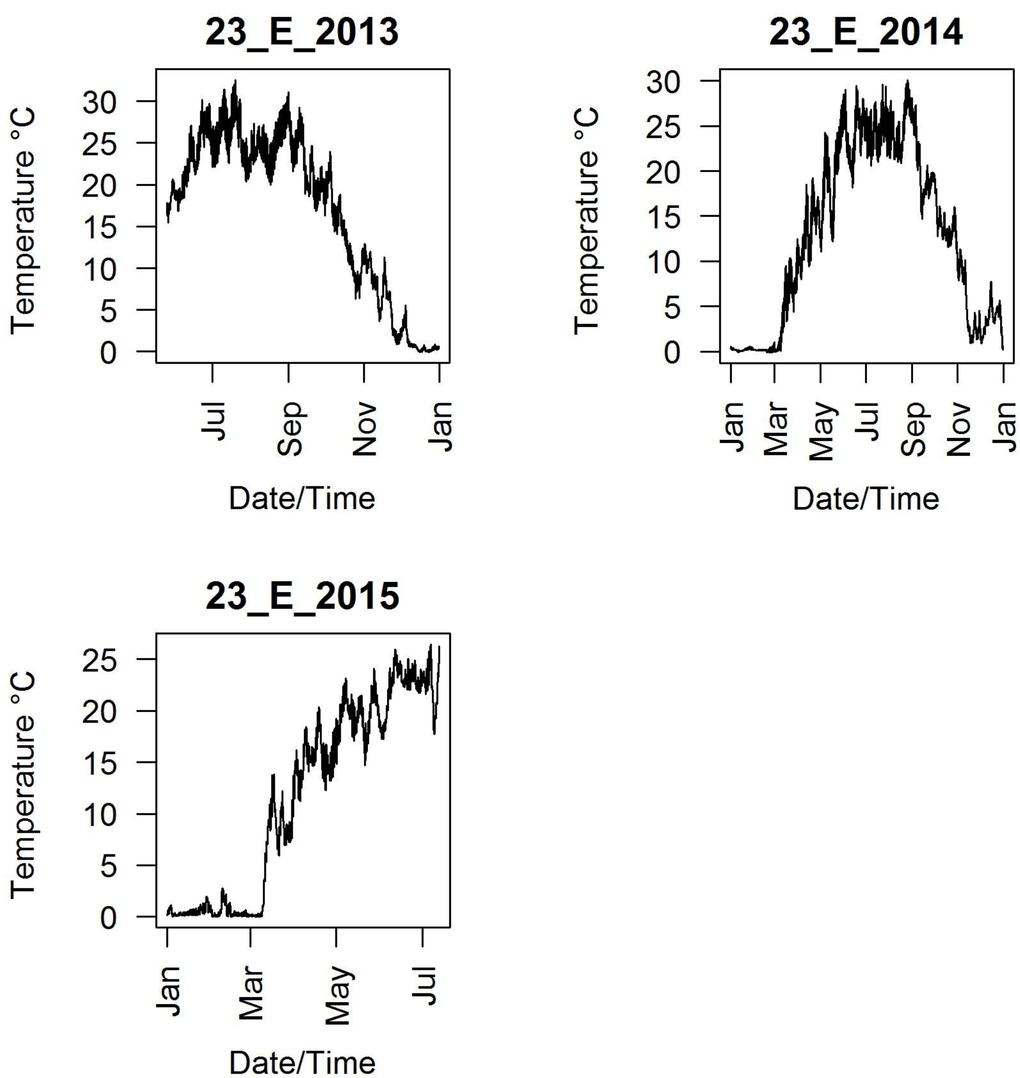


*Figure 66. Site 24, Point A: Cuivre River near Troy, 2012 – 2014.***

Notes: 11/26/2013: when retrieved, logger was out of water. Based on increased variation in daily temperature, excluded data from Sept 1 – Nov 25, 2013.

Decision: used remaining records.

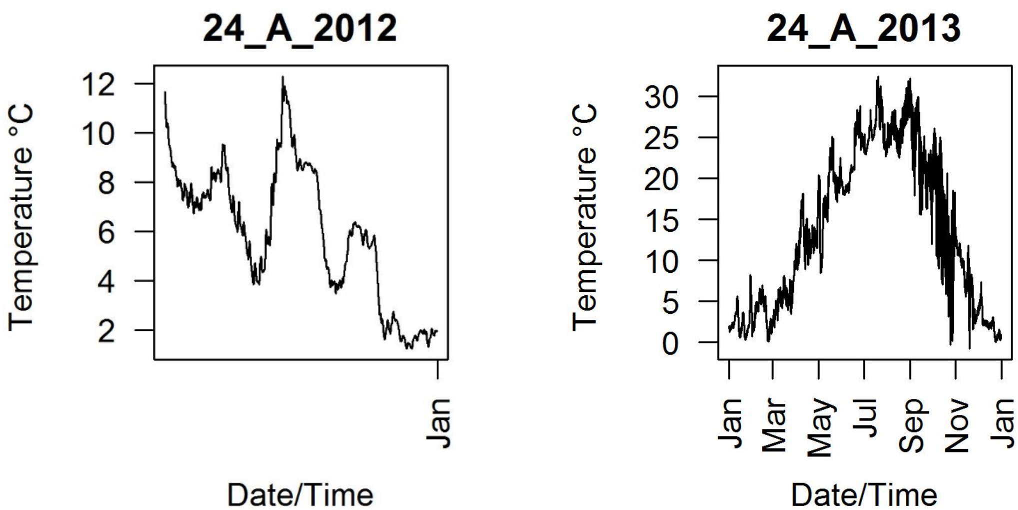


Figure 67. Site 24, Point B: Cuivre River near Troy, 2011 – 2012.
Decision: used all records.

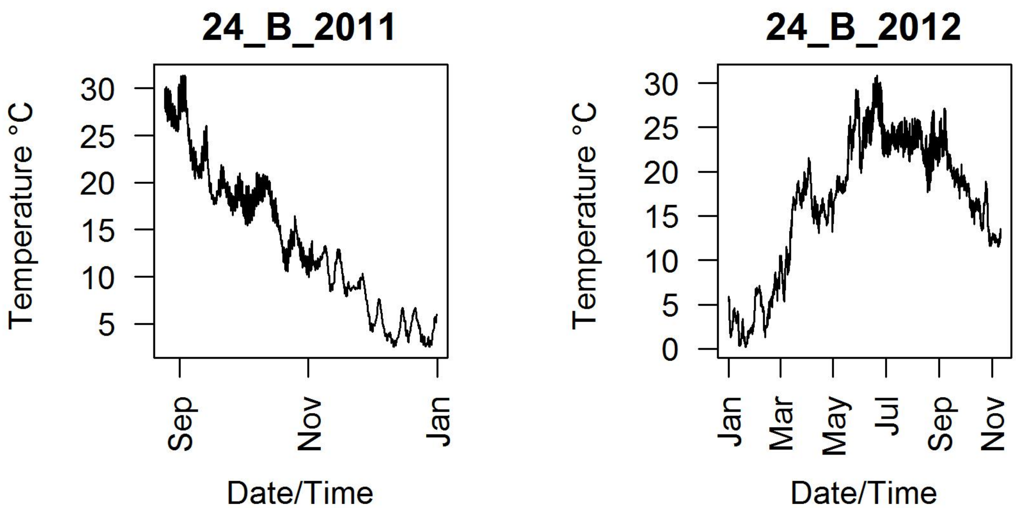


Figure 68. Site 24, Point D: Cuivre River near Troy, 2013 – 2014.

Notes: odd spike on 26 Sept 2014. Could not determine probable cause; left as is.

Decision: used all records.

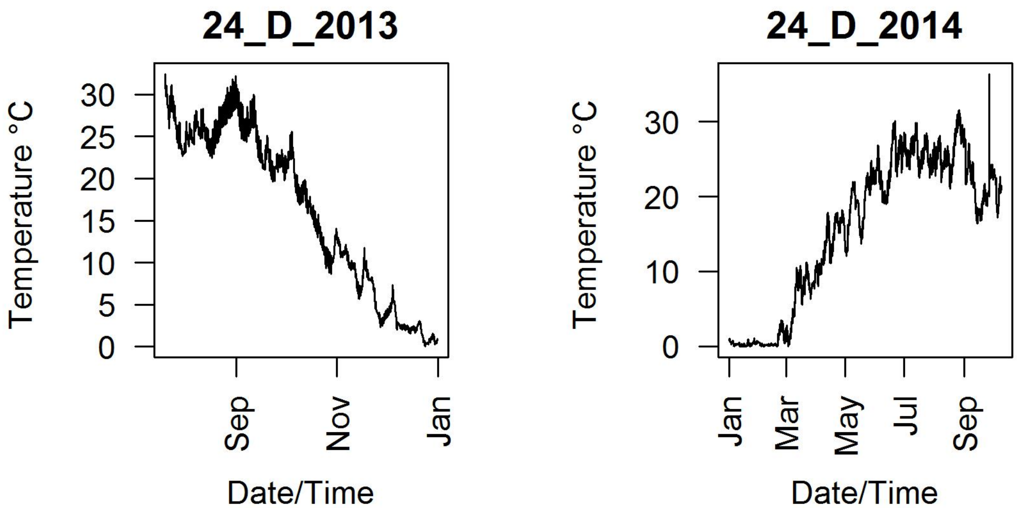
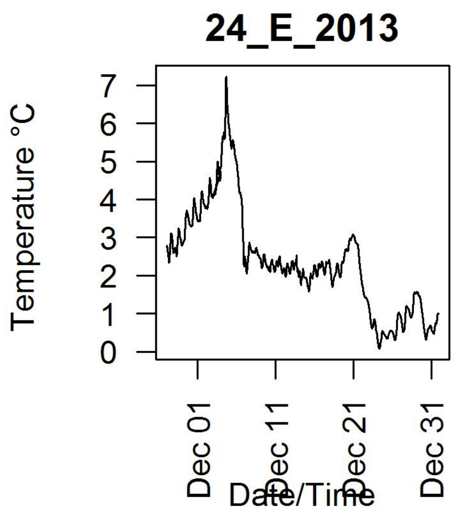
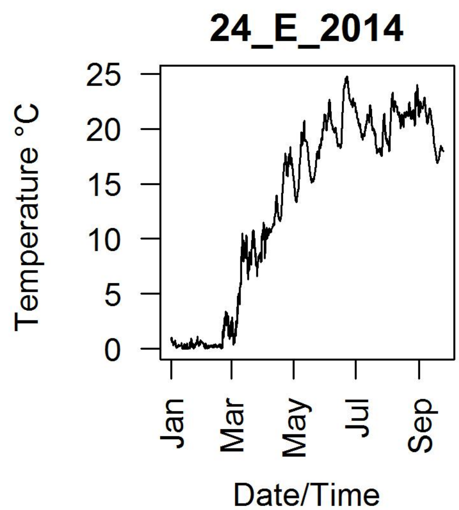


*Figure 69. Site 24, Point E: Cuivre River near Troy, 2013 – 2014.***

Note: logger was buried when retrieved on 25 Sept 2014.

Decision: Based on differences between daily variation and dampened temperature compared to Point D, did not use records after 1 Apr 2014. Used remaining records.





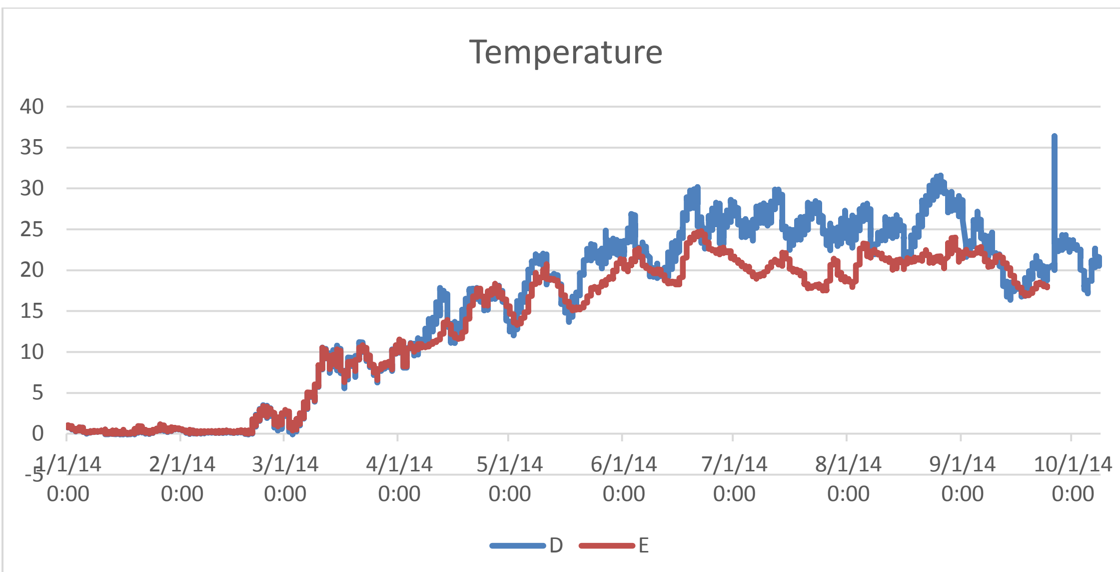


Figure 70. Site 25, Point A: Nodaway River near Graham, 2012 – 2013.
Decision: used all records.

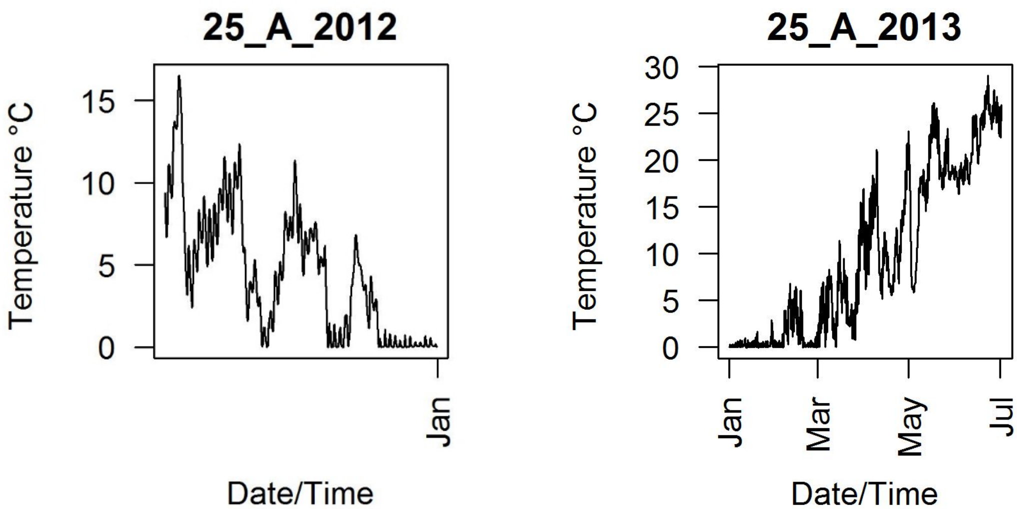
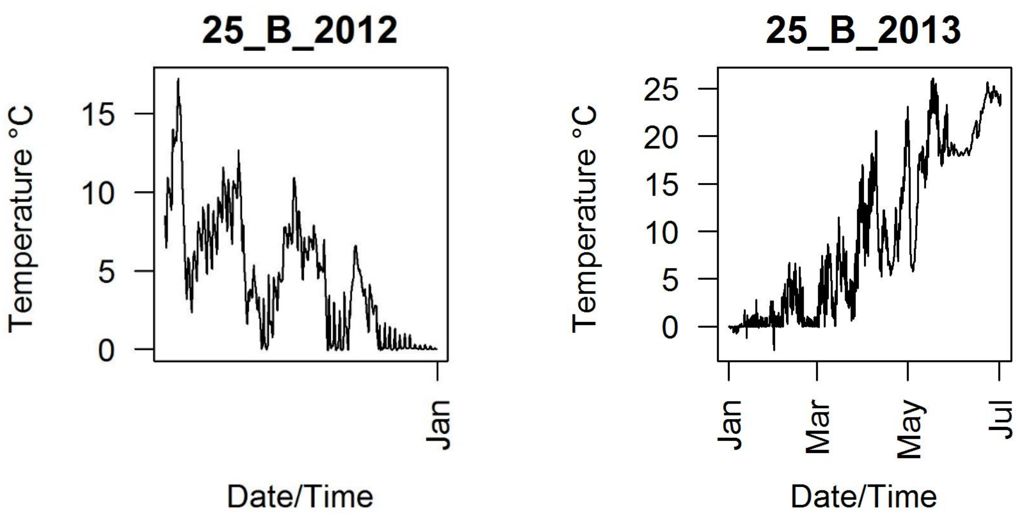


*Figure 71. Site 25, Point B: Nodaway River near Graham, 2012 – 2013.***

Notes: there are a few isolated hourly records below 0°C and a few days in early Jan 2013 where the logger may have gone dry based on consecutive temperatures below zero. Logger was buried when retrieved on 2 July 2013 – daily variation changed substantially on 28 May 2013.

Decision: Did not use records between 1 Jan and 7 Jan, 2013 or records after 28 May 2013; used remaining records.



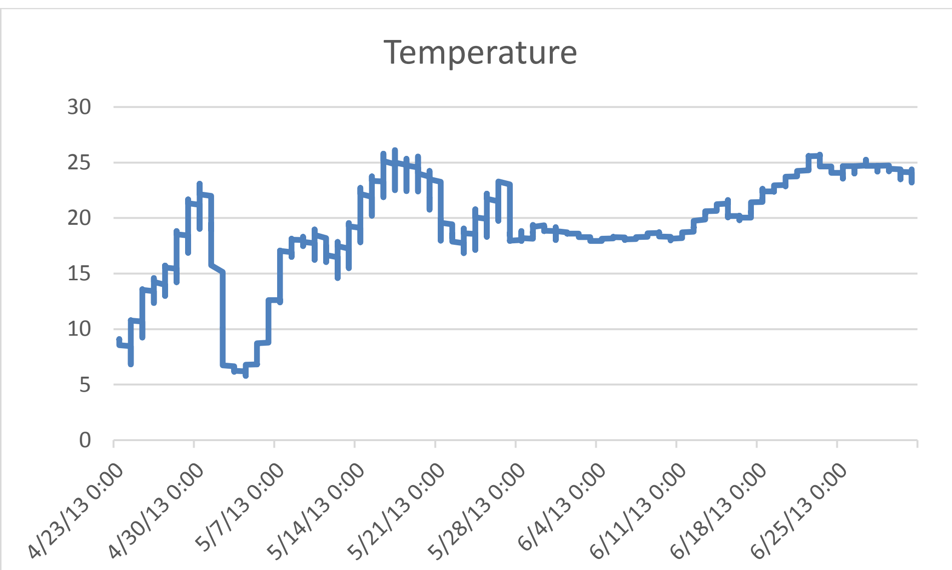


Figure 72. Site 26, Point C: One Hundred Two River near Bolckow, 2012 – 2013.
Decision: used all records.

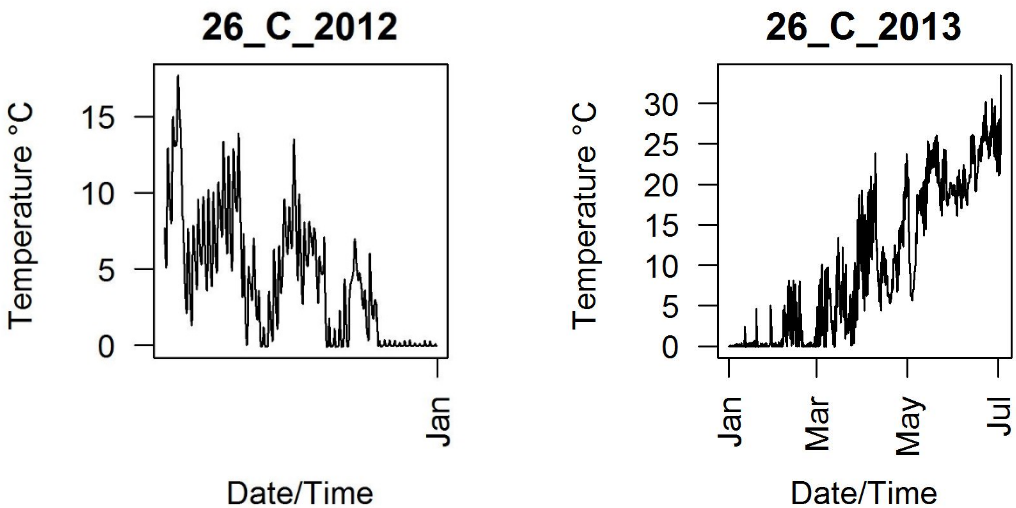


Figure 73. Site 26, Point. D: One Hundred Two River near Bolckow, 2012 – 2013.
Decision: used all records.

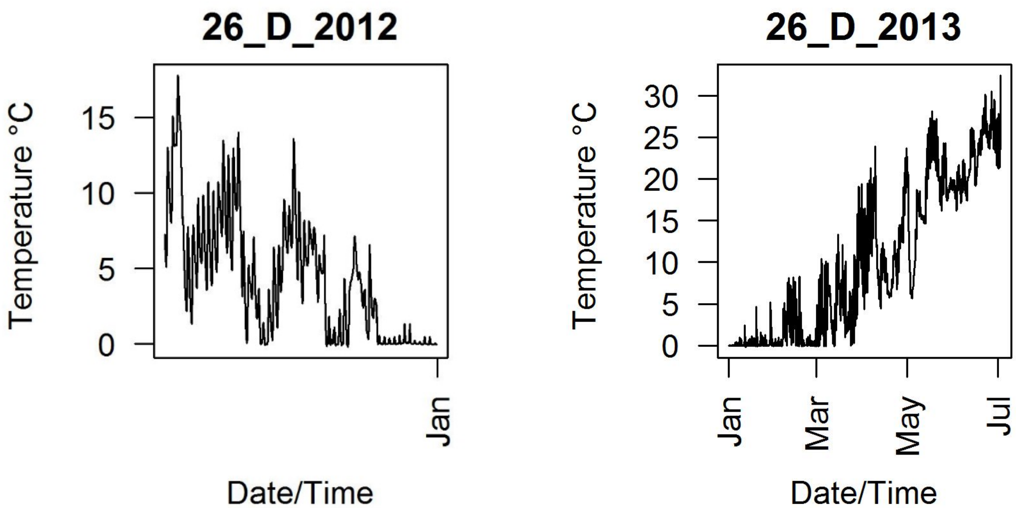


Figure 74. Site 27, Point A: Platte River near Agency, 2012 – 2013.
Decision: used all records.

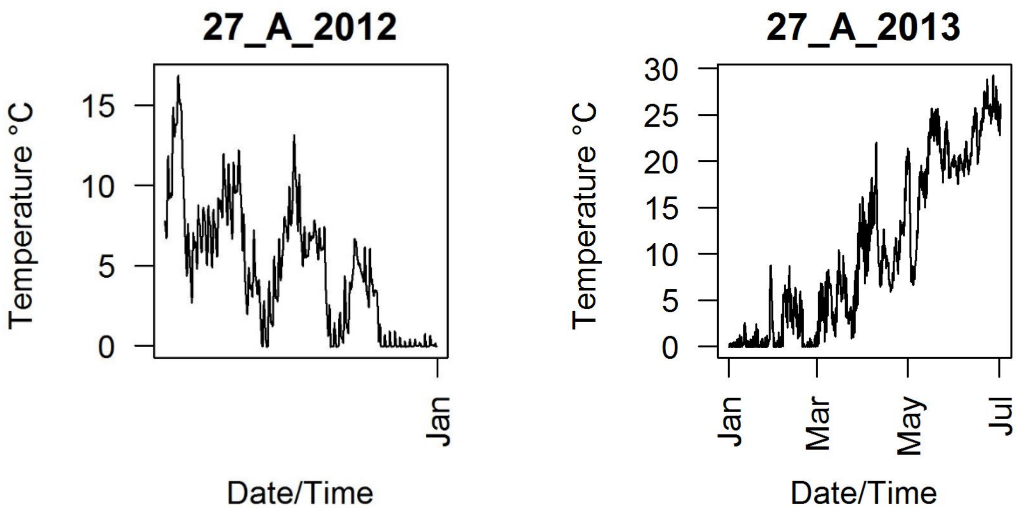


Figure 75. Site 27, Point B: Platte River near Agency, 2012 – 2013.
Decision: used all records.

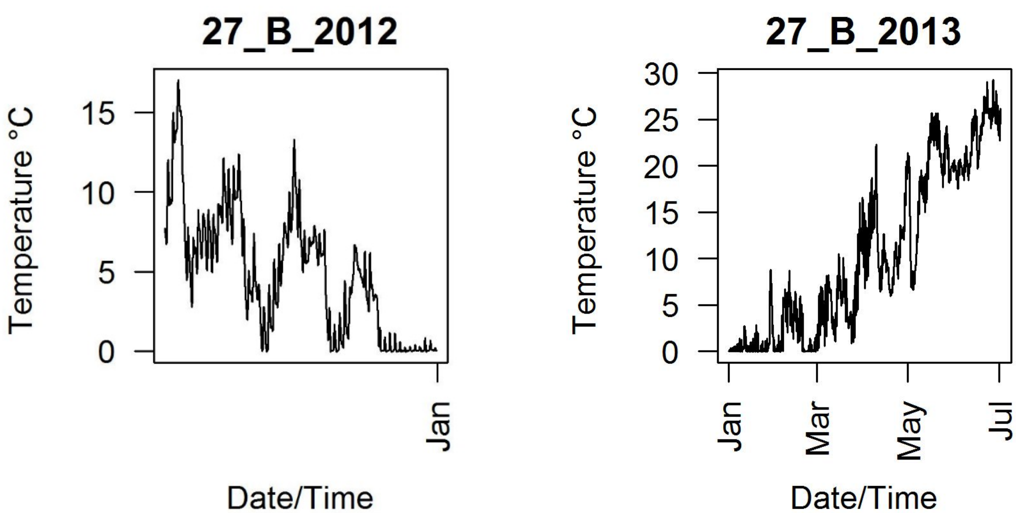


Figure 76. Site 28, Point B: Little Platte River near Plattsburg, 2011 – 2014.
Decision: used all records.

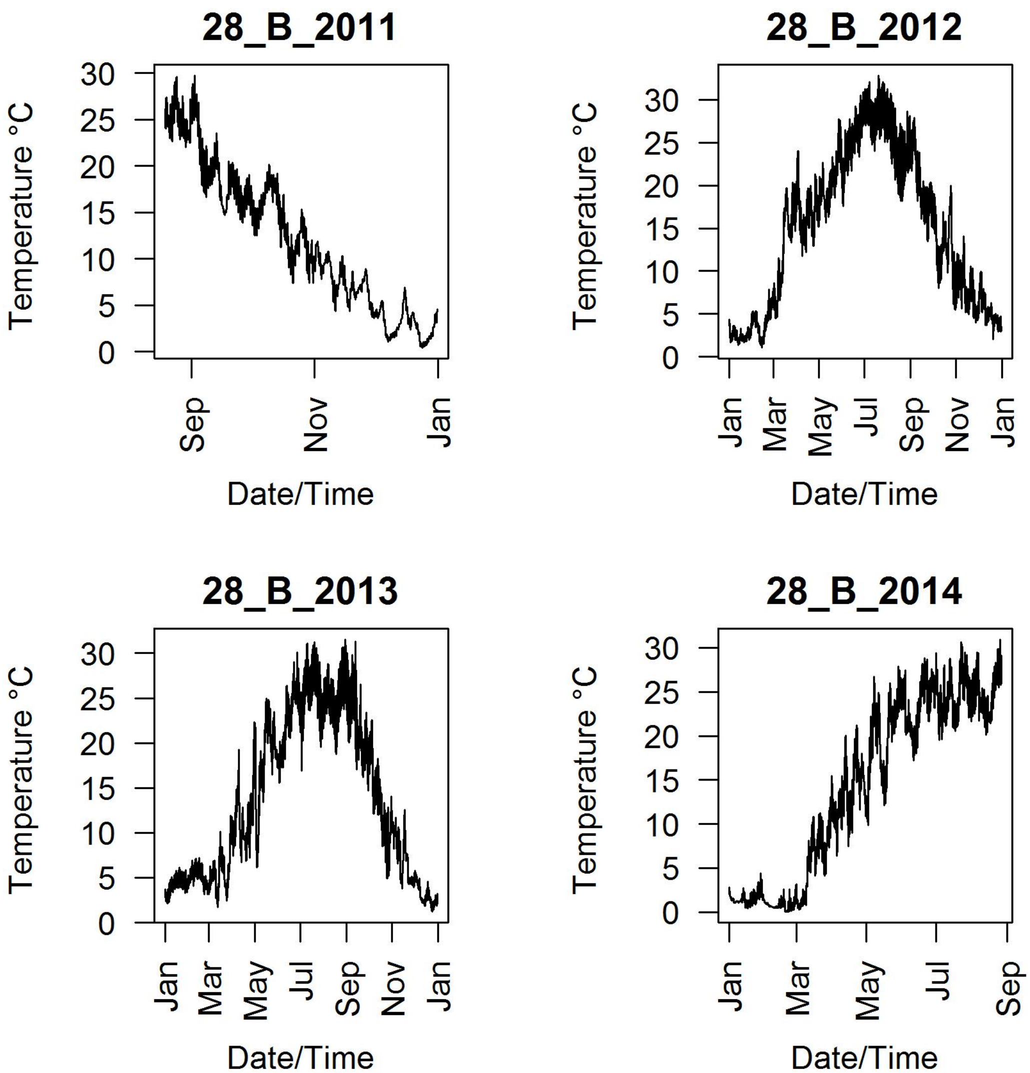


Figure 77. Site 28, Point C. Little Platte River near Plattsburg, 2012 – 2013.
Decision: used all records.

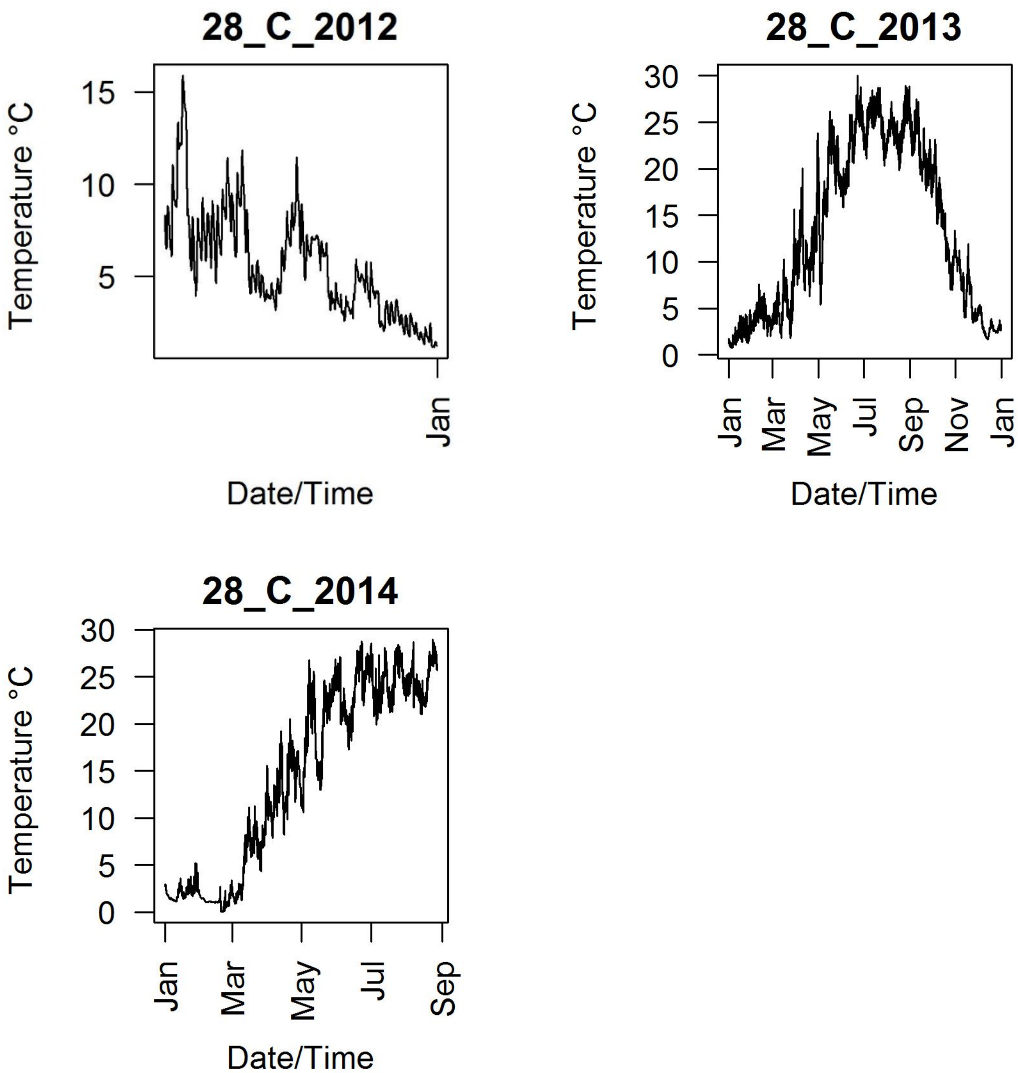


Figure 78. Site 29, Point A: Platte River at Sharps Station, 2012 – 2013.
Decision: used all records.

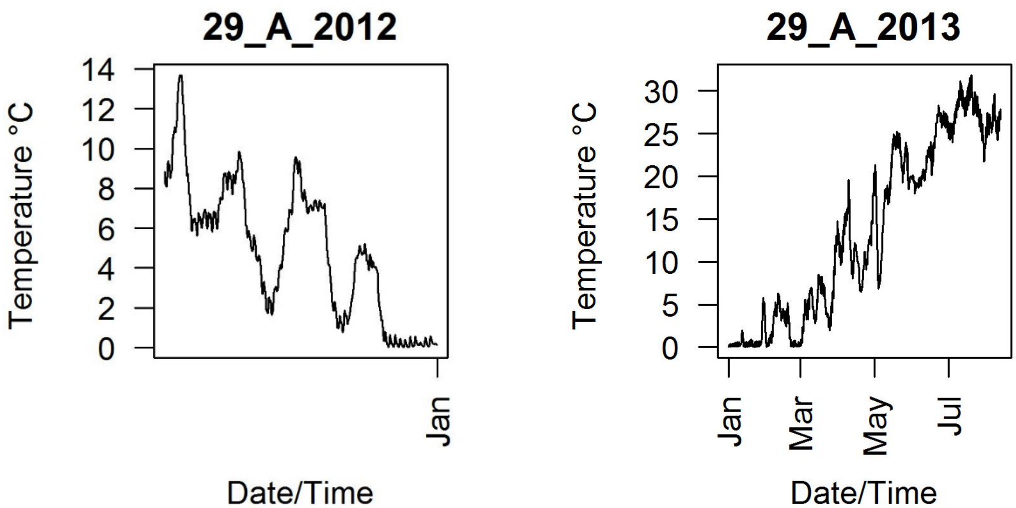


Figure 79. Site 30, Point A. Meramec River near Steelville, 2013 – 2014.
Decision: used all records.

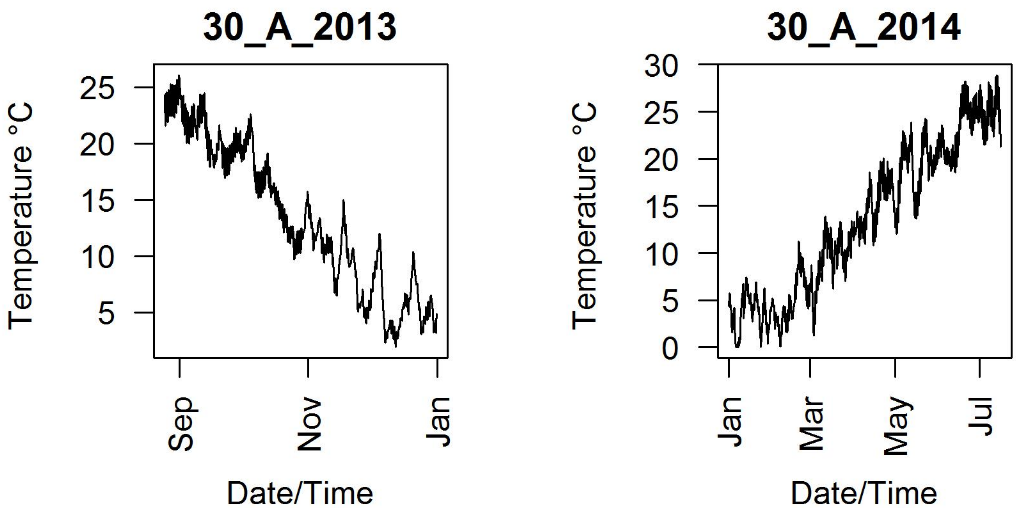


Figure 80. Site 30, Point B: Meramec River near Steelville, 2011 – 2012.
Decision: used all records.

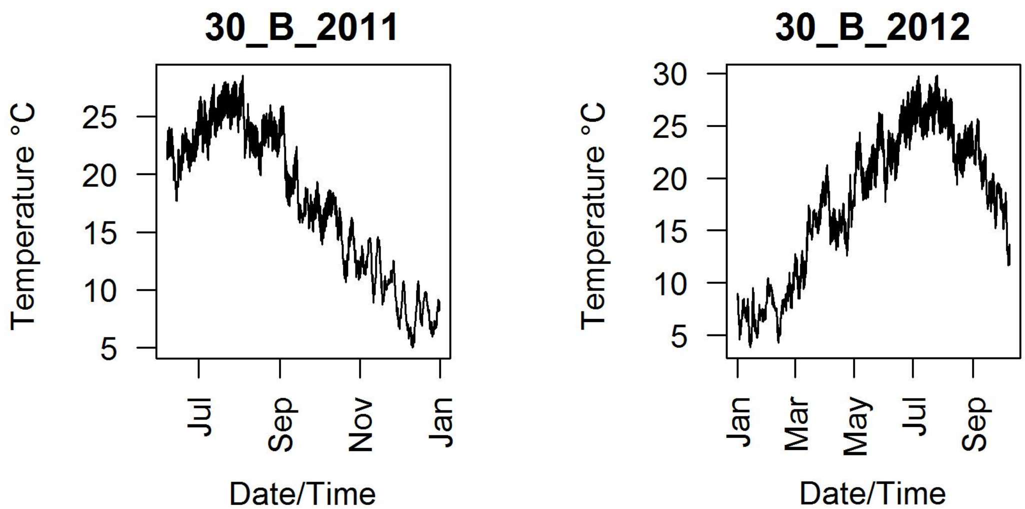


Figure 81. Site 30, Point C. Meramec River near Steelville, 2013 – 2014.

Note: temperature logger stopped on June 14, 2014 for no apparent reason.

Decision: used all records.

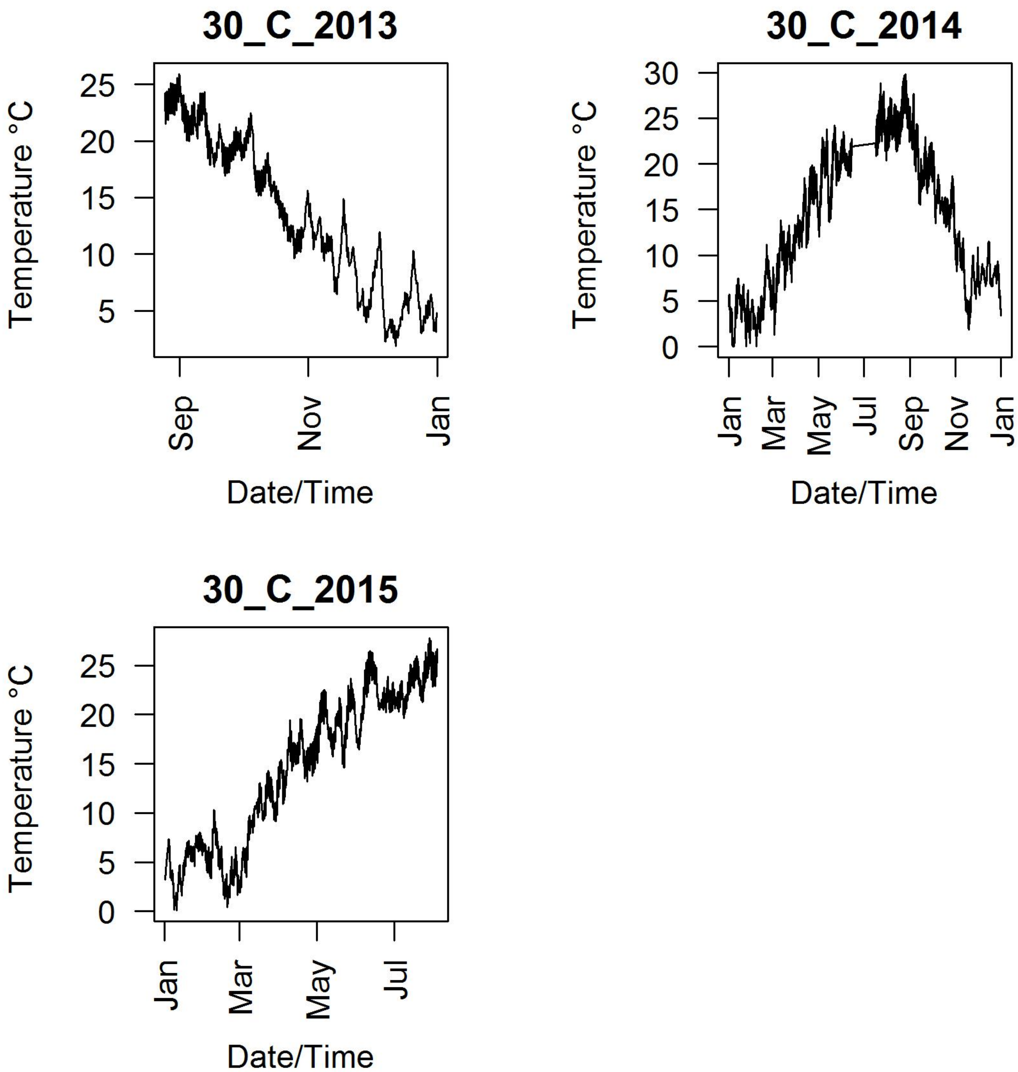


Figure 82. Site 31, Point A: Meramec River near Sullivan, 2011 – 2012.
Decision: used all records.

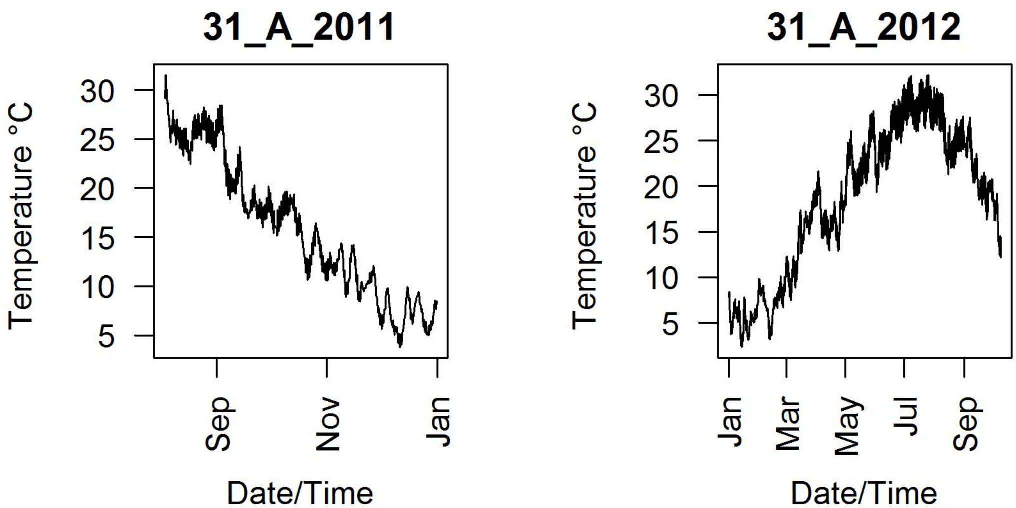


Figure 83. Site 31, Point B: Meramec River near Sullivan, 2011 – 2012.
Decision: used all records.

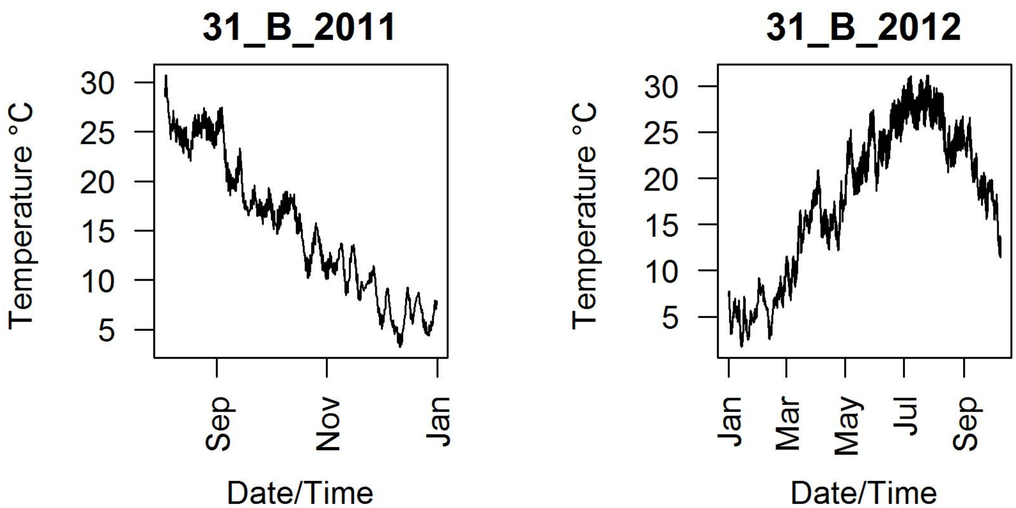


Figure 84. Site 31, Point C: Meramec River near Sullivan, 2013 – 2015.
Decision: used all records.

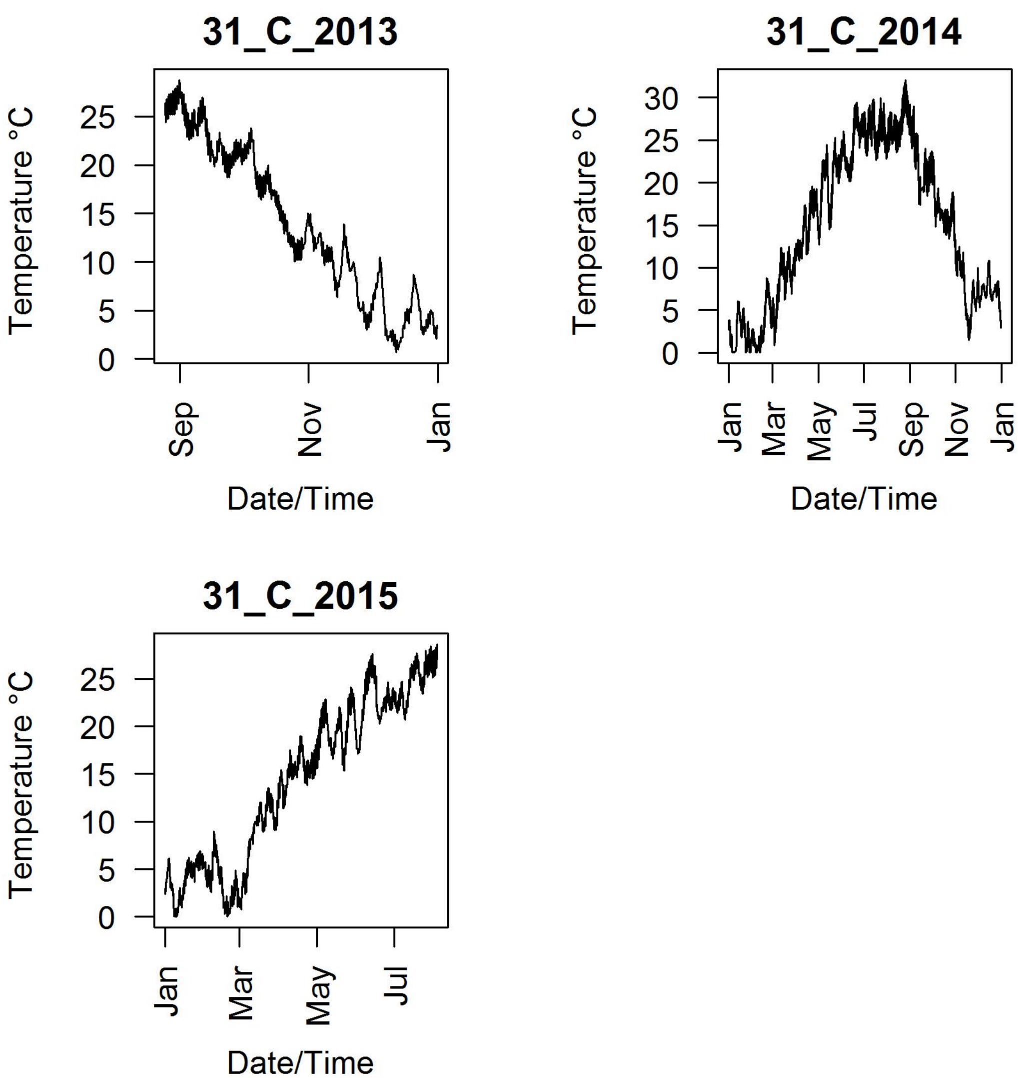
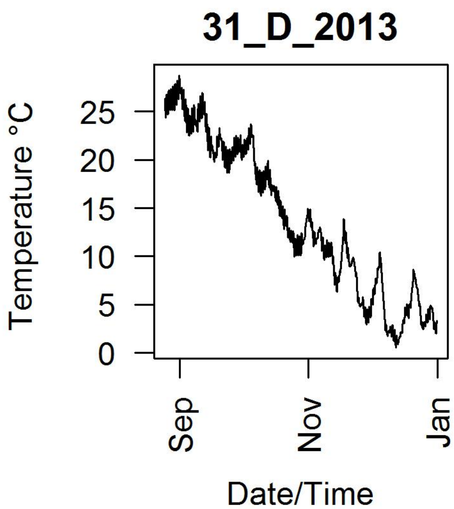


Figure 85. Site 31, Point D: Meramec River near Sullivan, 2011 – 2012.
Decision: used all records.



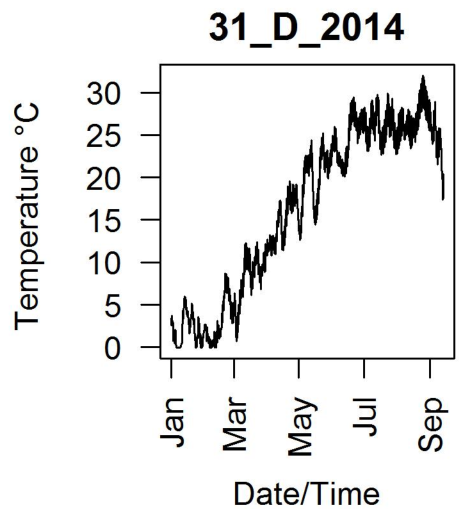
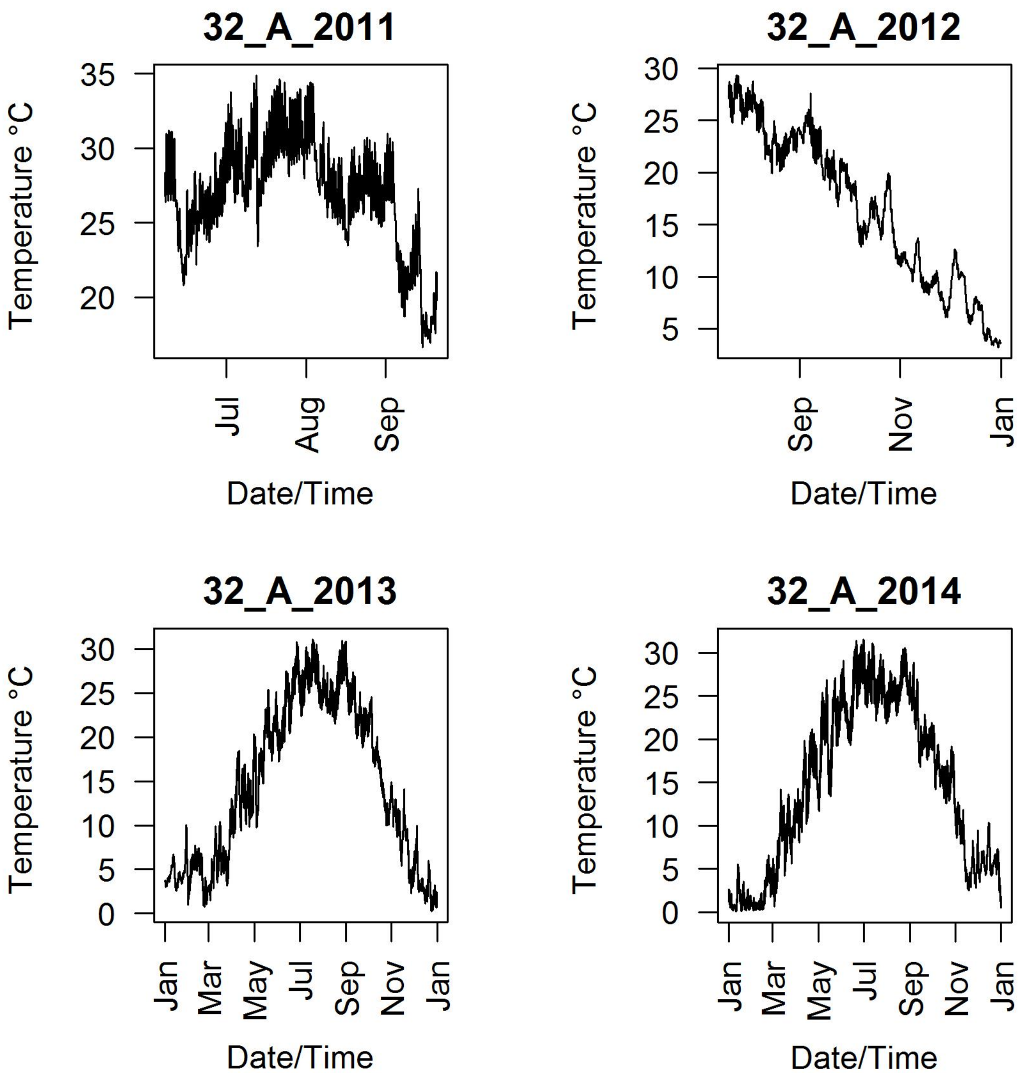
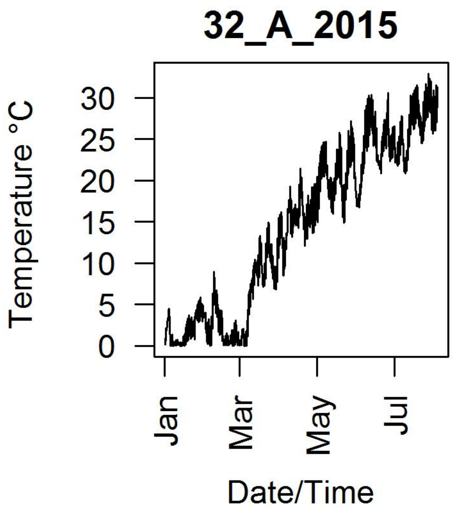


Figure 86. Site 32, Point A: Bourbeuse River near High Gate, 2011 – 2015.
Decision: used all records.




32_A_2015
Temperature °C
30
25
20
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10
5
0
Jan
Mar
May
Jul
Date/Time

Figure 87. Site 32, Point B: Bourbeuse River near High Gate, 2011 – 2012.
Decision: used all records.

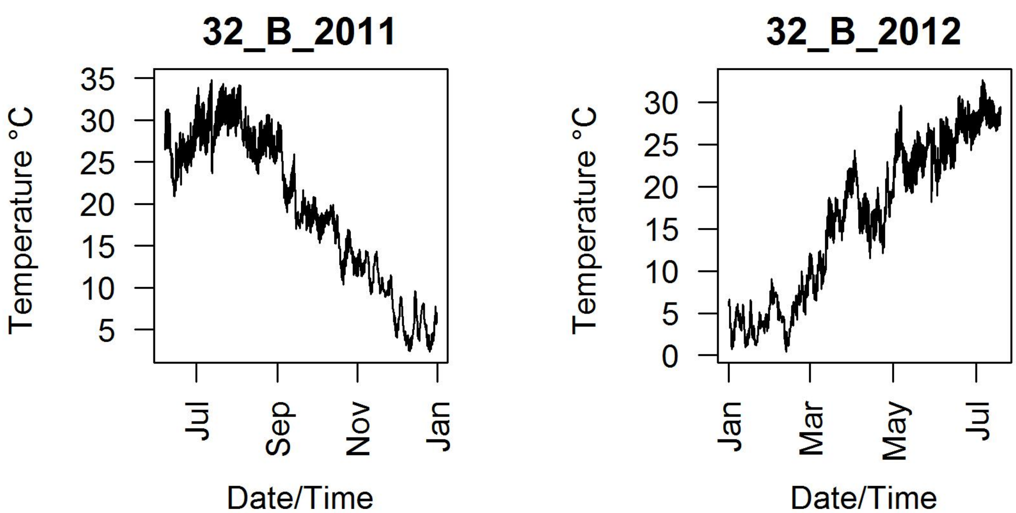


Figure 88. Site 32, Point C: Bourbeuse River near High Gate, 2013 – 2015.
Decision: used all records.

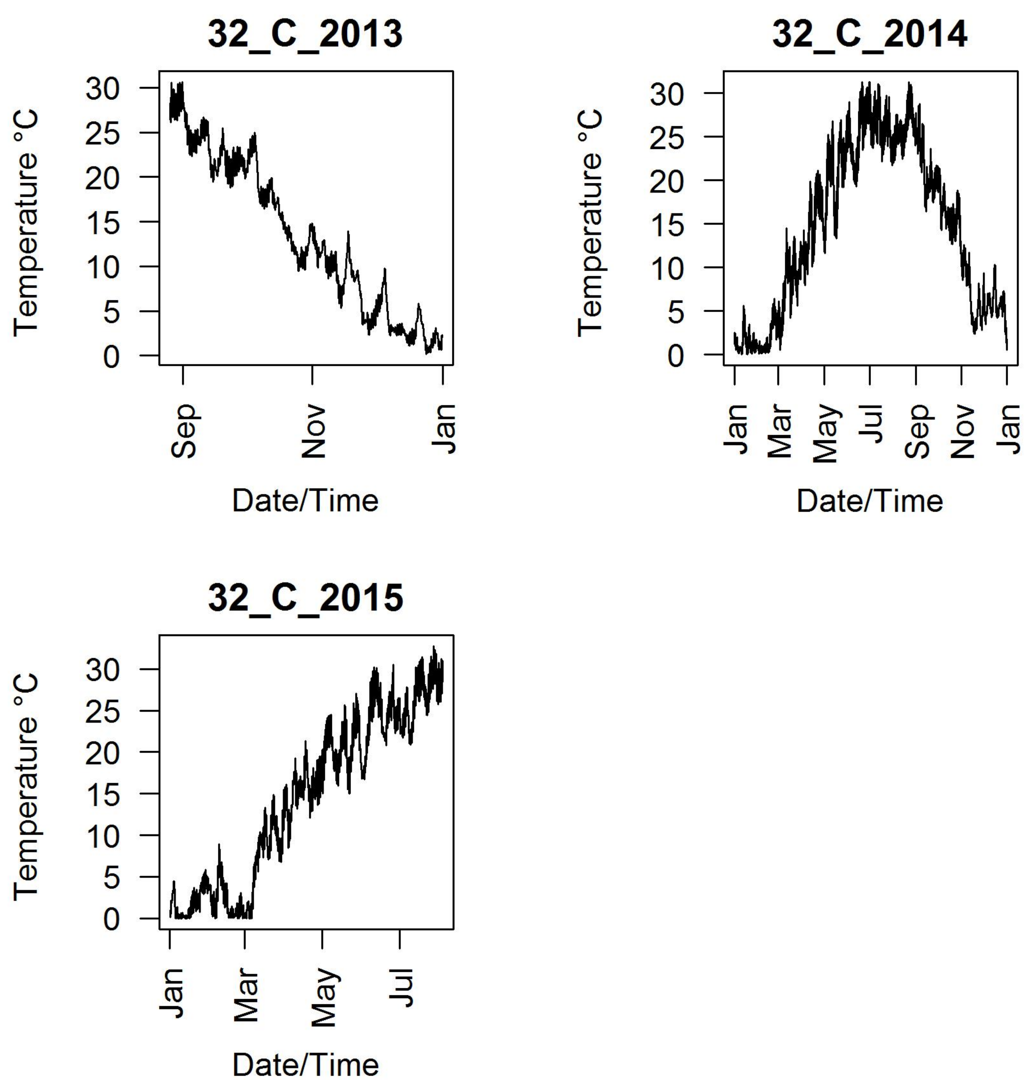


Figure 89. Site 33, Point A: Bourbeuse River at Union, 2011 – 2012.

Notes: when logger retrieved on 10 Oct 2012 the data end was buried in silt. Pattern of daily fluctuation is similar to loggers at point B.

Decision: used all records.

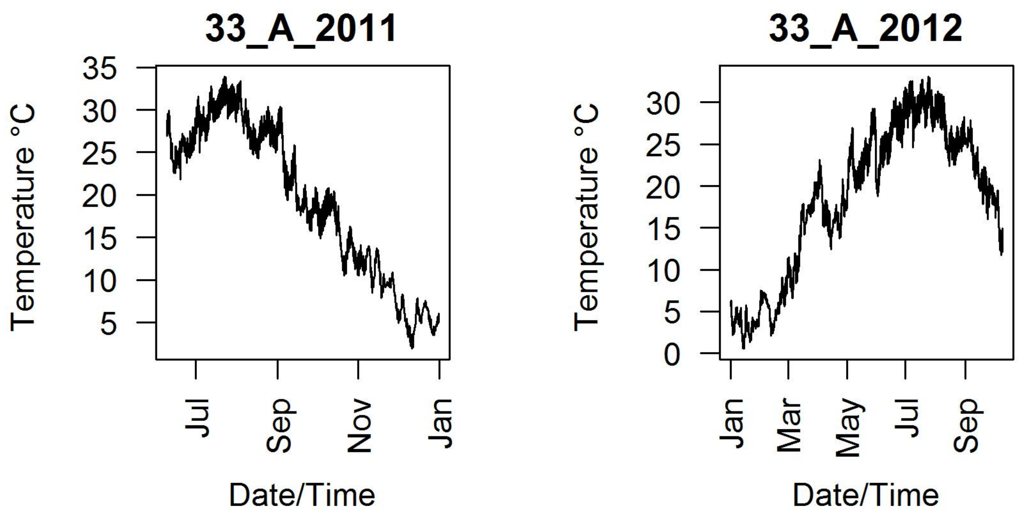
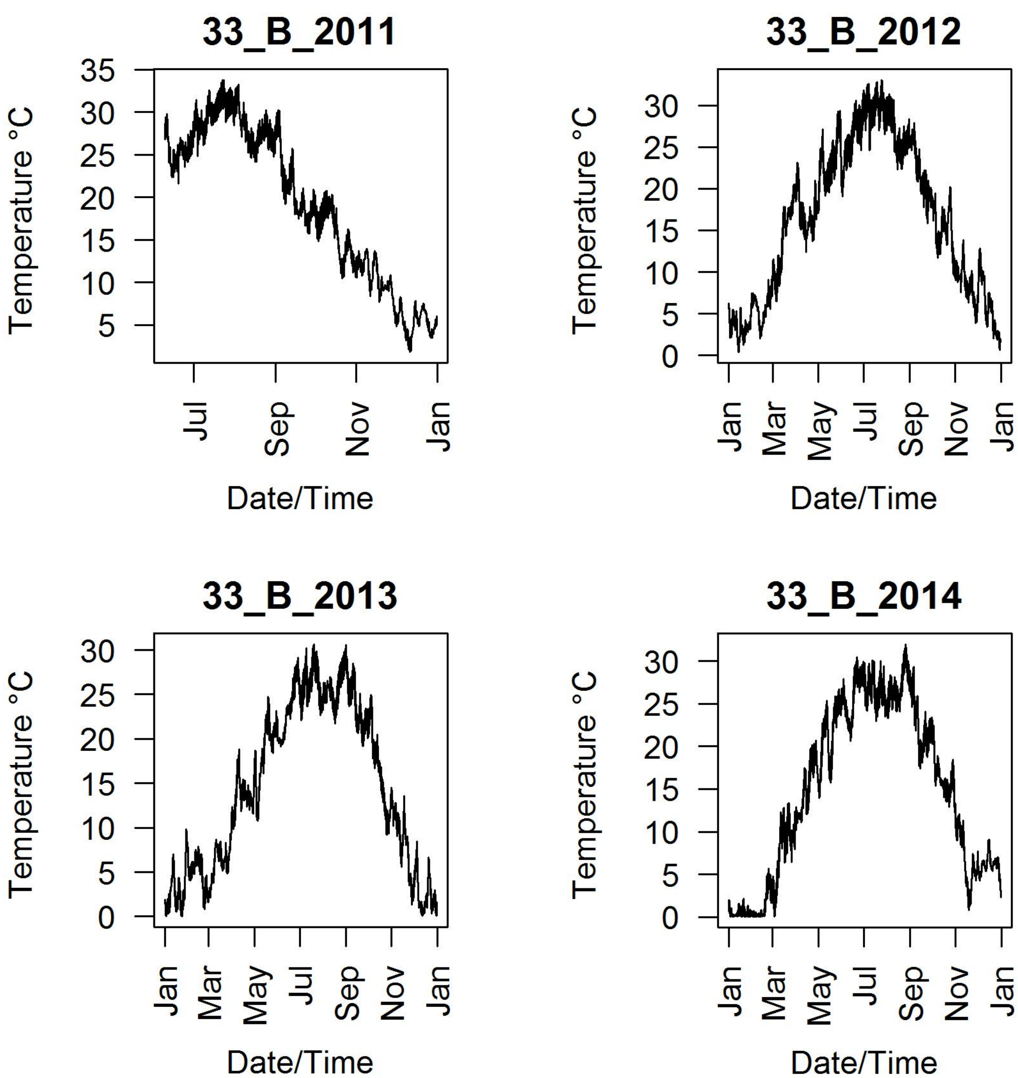


Figure 90. Site 33, Point B: Bourbeuse River at Union, 2011 – 2015.
Decision: used all records.



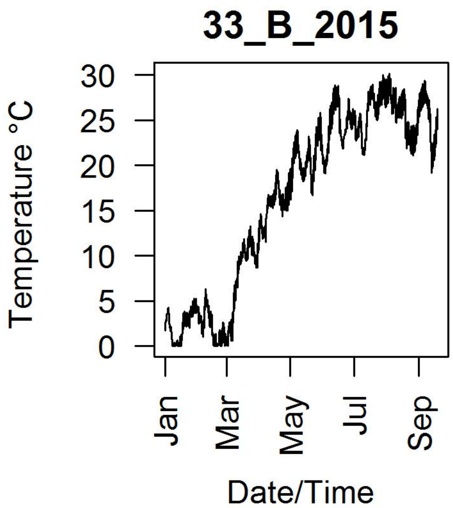

33_B_2015
Temperature °C
30
25
20
15
10
5
0
Jan
Mar
May
Jul
Sep
Date/Time

Figure 91. Site 33, Point D: Bourbeuse River at Union, 2013 – 2015.

Decision: used all records

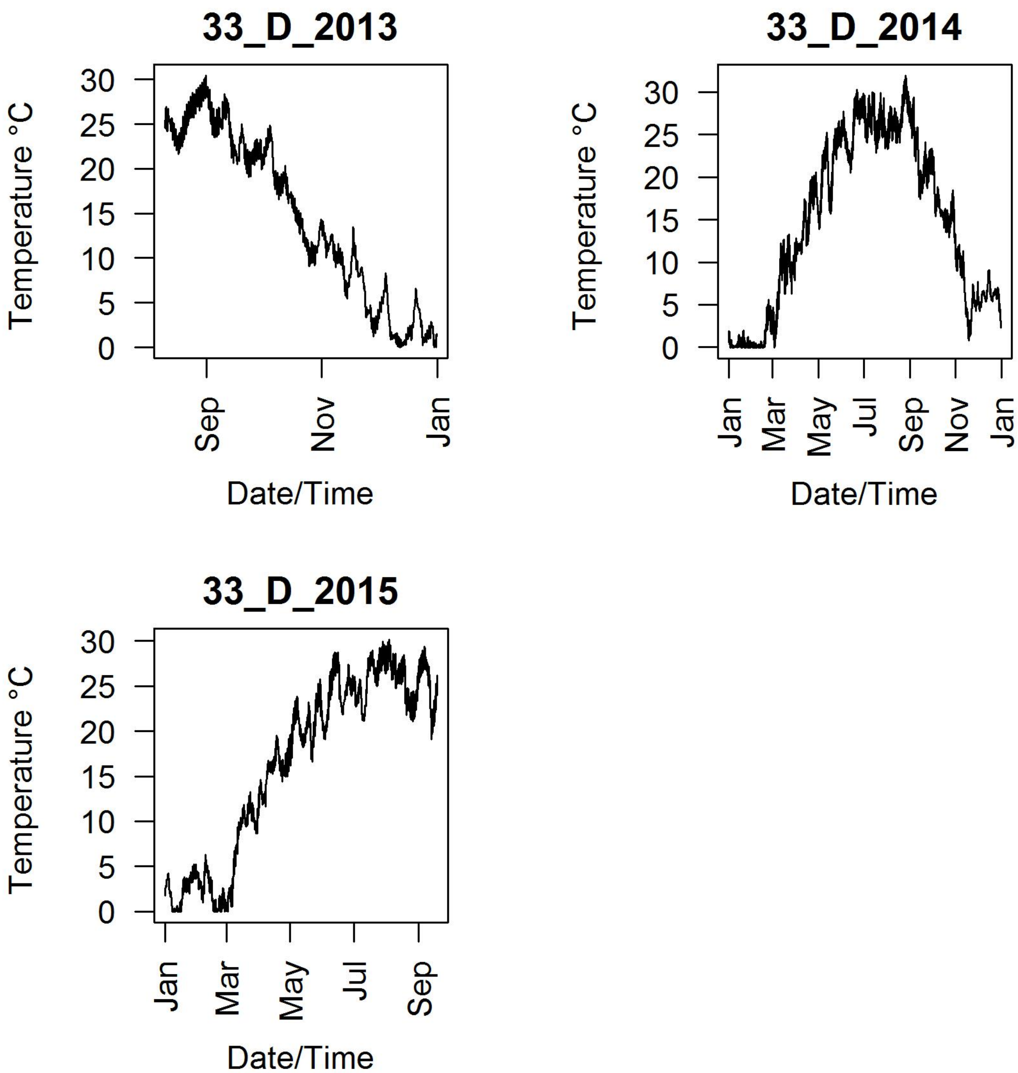


Figure 92. Site 34, Point A: Big River at Irondale, 2011.
Decision: used all records.

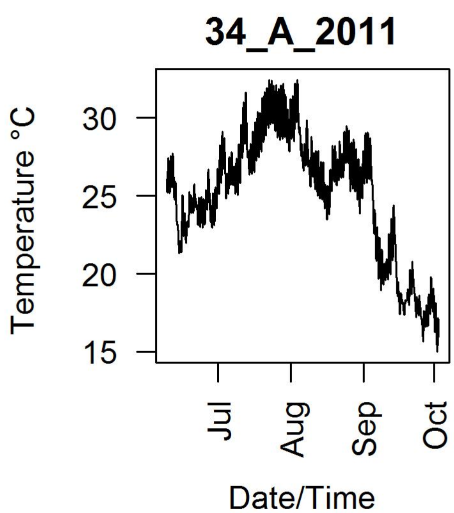


Figure 93. Site 34, Point B: Big River at Irondale, 2011.
Decision: used all records.

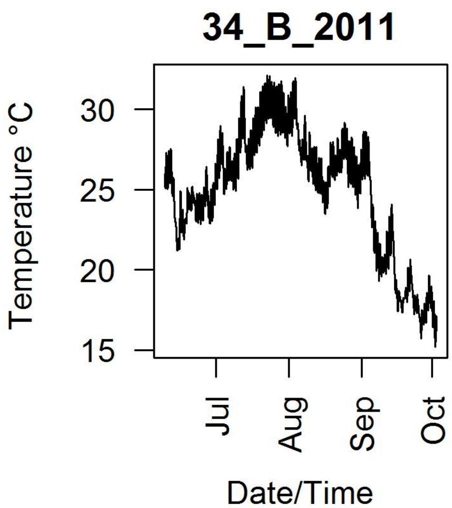
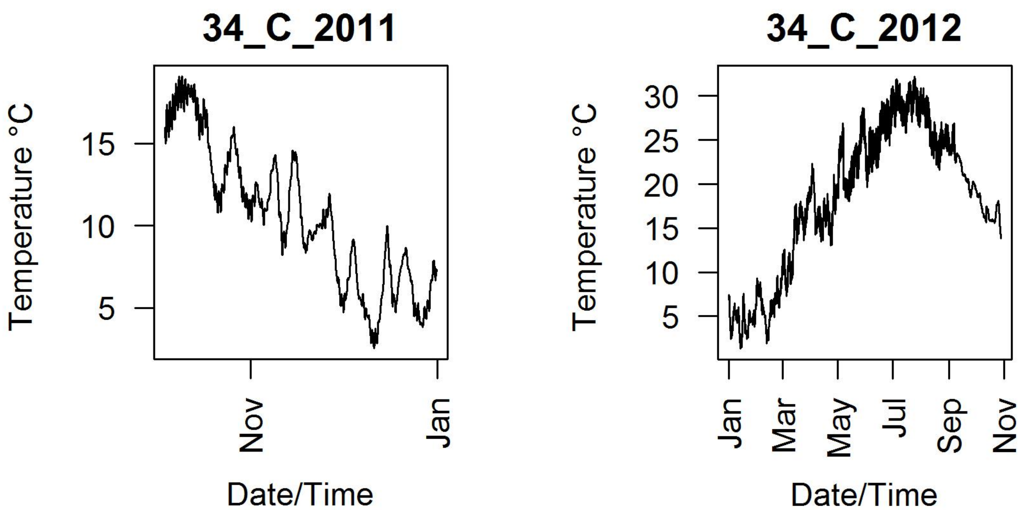


*Figure 94. Site 34, Point C: Big River at Irondale, 2011 – 2012.***

Notes: records indicate that this logger was retrieved in good condition however the Sept 10 – Oct 28, 2012 data are typical of a buried logger with a reduced variation in daily temperatures.

Decision: did not use records after Sept 9. Used remaining records.



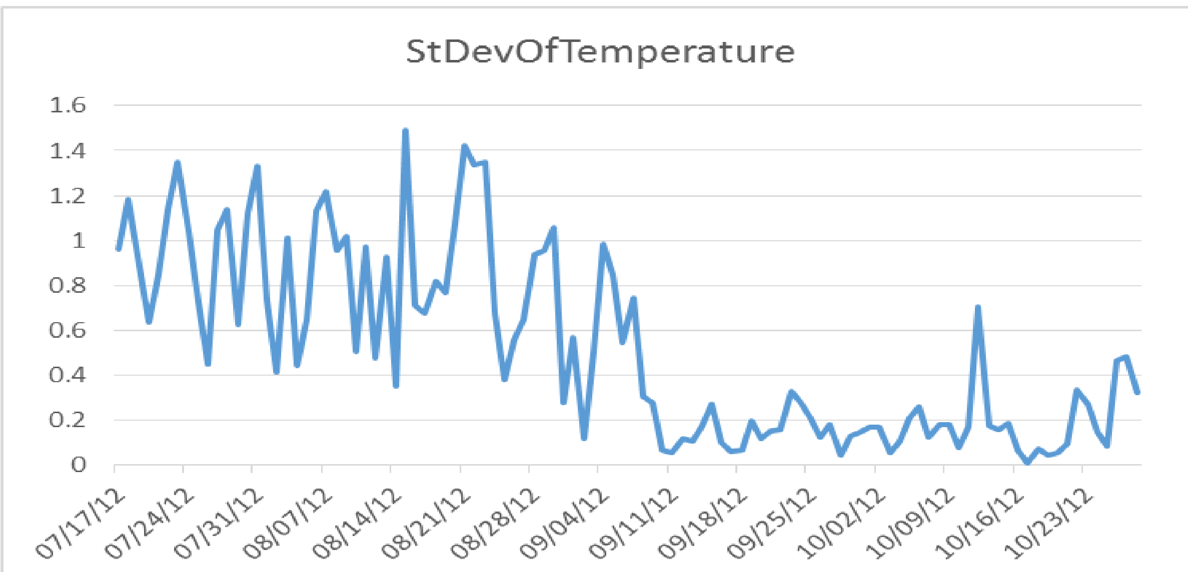


Figure 95. Site 34, Point D: Big River at Irondale, 2011 – 2012.
Decision: used all records.

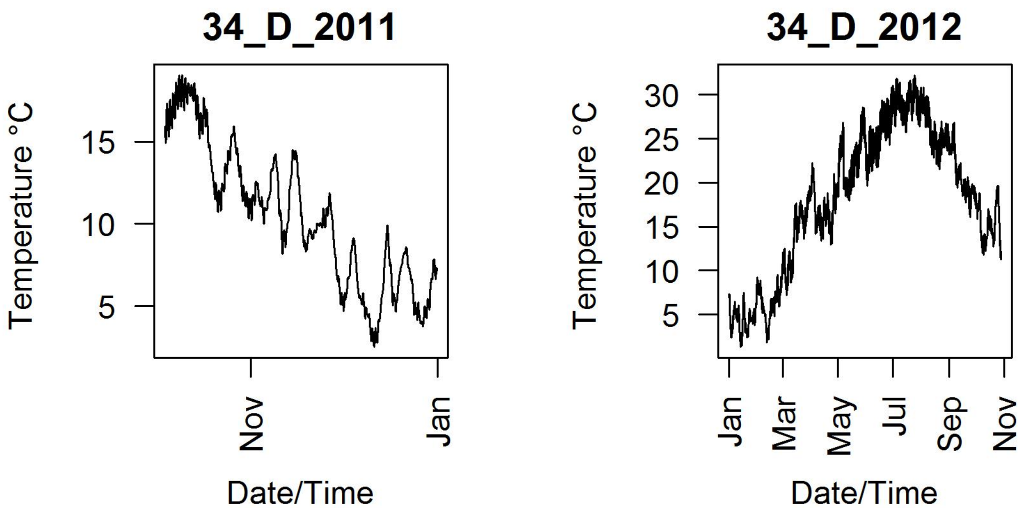


Figure 96. Site 34, Point E: Big River at Irondale, 2012 – 2015.
Decision: used all records.

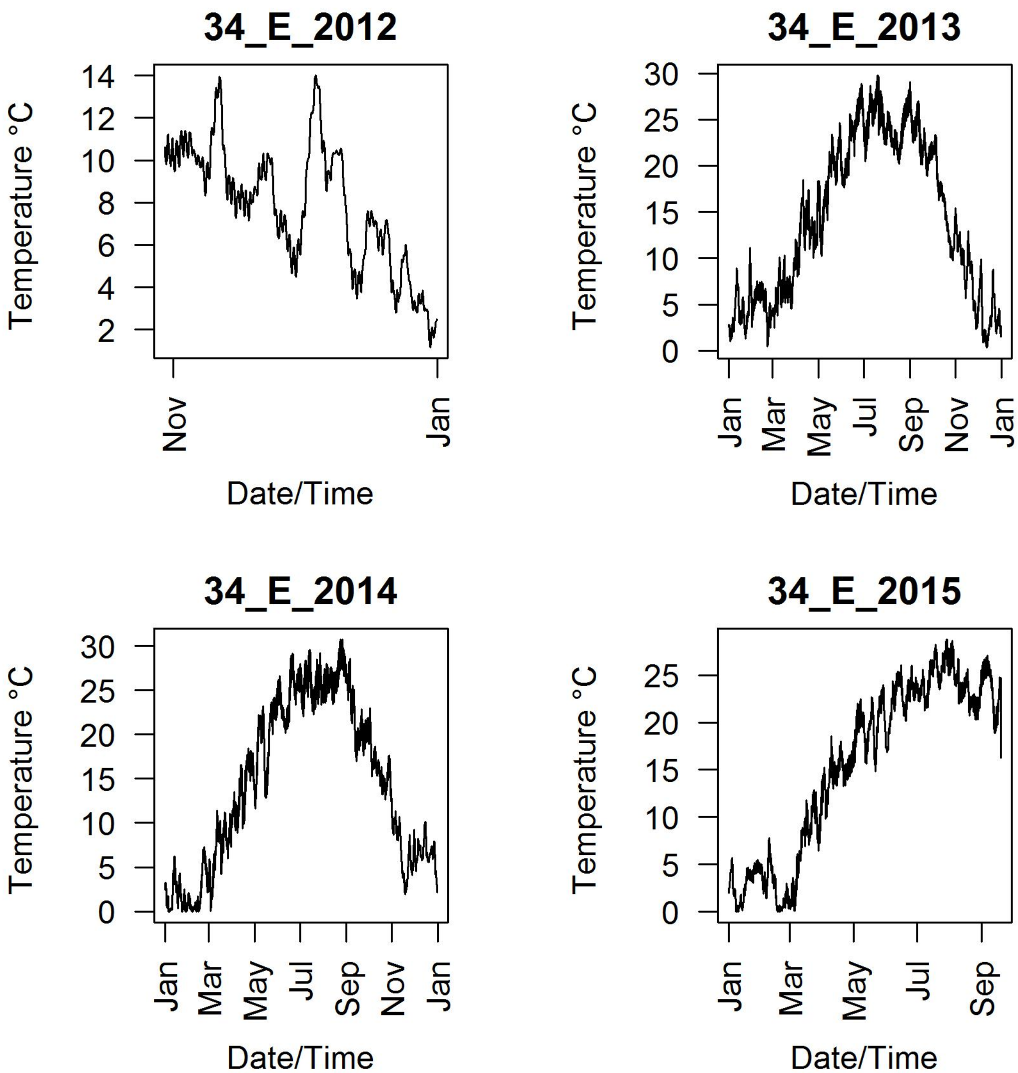


Figure 97. Site 34, Point E: Big River at Irondale, 2012 – 2015.
Decision: used all records.

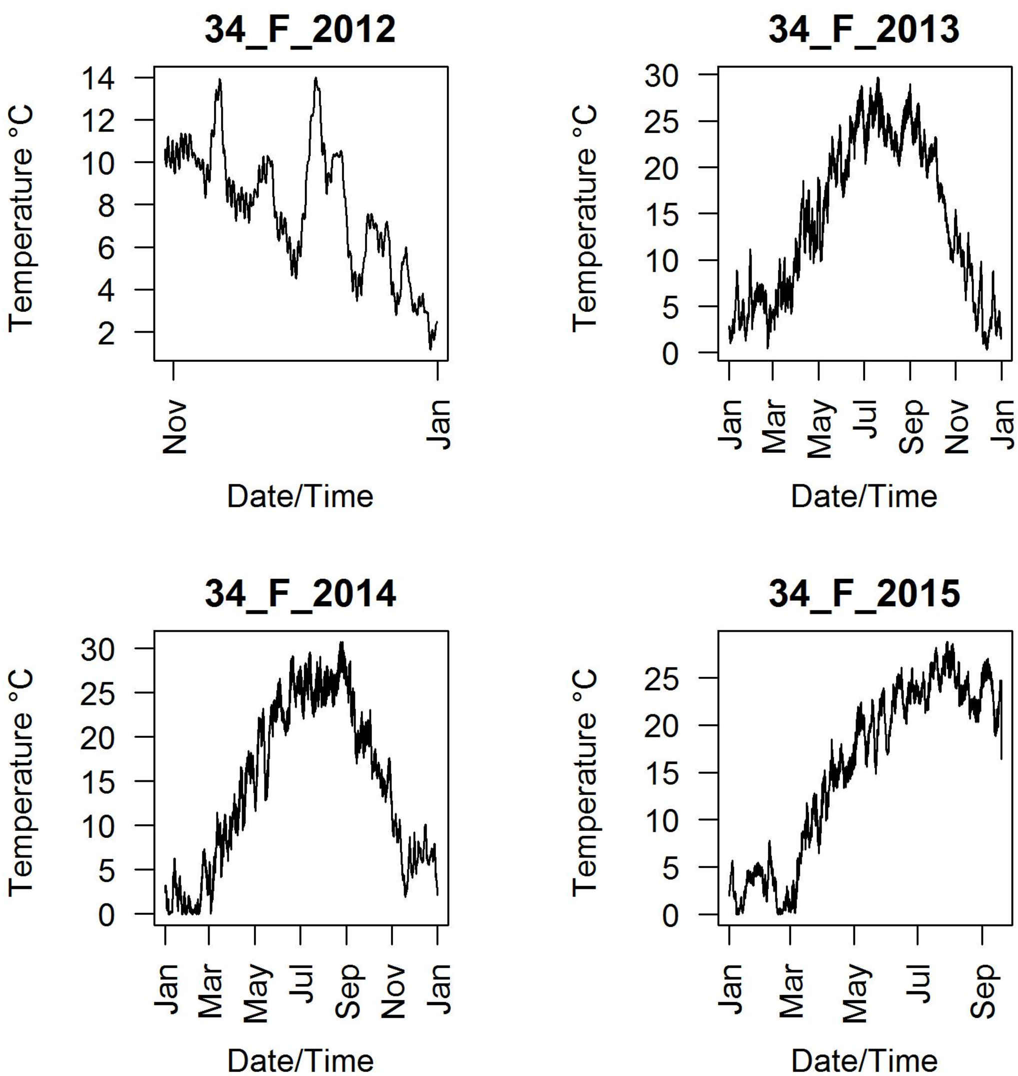
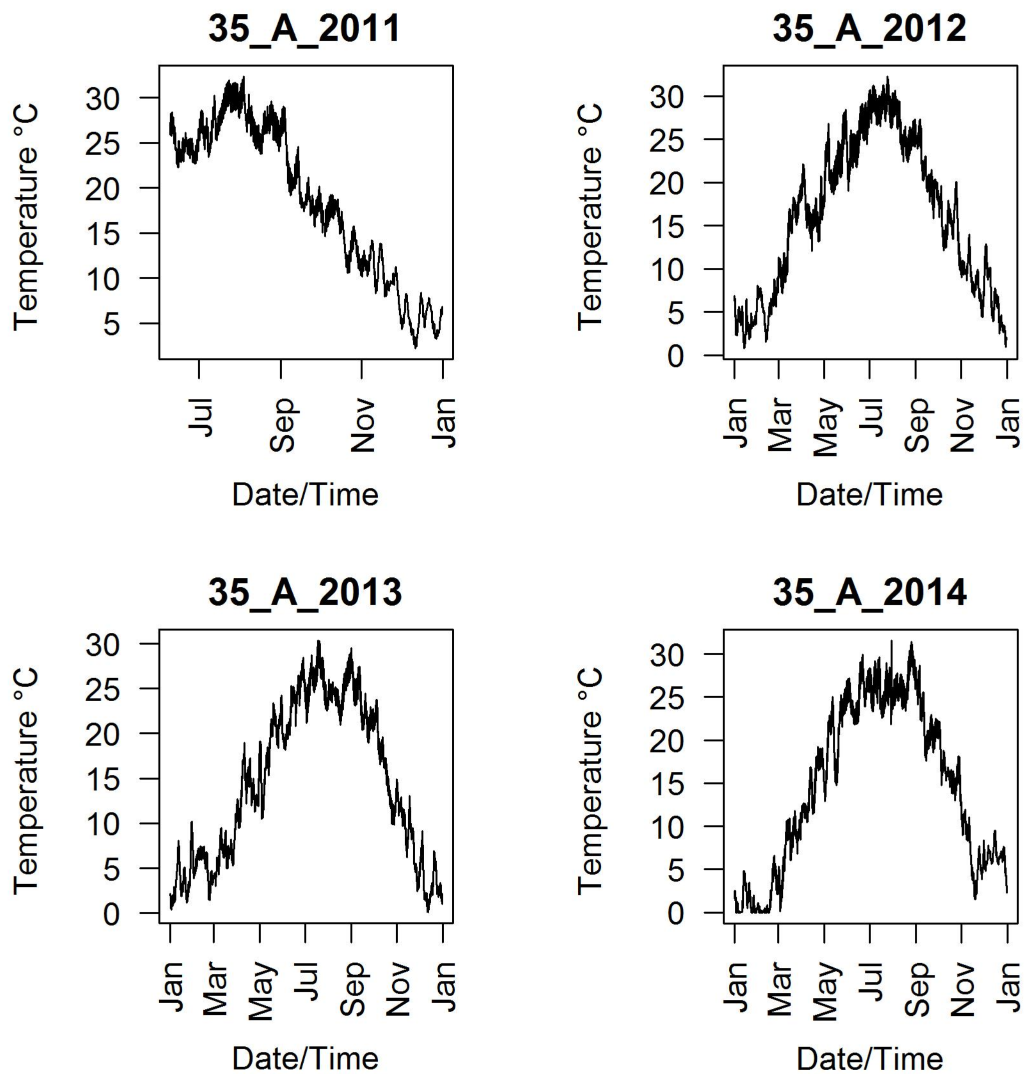
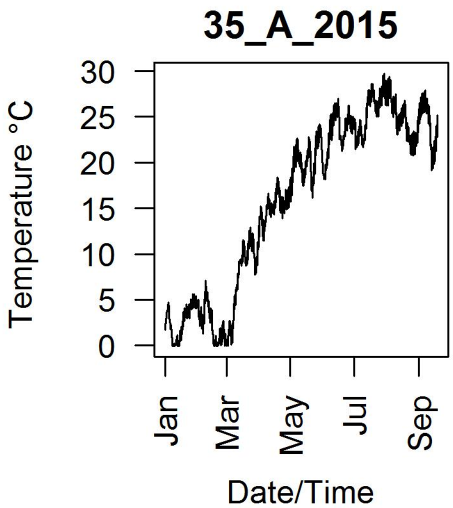


*Figure 98. Site 35, Point A: Big River near Richwoods, 2011 – 2015***

Notes: 10/9/2012: logger was 3 h 24 m ahead of time when retrieved. Calculated difference in temperatures recorded at A and B. Differences remained fairly consistent through early Feb 2012.

Decision: Excluded records from Feb 15, 2012 – Oct 9, 2012. Used remaining records.




35_A_2015
Temperature °C
0
5
10
15
20
25
30
Jan
Mar
May
Jul
Sep
Date/Time

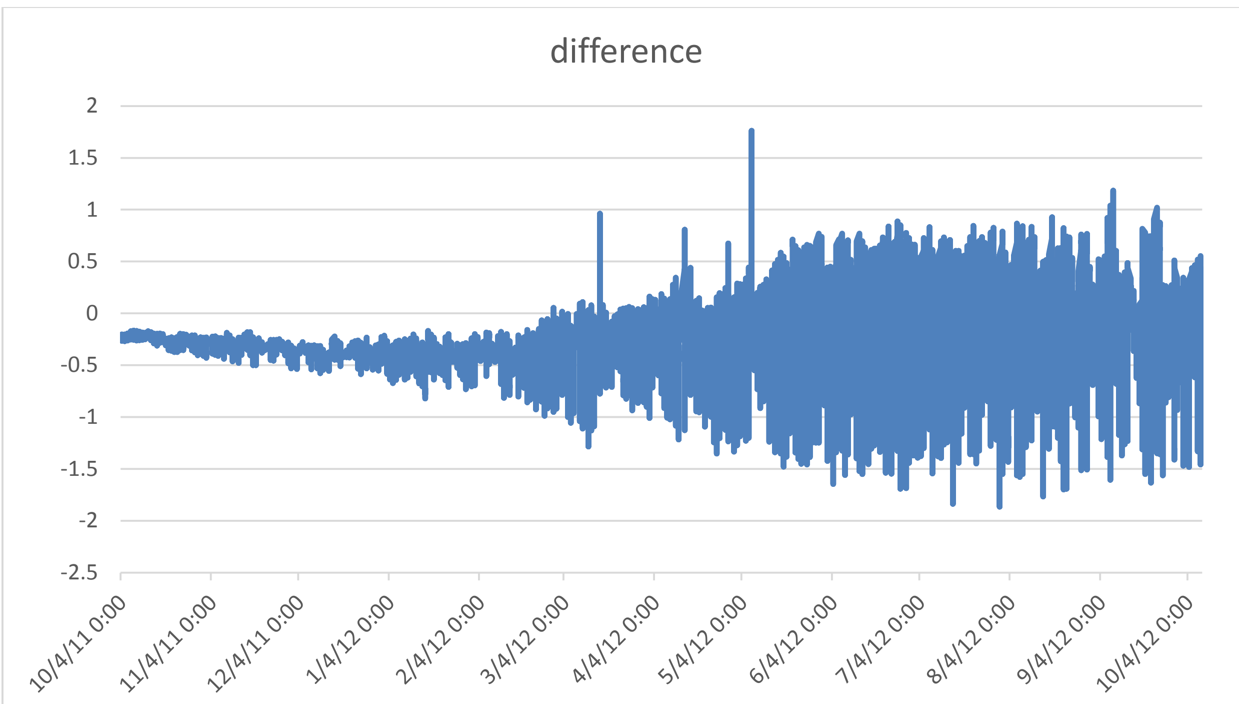
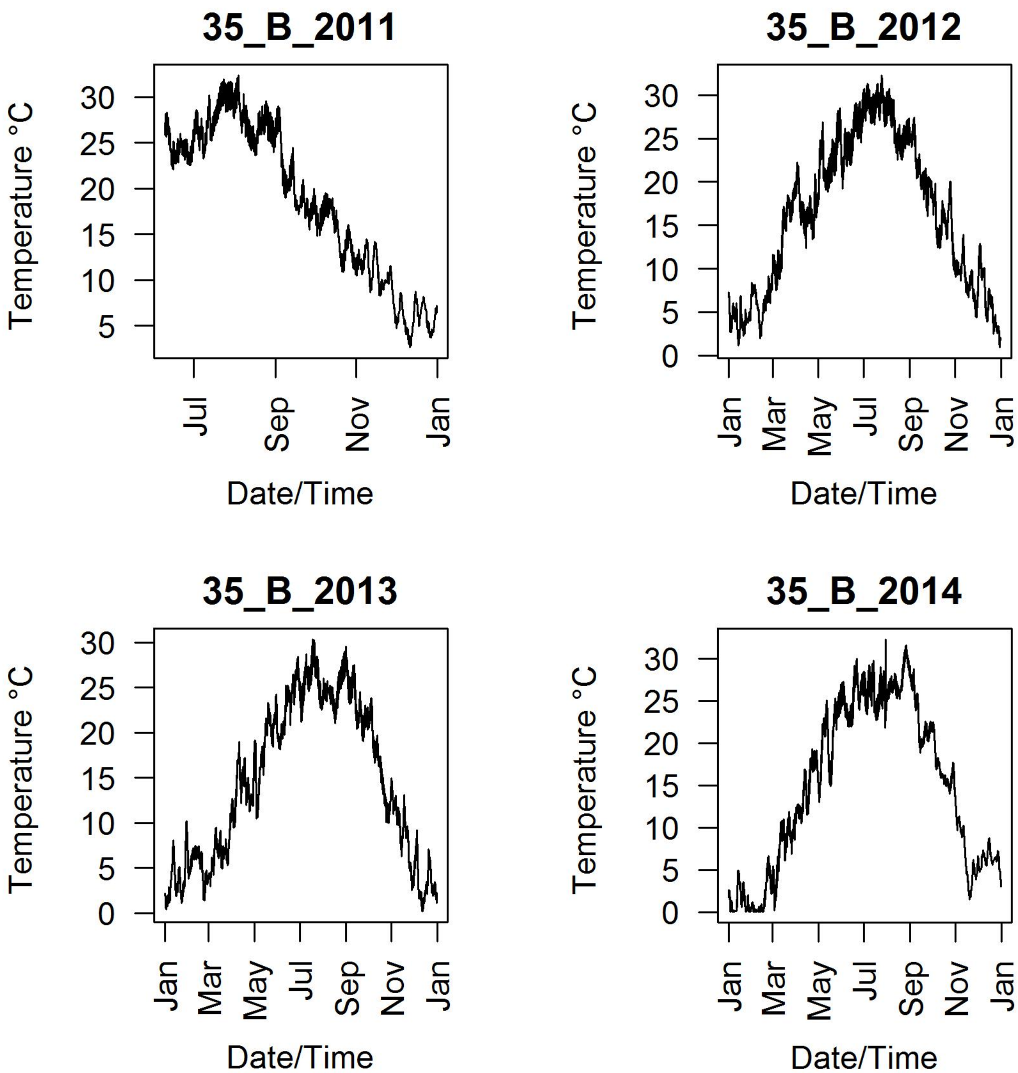

difference
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
10/4/11 0:00
11/4/11 0:00
12/4/11 0:00
1/4/12 0:00
2/4/12 0:00
3/4/12 0:00
4/4/12 0:00
5/4/12 0:00
6/4/12 0:00
7/4/12 0:00
8/4/12 0:00
9/4/12 0:00
10/4/12 0:00

Figure 99. Site 35, Point B: Big River near Richwoods, 2011 – 2015.
Decision: used all records.



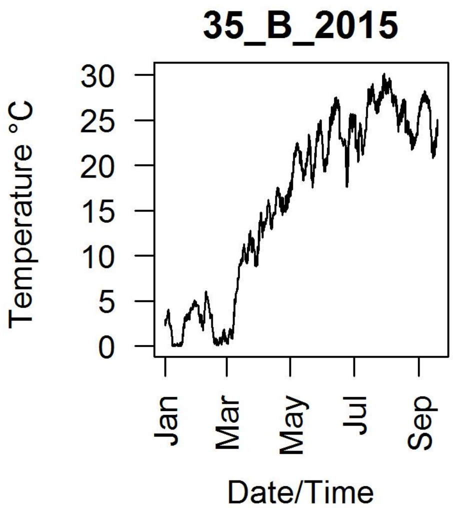

35_B_2015
Temperature °C
0
5
10
15
20
25
30
Jan
Mar
May
Jul
Sep
Date/Time

Figure 100. Site 36, Point A: Big River at Byrnesville, 2011 – 2012.
Decision: used all records.

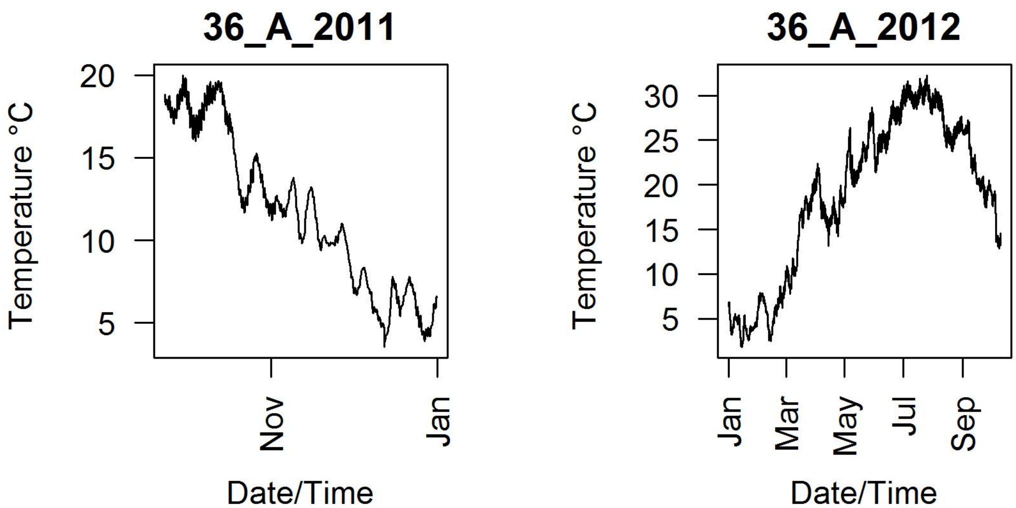
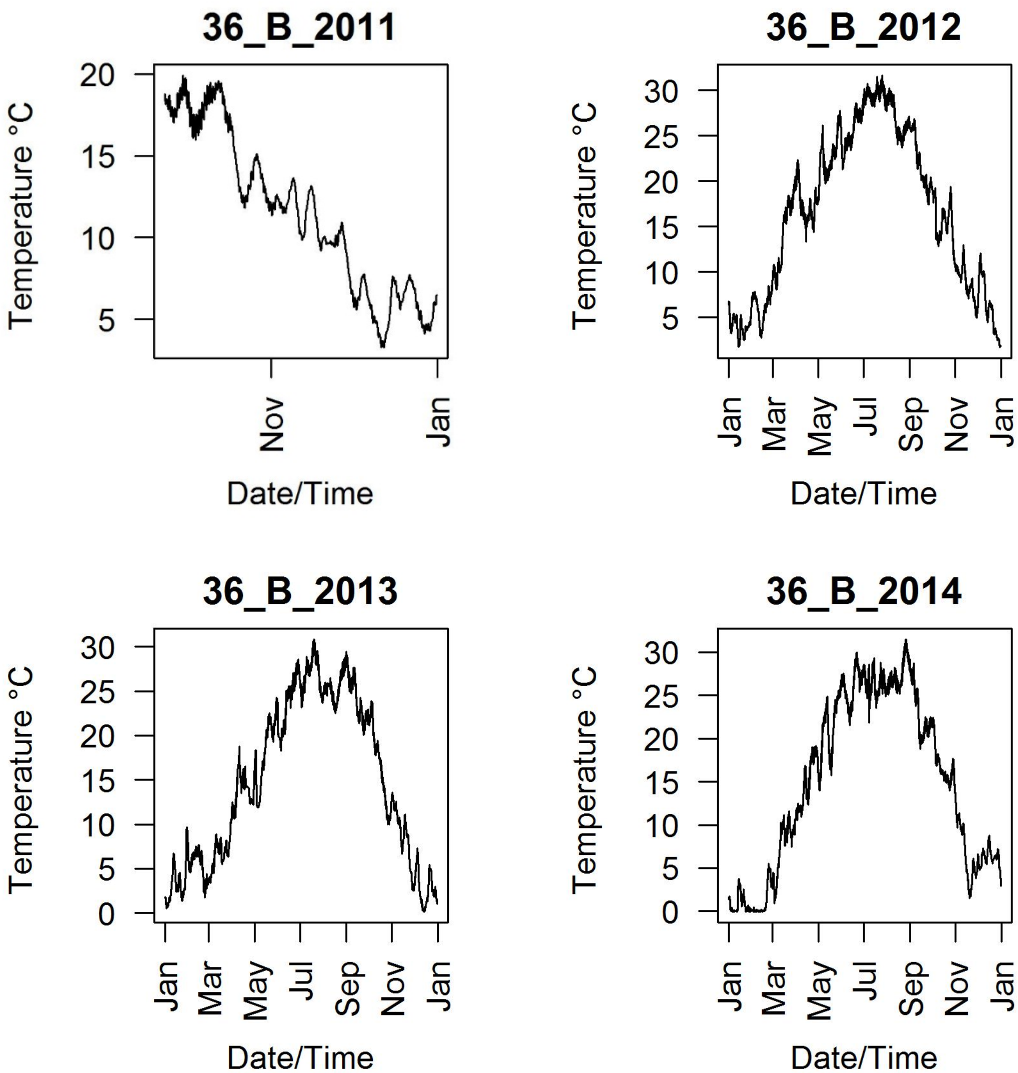


Figure 101. Site 36, Point B: Big River at Byrnesville, 2011 – 2015.
Decision: used all records.



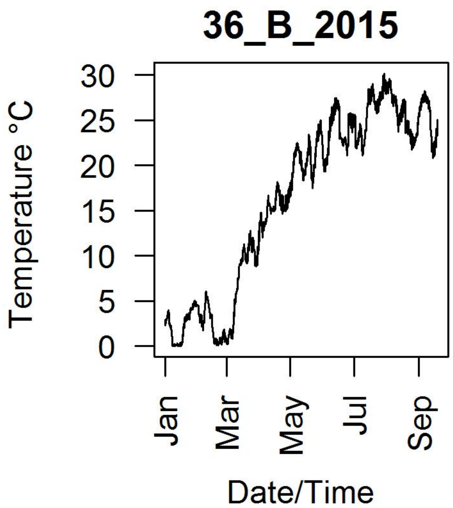

36_B_2015
Temperature °C
30
25
20
15
10
5
0
Jan
Mar
May
Jul
Sep
Date/Time

Figure 102. Site 36, Point C: Big River at Byrnesville, 2014 – 2015.
Decision: used all records.

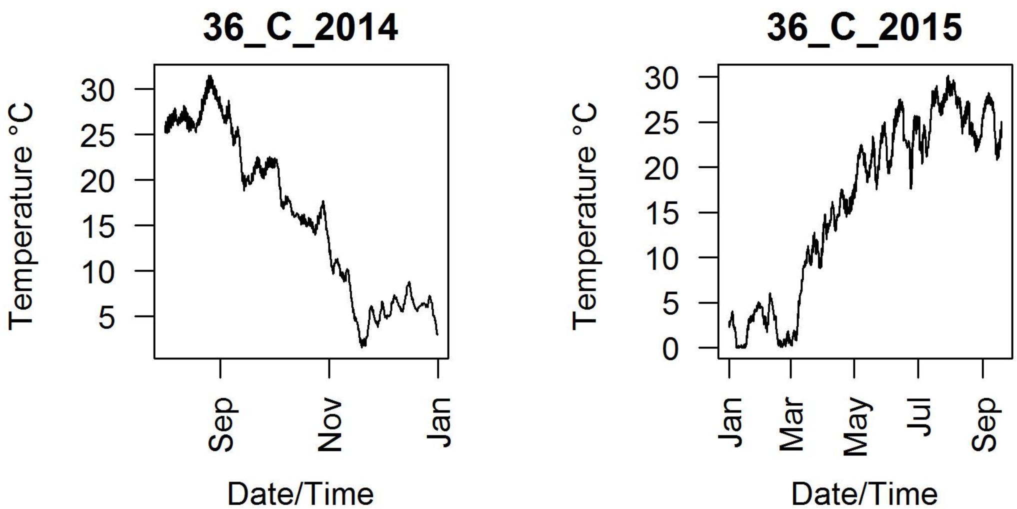


Figure 103. Site 37. Point A: Meramec River near Eureka, 2011.
Decision: used all records.

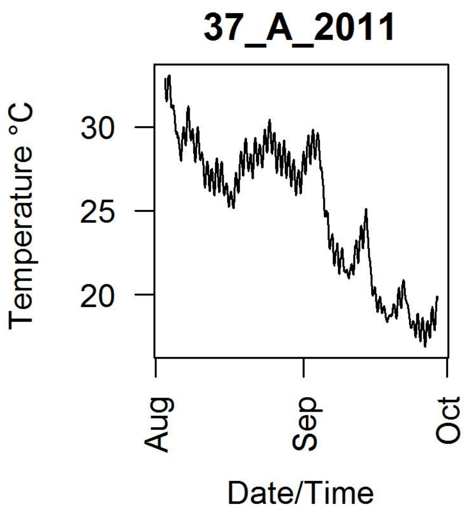


Figure 104. Site 37. Point B: Meramec River near Eureka, 2011 – 2012.
Decision: used all records.

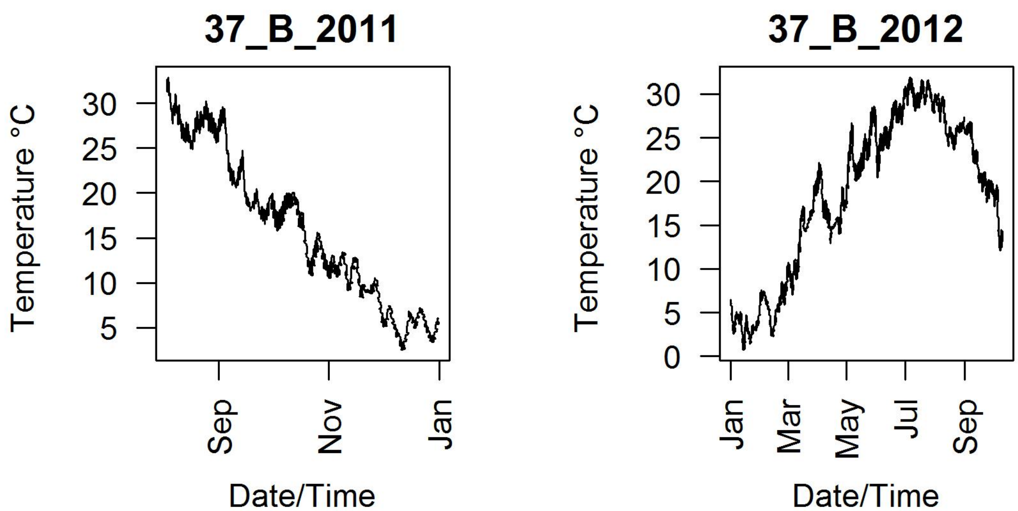


Figure 105. Site 37. Point C: Meramec River near Eureka, 2013 – 2015.
Decision: used all records.

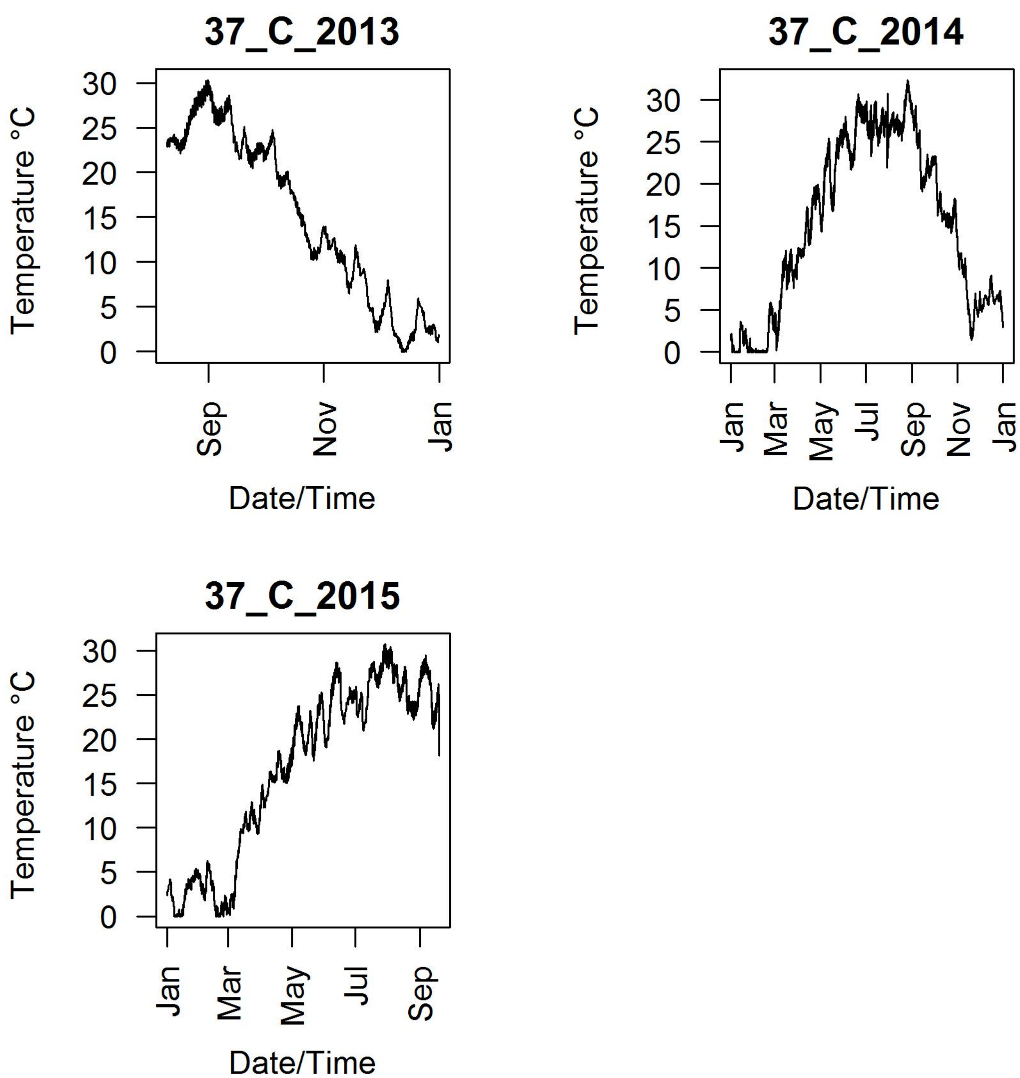


Figure 106. Site 37. Point D: Meramec River near Eureka, 2013 – 2014.
Decision: used all records.

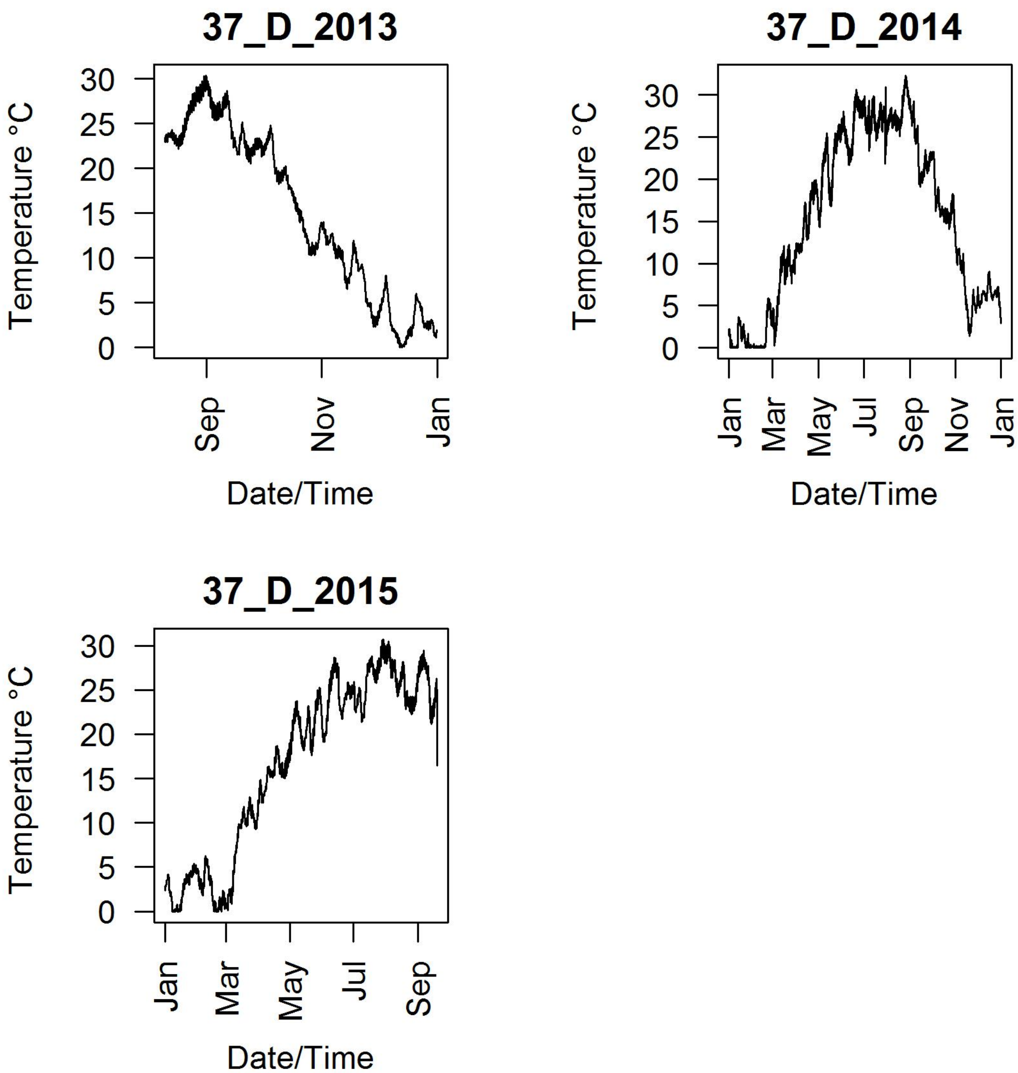


Figure 107. Site 38, Point A: Big Creek at Sam A Baker State Park, 2011 – 2012.
Decision: used all records.

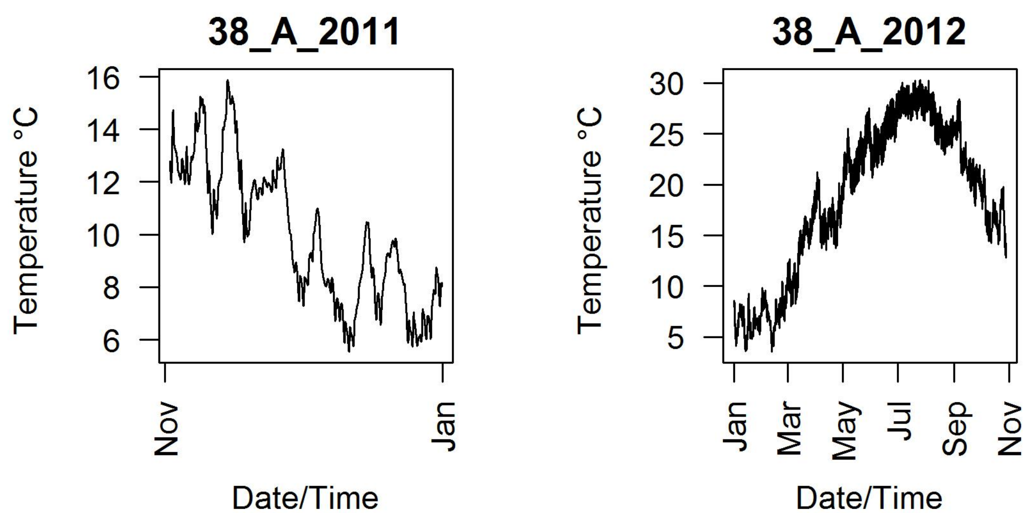


*Figure 108. Site 38, Point C: Big Creek at Sam A Baker State Park, 2013 – 2014***
Notes: 2 Oct 2014: buried when retrieved; did not use records from Sept 8 – Oct 2, 2014.

Decision: used remaining records.

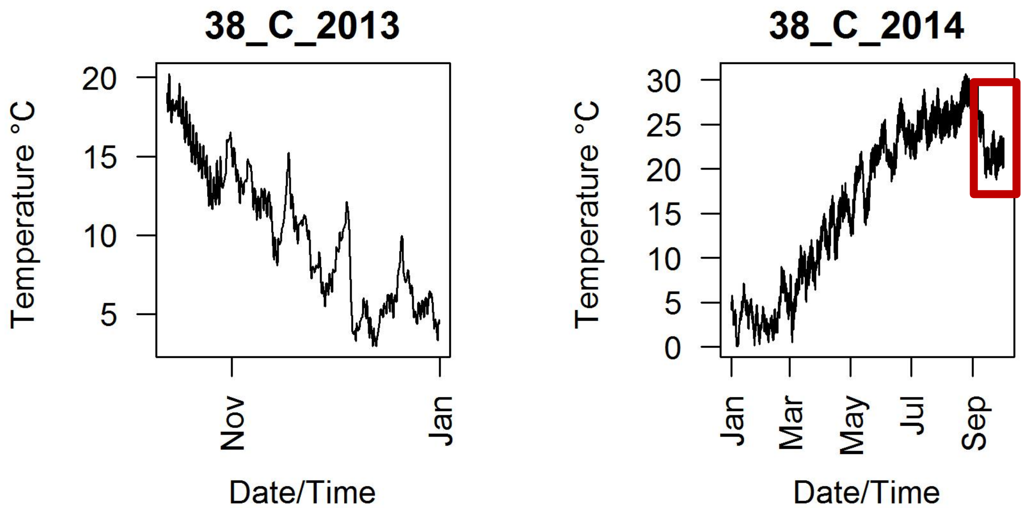


Figure 109. Site 38, Point D: Big Creek at Sam A Baker State Park, 2014 – 2015.
Decision: used all records.

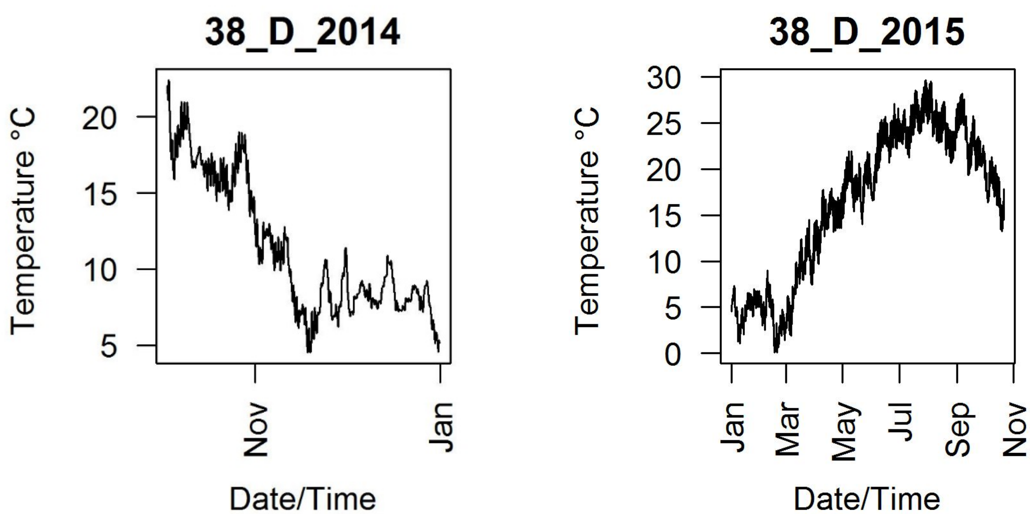


Figure 110. Site 38, Point E: Big Creek at Sam A Baker State Park, 2014 – 2015.
Decision: used all records.

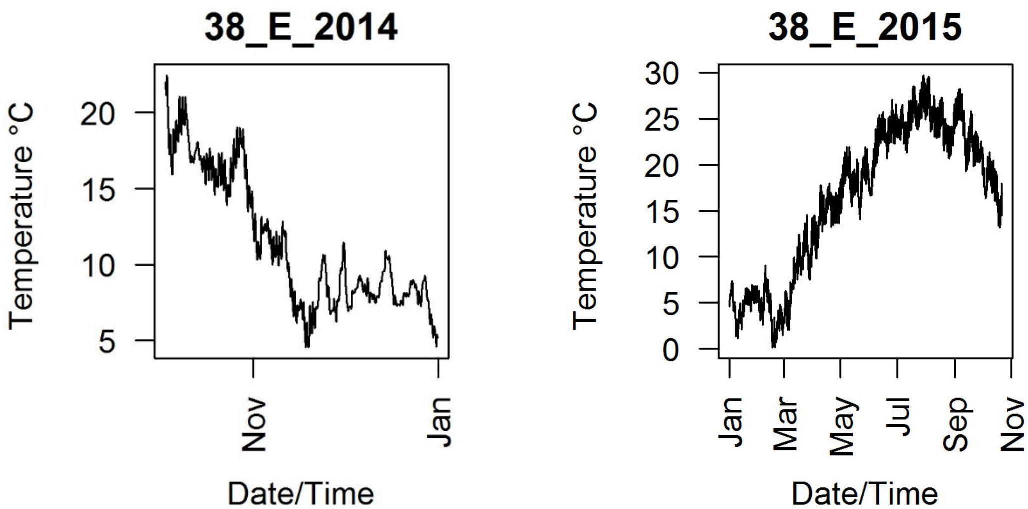


Figure 111. Site 39, Point A: Pearson Creek near Springfield, 2012 – 2015.
Decision: used all records.

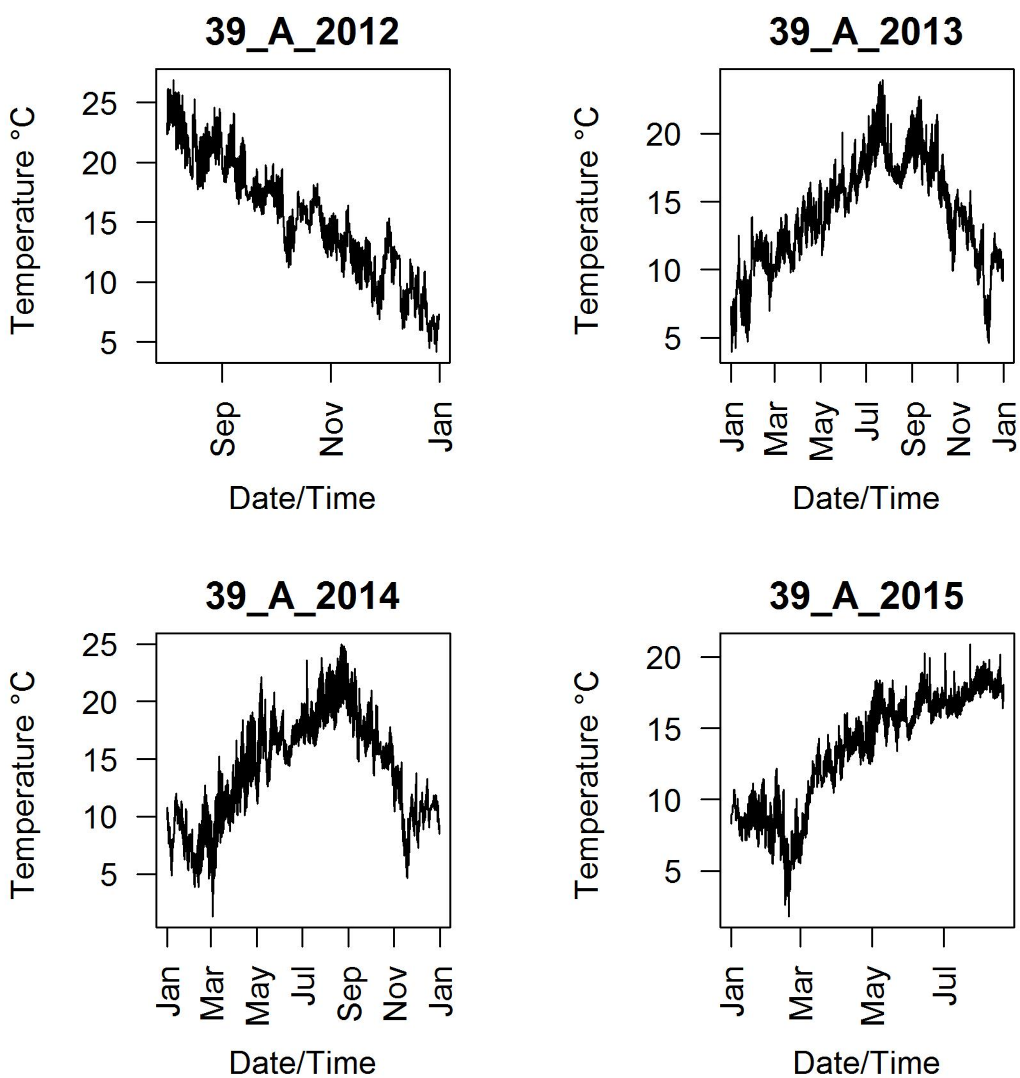


Figure 112. Site 39, Point B: Pearson Creek near Springfield, 2012 – 2013.
Decision: used all records.

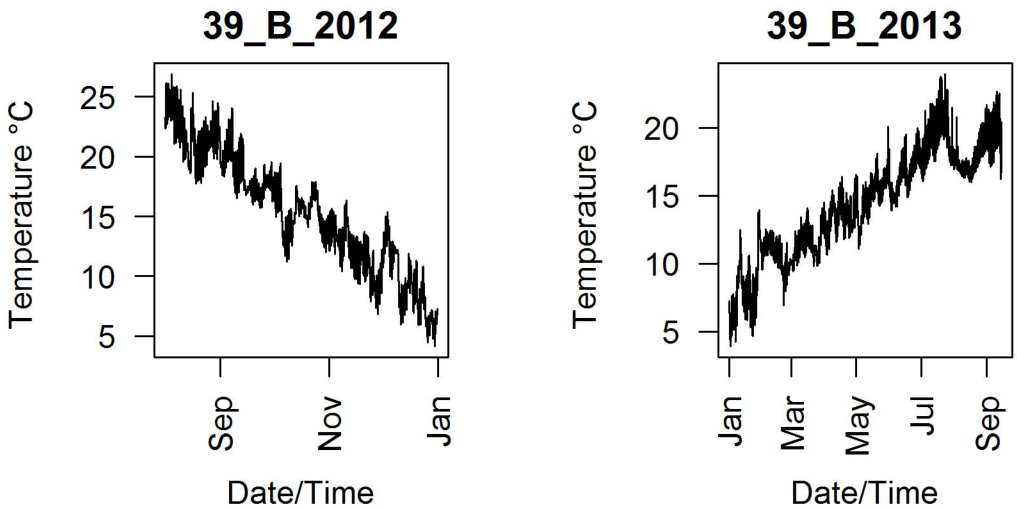


Figure 113. Site 39, Point C: Pearson Creek near Springfield, 2013 – 2015.
Decision: used all records.

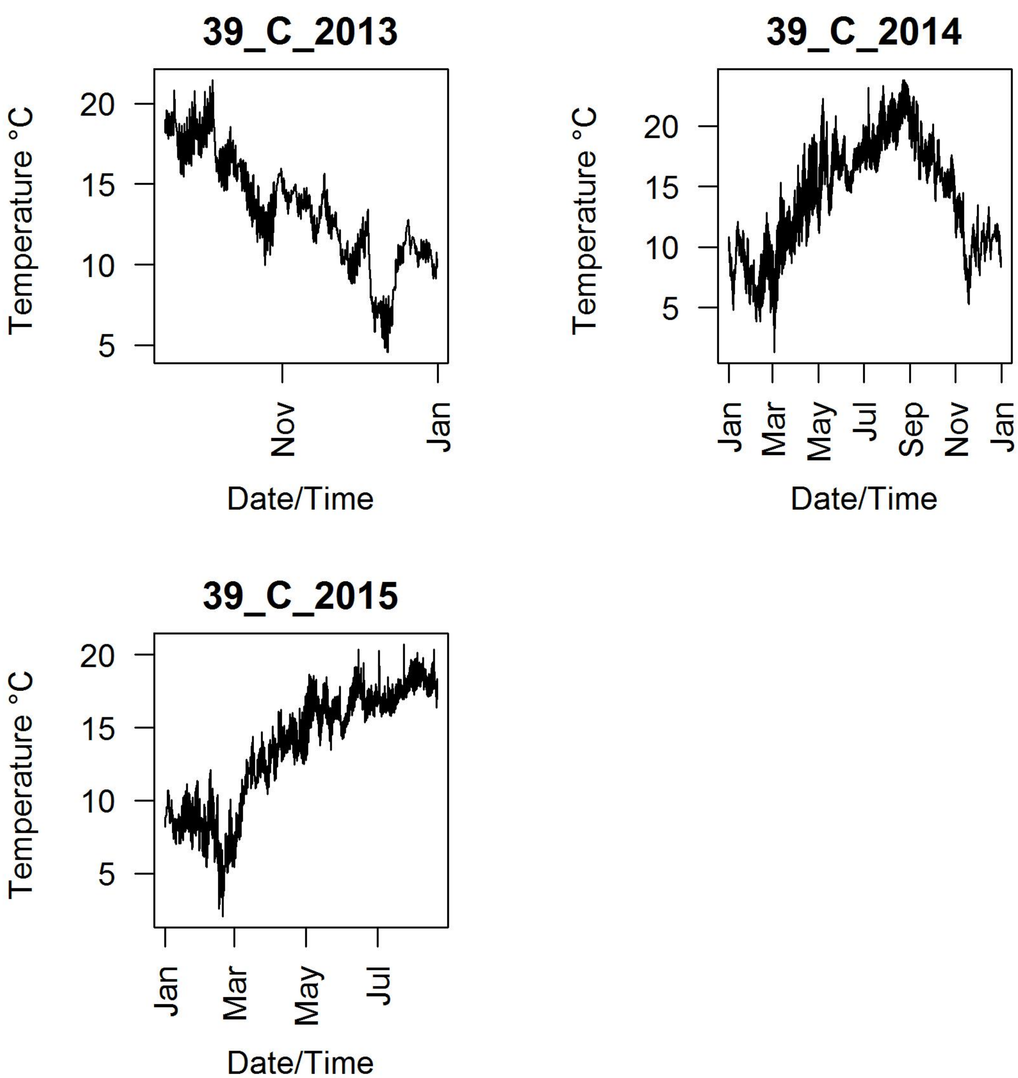


Figure 114. Site 40, Point A: James River near Springfield, 2012 – 2015.

Note: unusual pattern in July/Aug 2014. Also seen in data from associated logger. All loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.

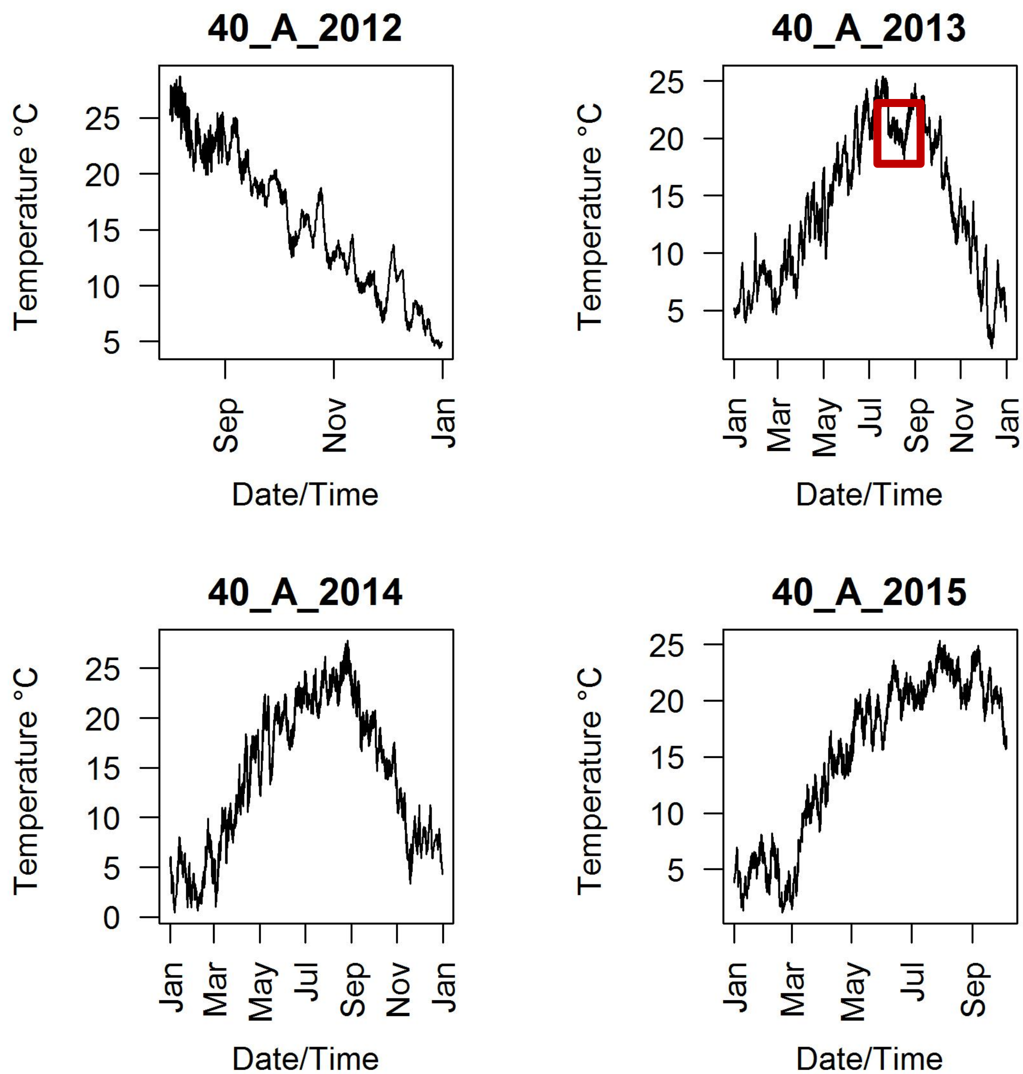
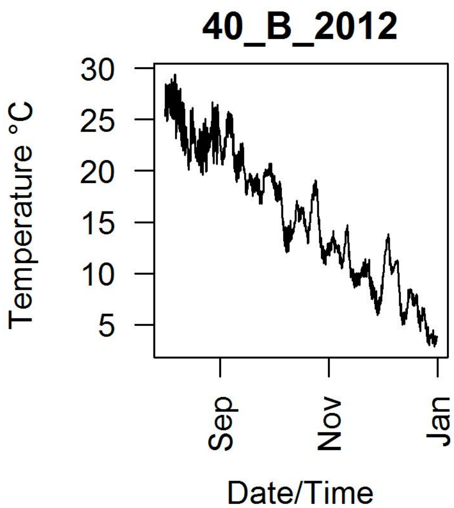


Figure 115. Site 40, Point B: James River near Springfield, 2012 – 2013.
Note: unusual pattern in July/Aug 2014. Also seen in data from associated logger. All loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.



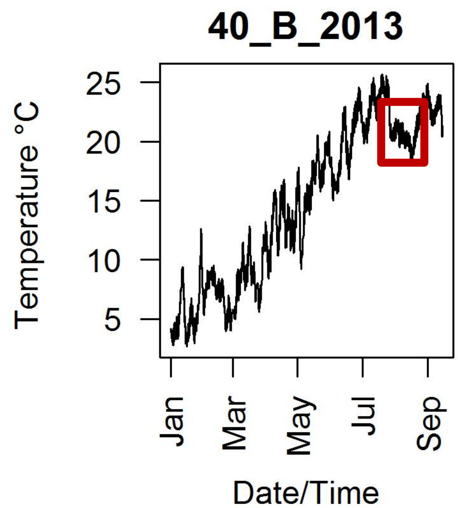


Figure 116. Site 40, Point C: James River near Springfield, 2013 – 2014.

Decision: used all records

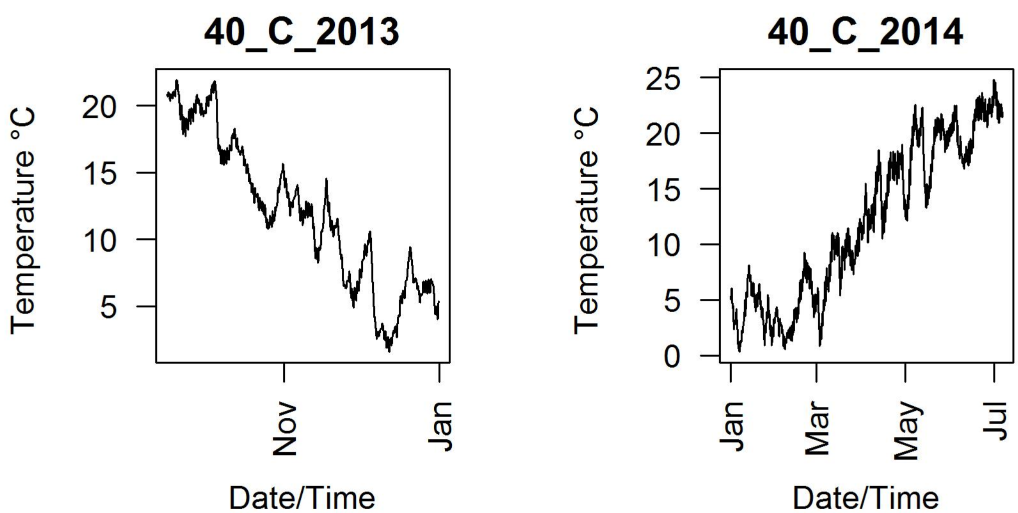


Figure 117. Site 44, Point A: James River near Boaz, 2012 – 2015.

Notes: all loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.

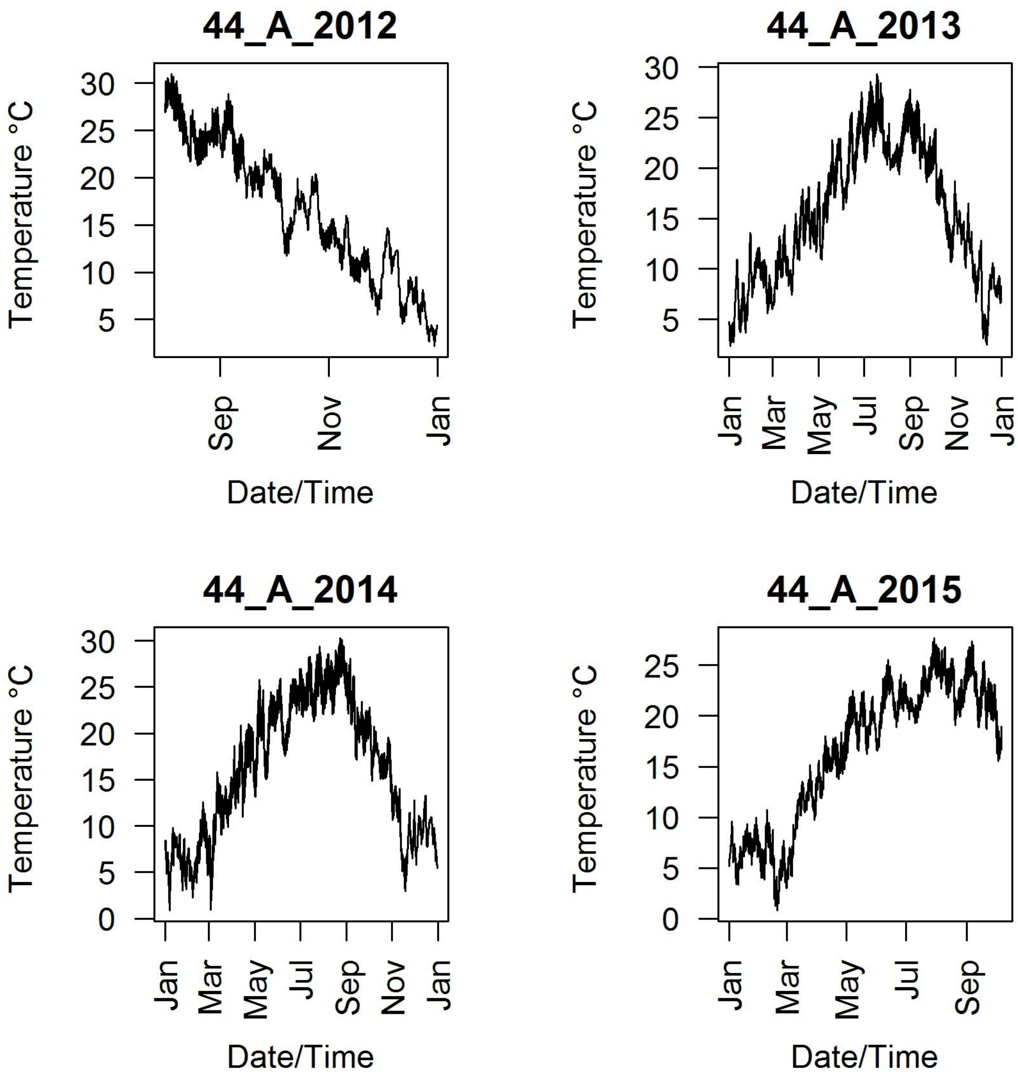


Figure 118. Site 44, Point C: James River near Boaz, 2013 – 2015.
Decision: used all records.

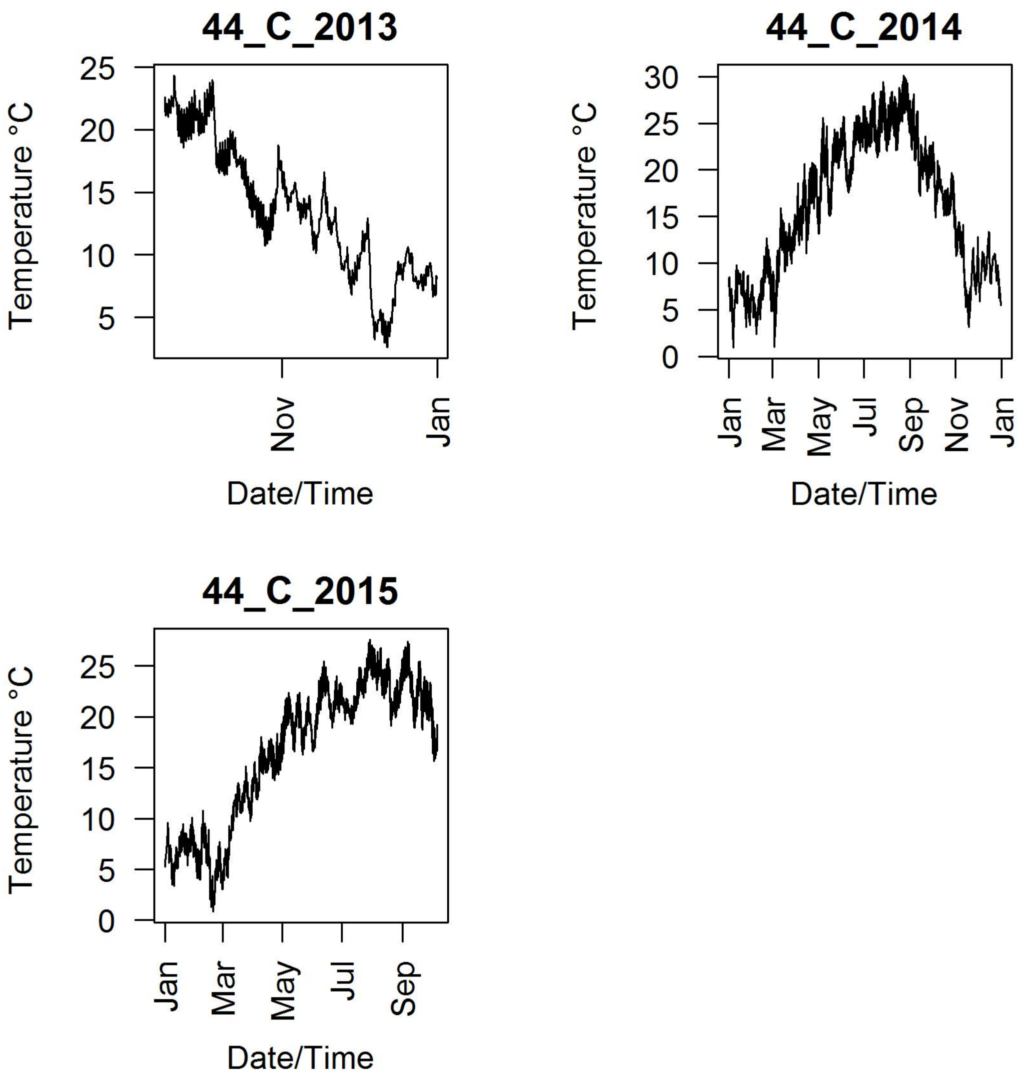


Figure 119. Site 45, Point A: Finley Creek below Riverdale, 2012 – 2014.

Notes: all loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.

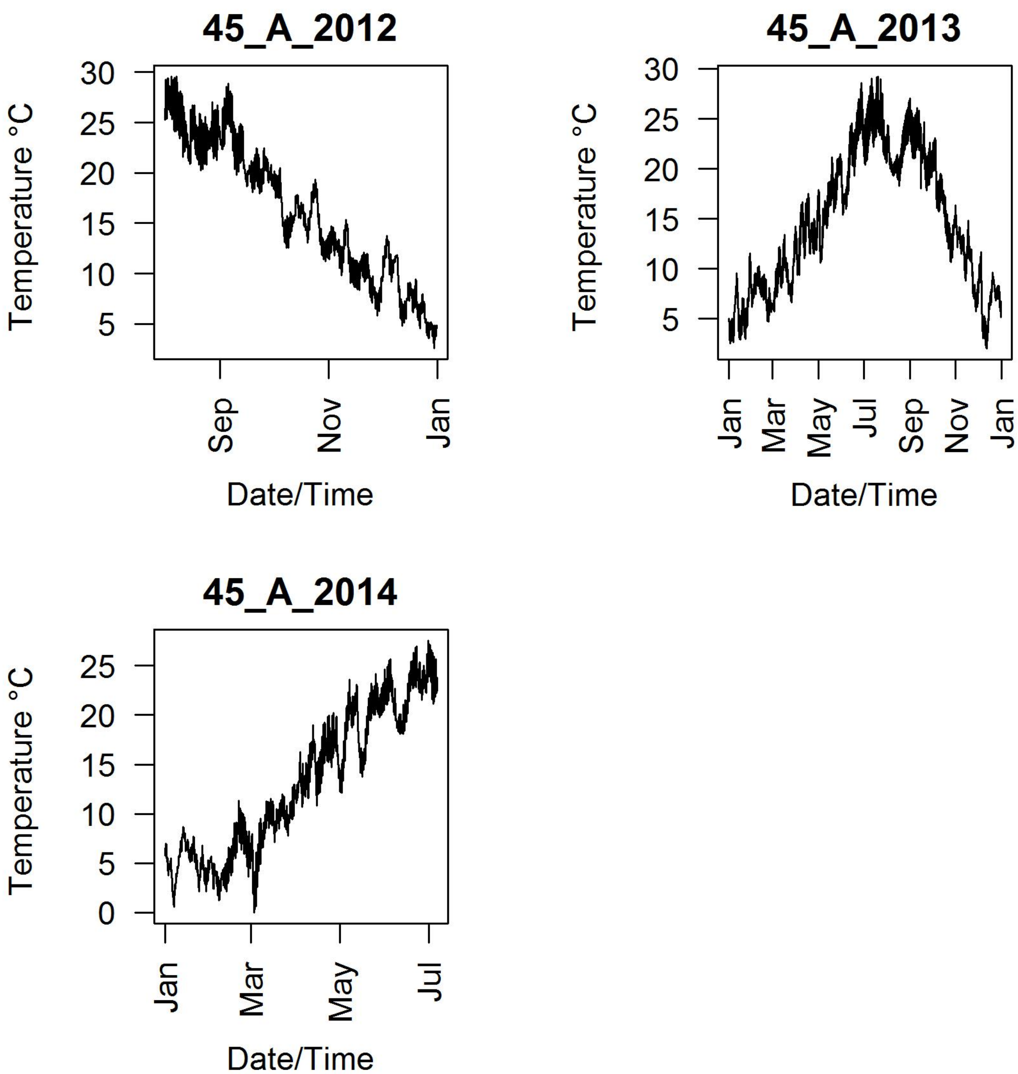
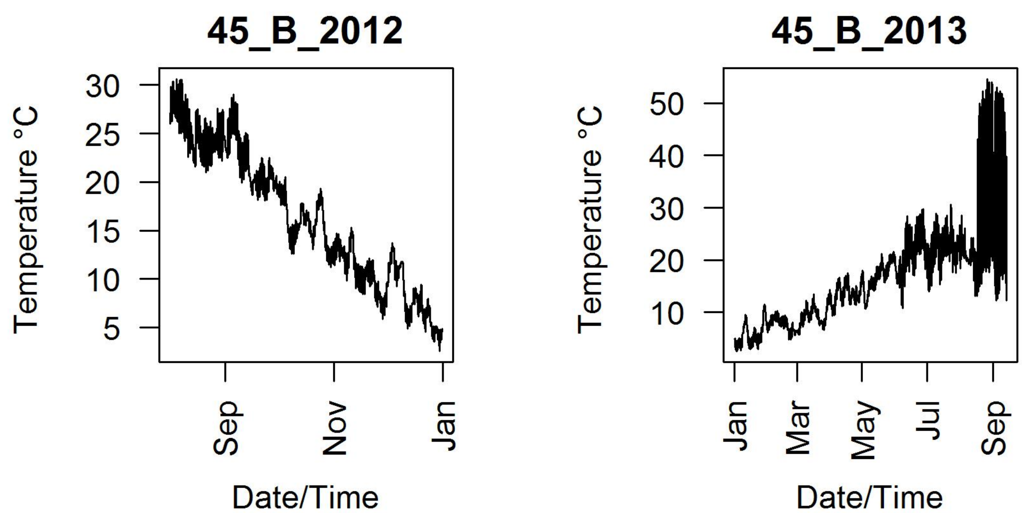


*Figure 120. Site 45, Point B: Finley Creek below Riverdale, 2012 – 2013.** RERUN VIOLIN PLOTS*
Note: logger was exposed when retrieved on 14 Sept 2013.

Decision: Excluded records after 15 Aug 2013. Used remaining records.



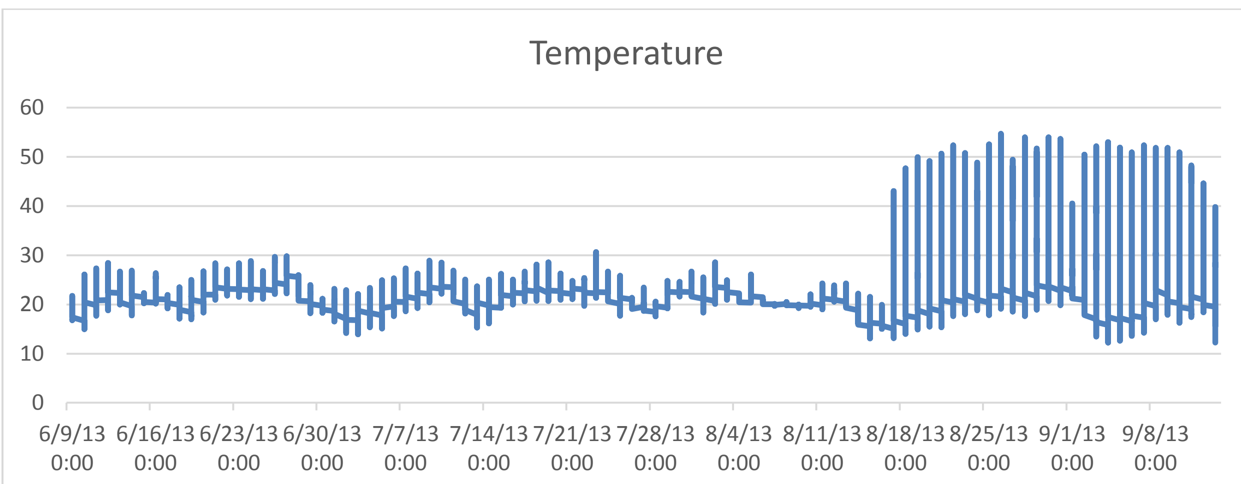


Figure 121. Site 45, Point C: Finley Creek below Riverdale, 2013 – 2015.
Decision: use all records.

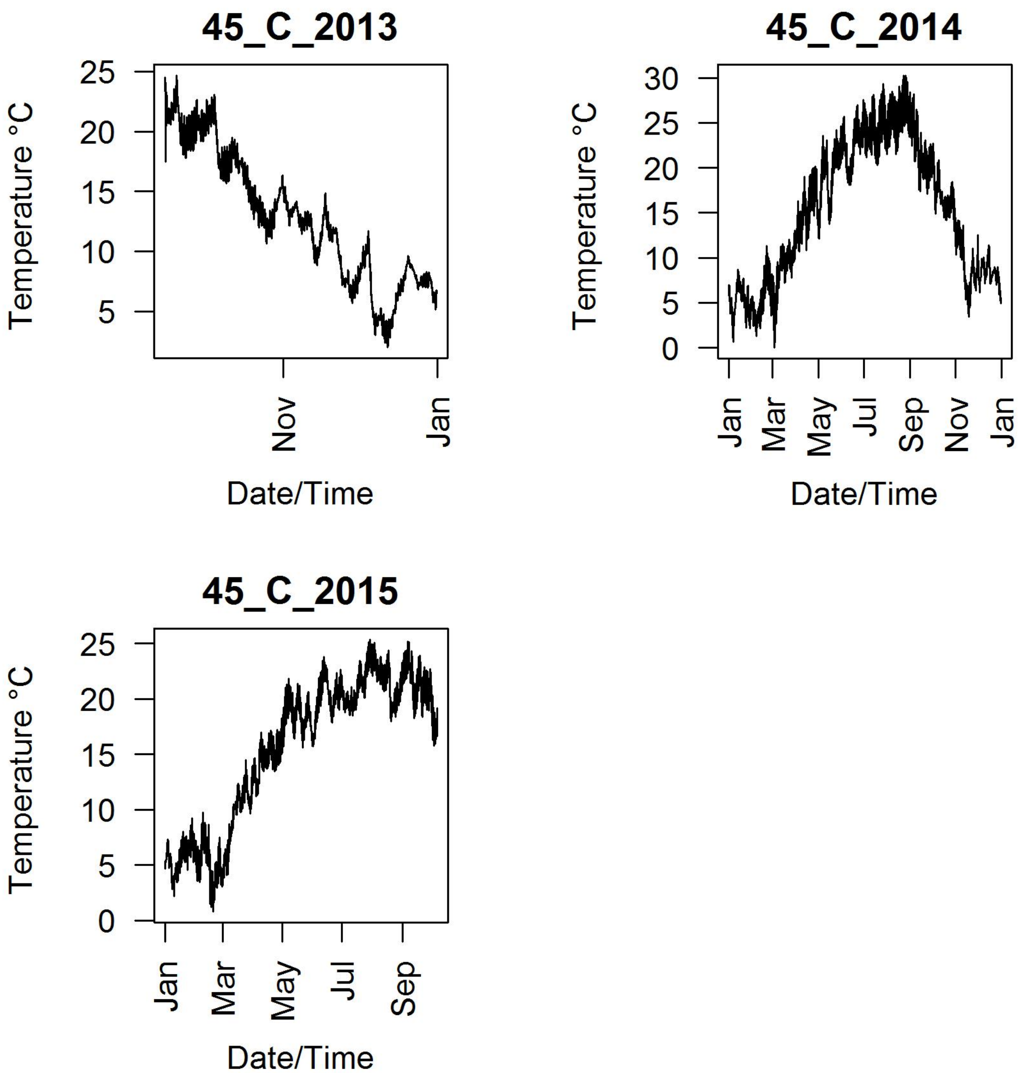


Figure 122. Site 46, Point A: James River at Galena, 2012 – 2014.

Notes: all loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.

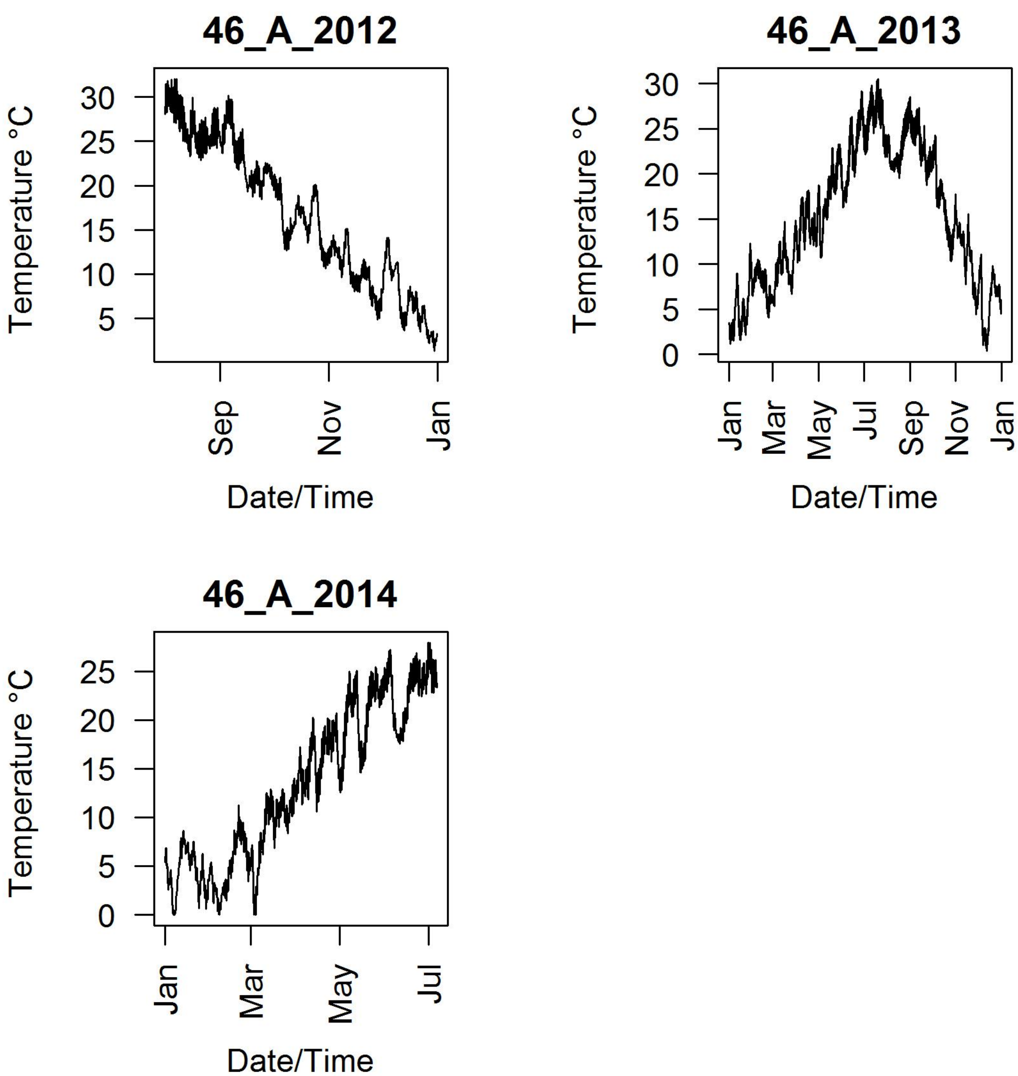


Figure 123. Site 46, Point C: James River at Galena, 2013 – 2014.
Decision: used all records.

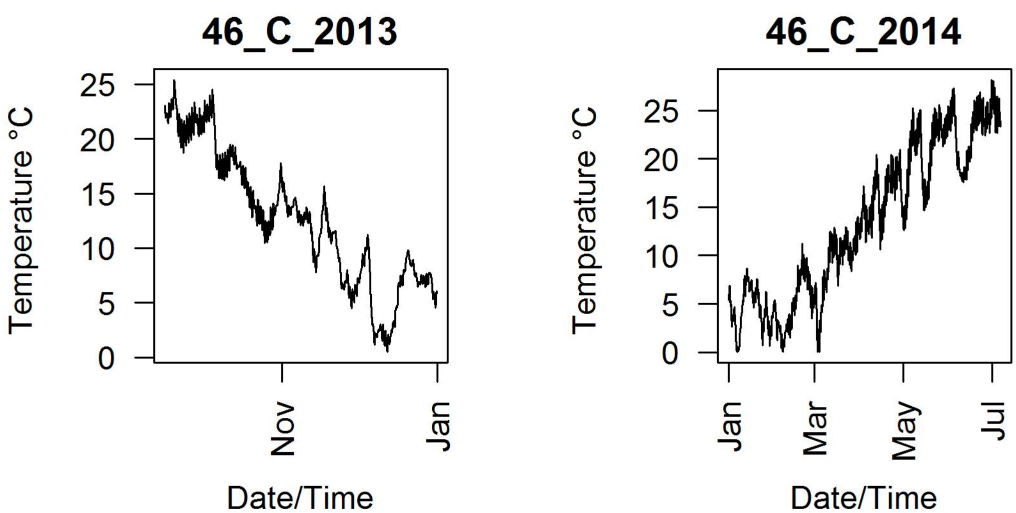


Figure 124. Site 47, Point A: Bull Creek near Walnut Shade, 2012 – 2014.

Note: all loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.

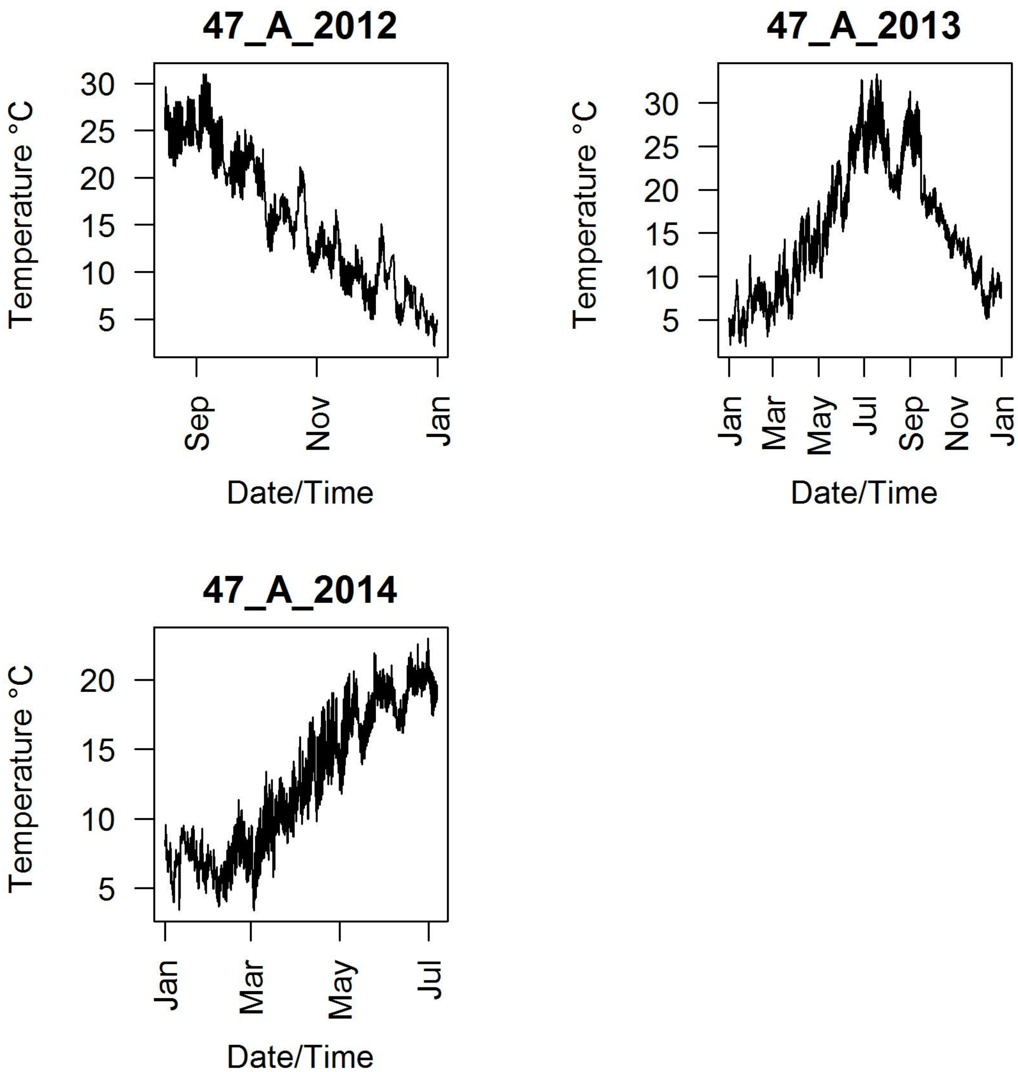


*Figure 125. Site 47, Point B: Bull Creek near Walnut Shade, 2012 – 2013.***

Note: logger was buried when retrieved on 14 Sept 2013.

Decision: Excluded records from 5 Aug – 14 Sept 2013. Used remaining records.

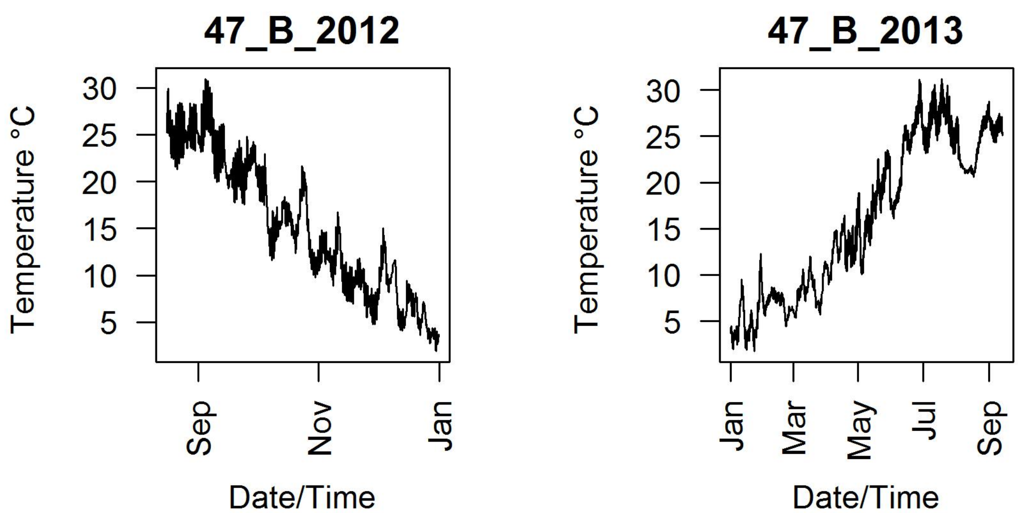
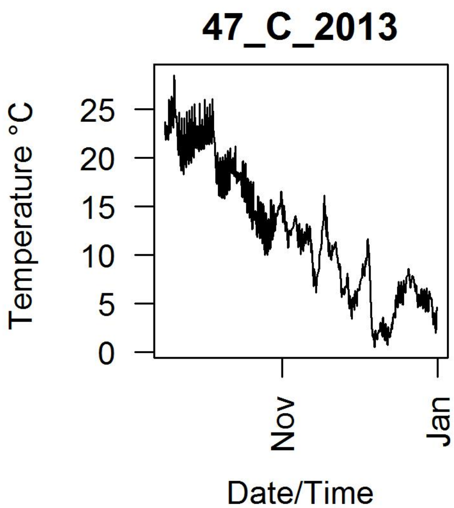


Figure 126. Site 47, Point C: Bull Creek near Walnut Shade, 2013 – 2014.
Decision: used all records.



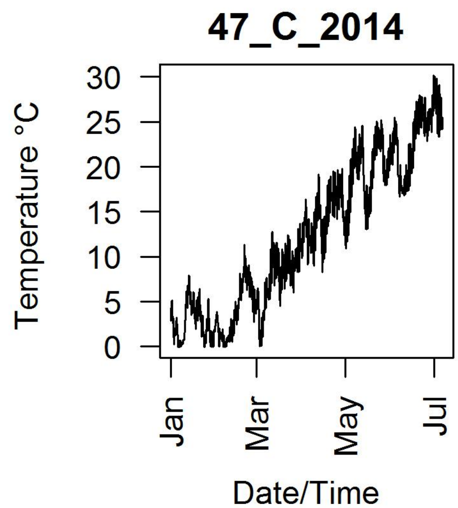


Figure 127. Site 48, Point. A: Beaver Creek at Bradleyville, 2012 – 2014.

Note: all loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.

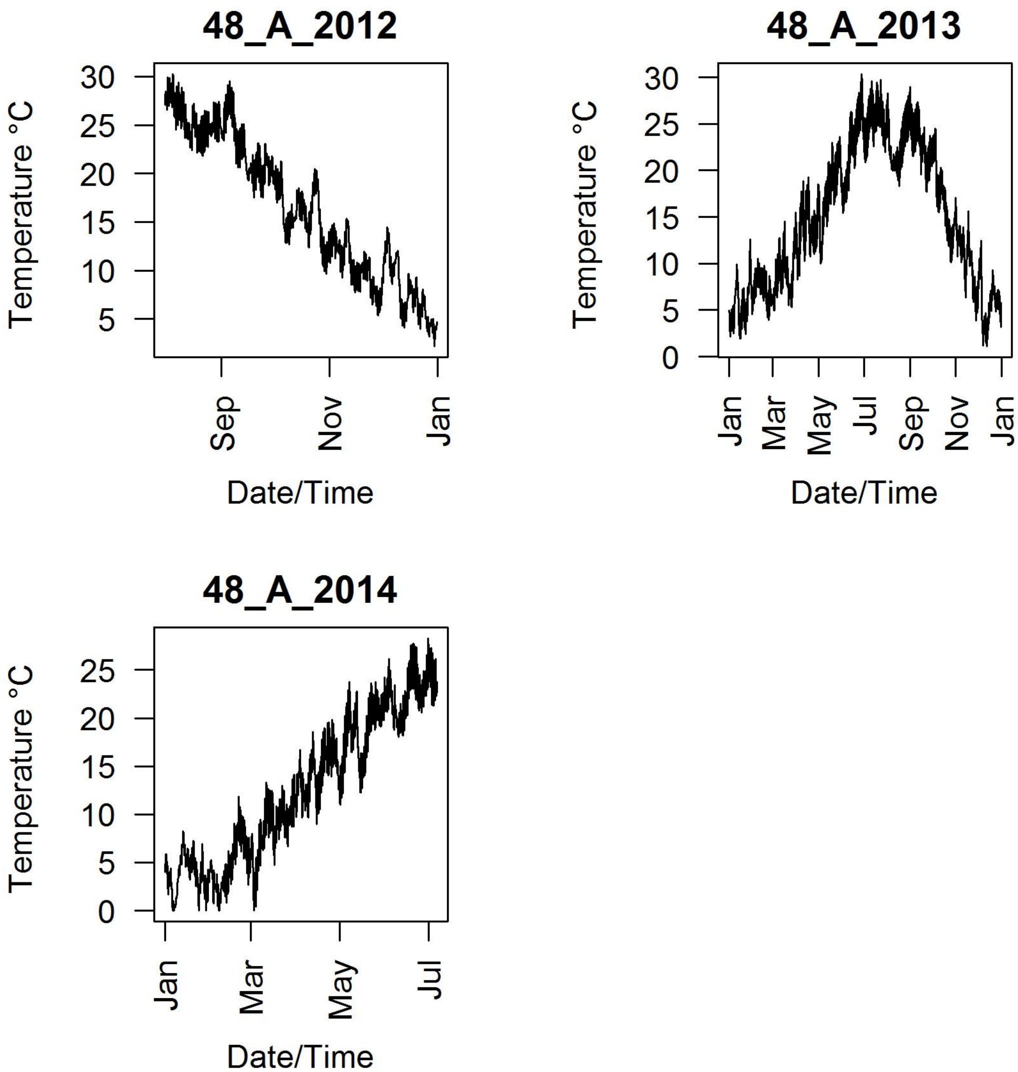


Figure 128. Site 48, Point B: Beaver Creek at Bradleyville, 2012 – 2014.

Note: all loggers in this watershed showed an unusual drop in temperature in August 2013.

Decision: used all records.

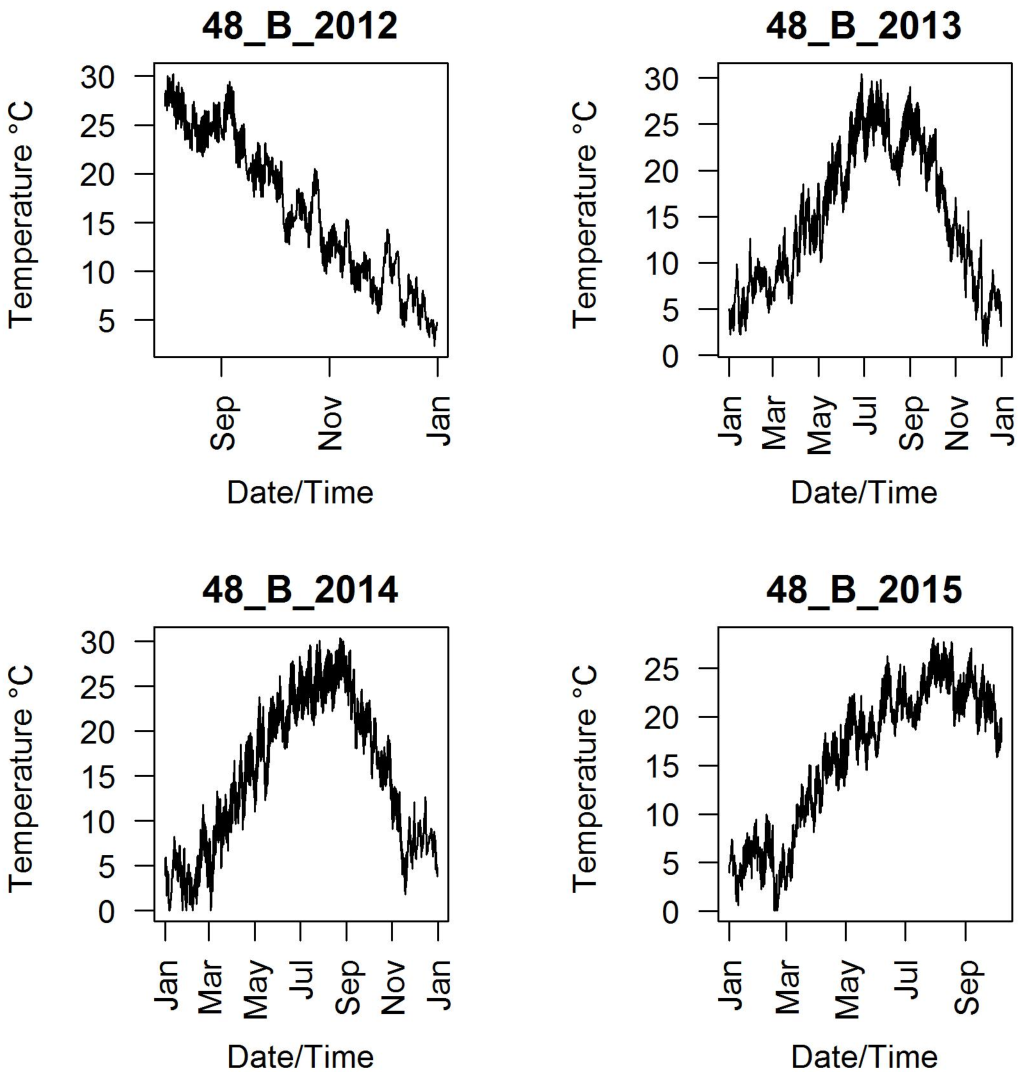


Figure 129. Site 49, Point B: Current River at Montauk State Park, 2012 – 2015. REDO VIOLIN PLOTS
Decision: used all records.

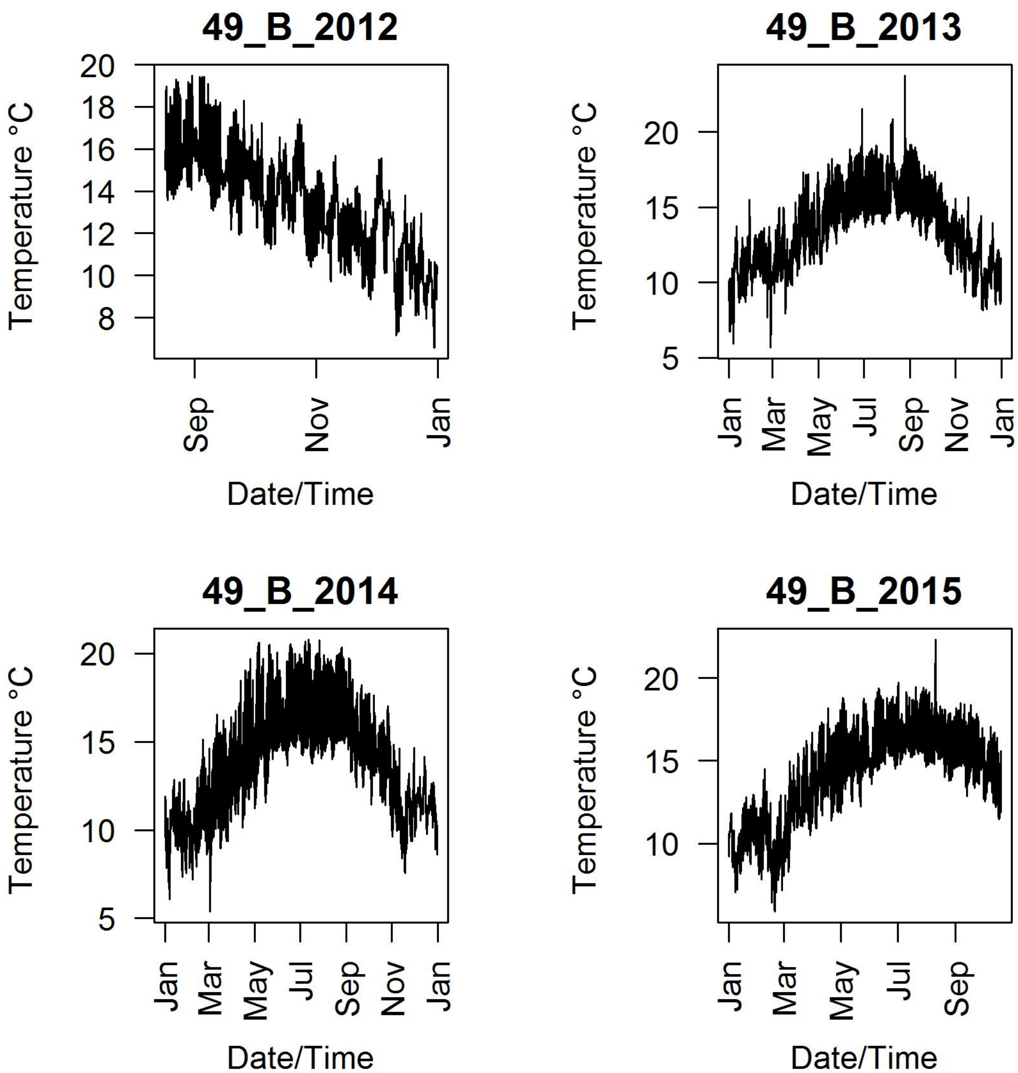


Figure 130. Site 49 Point. C: Current River at Montauk State Park, 2013 – 2015.
Decision: used all records.

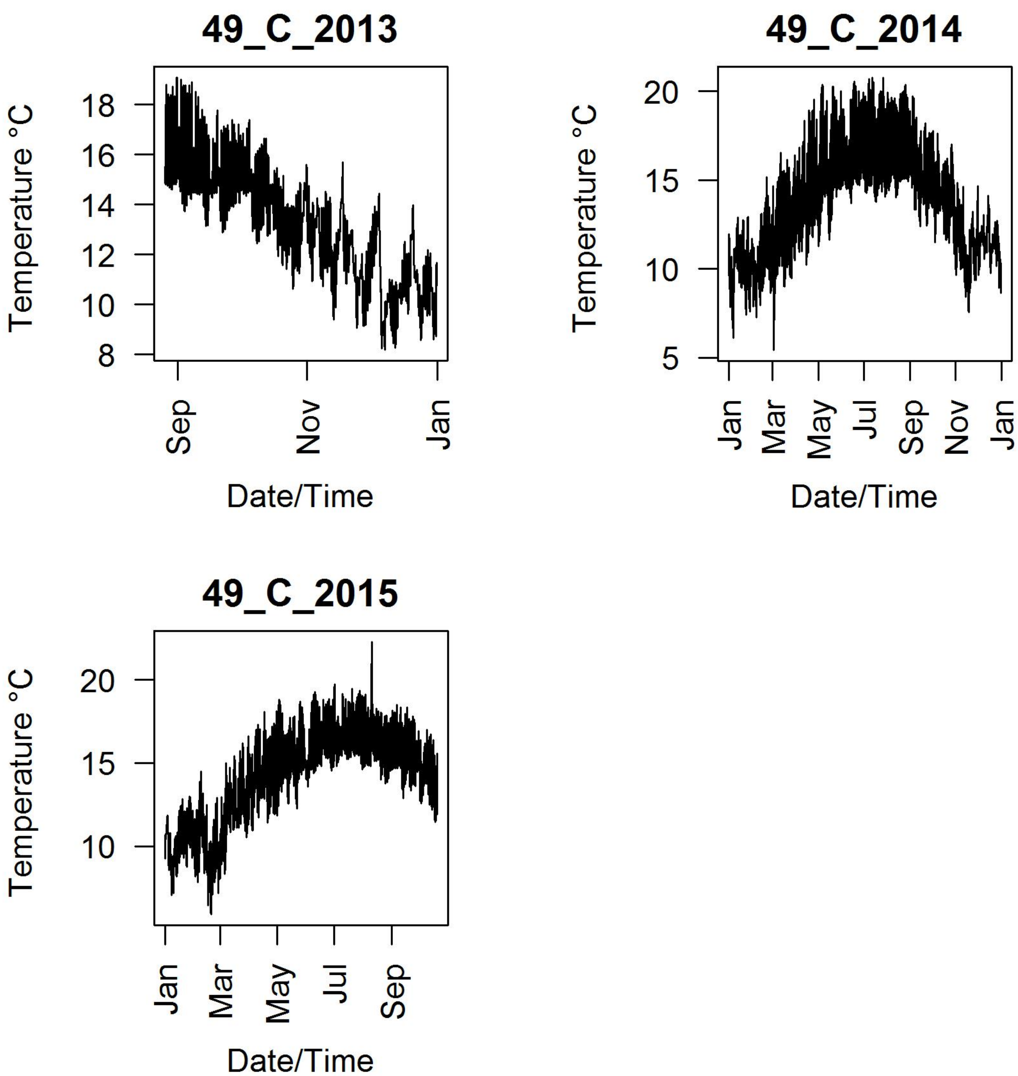


Figure 131. Site 50, Point A: Current River above Akers, 2012 – 2013.
Decision: used all records.

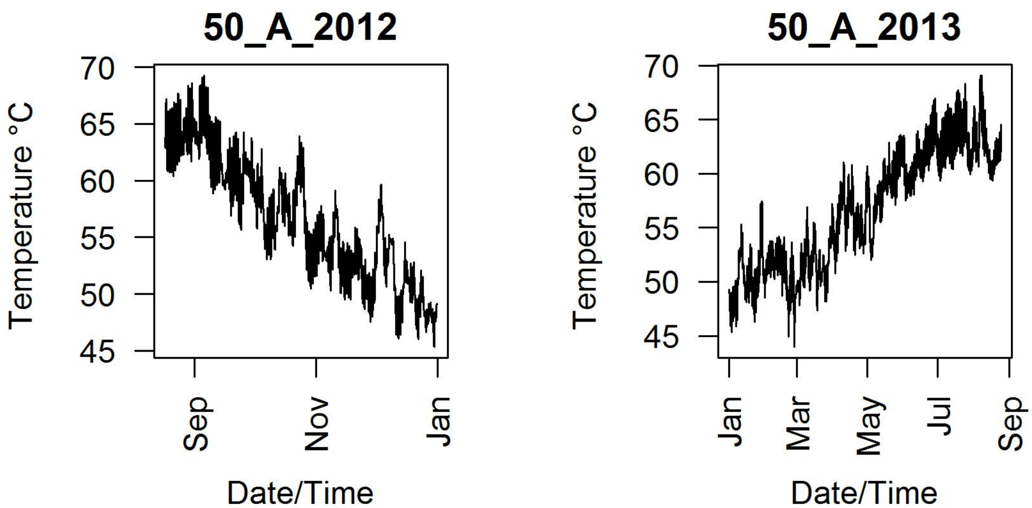


Figure 132. Site 50, Point B: Current River above Akers, 2012 – 2014.
Decision: used all records.

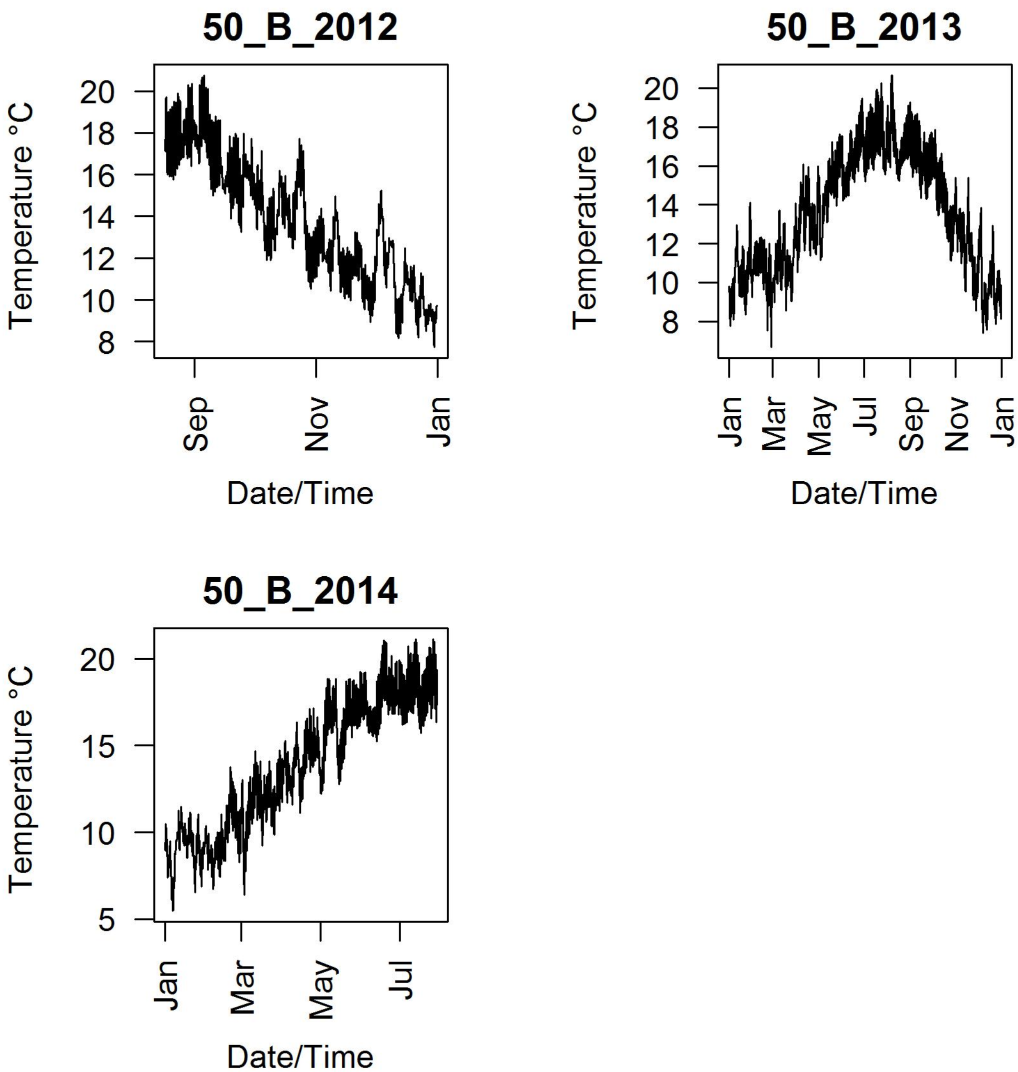


Figure 133. Site 51, Point A: Current River at Van Buren, 2013 – 2014.
Decision: used all records.

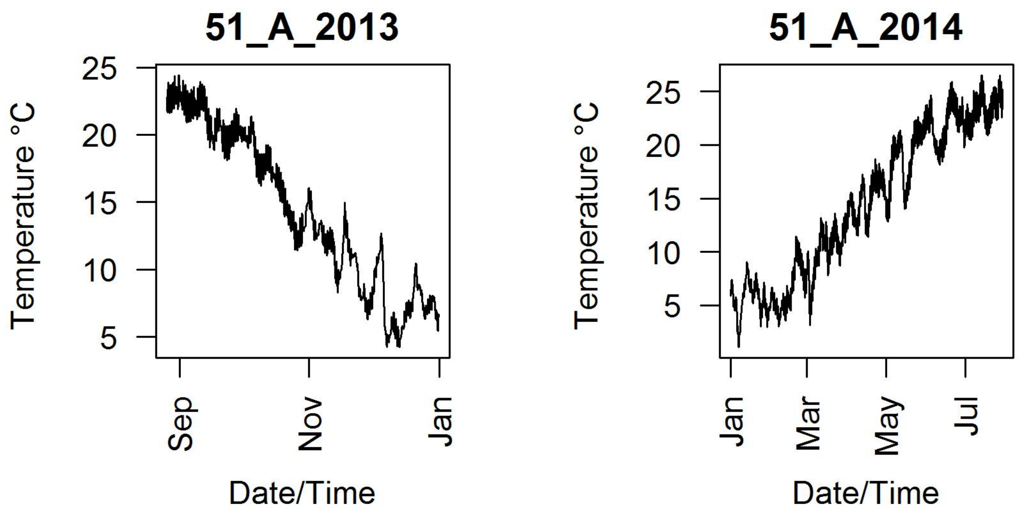


Figure 134. Site 51, Pt B: Current River at Van Buren, 2013 – 2014.
Decision: used all records.

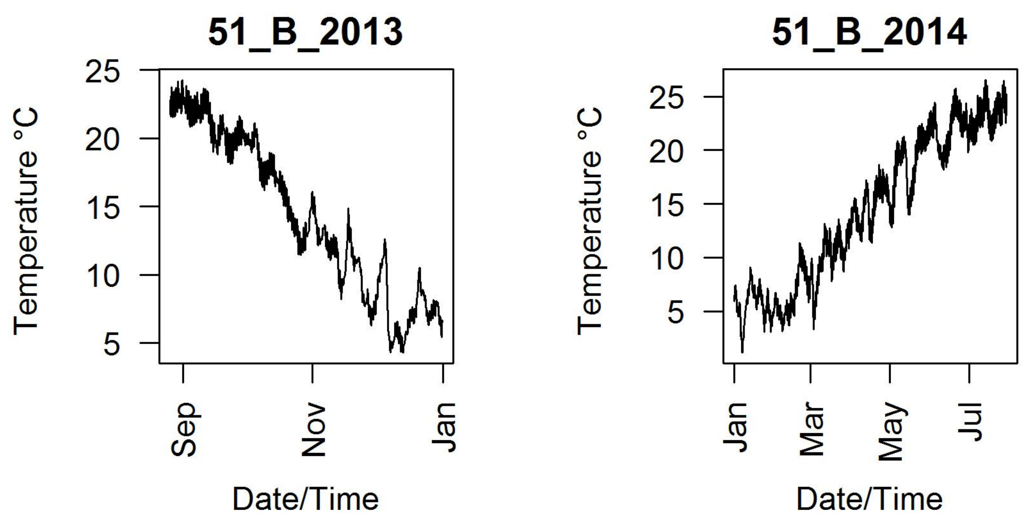


Figure 135. Site 52, Point A: Current River at Doniphan, 2012 – 2015.
Decision: used all records.

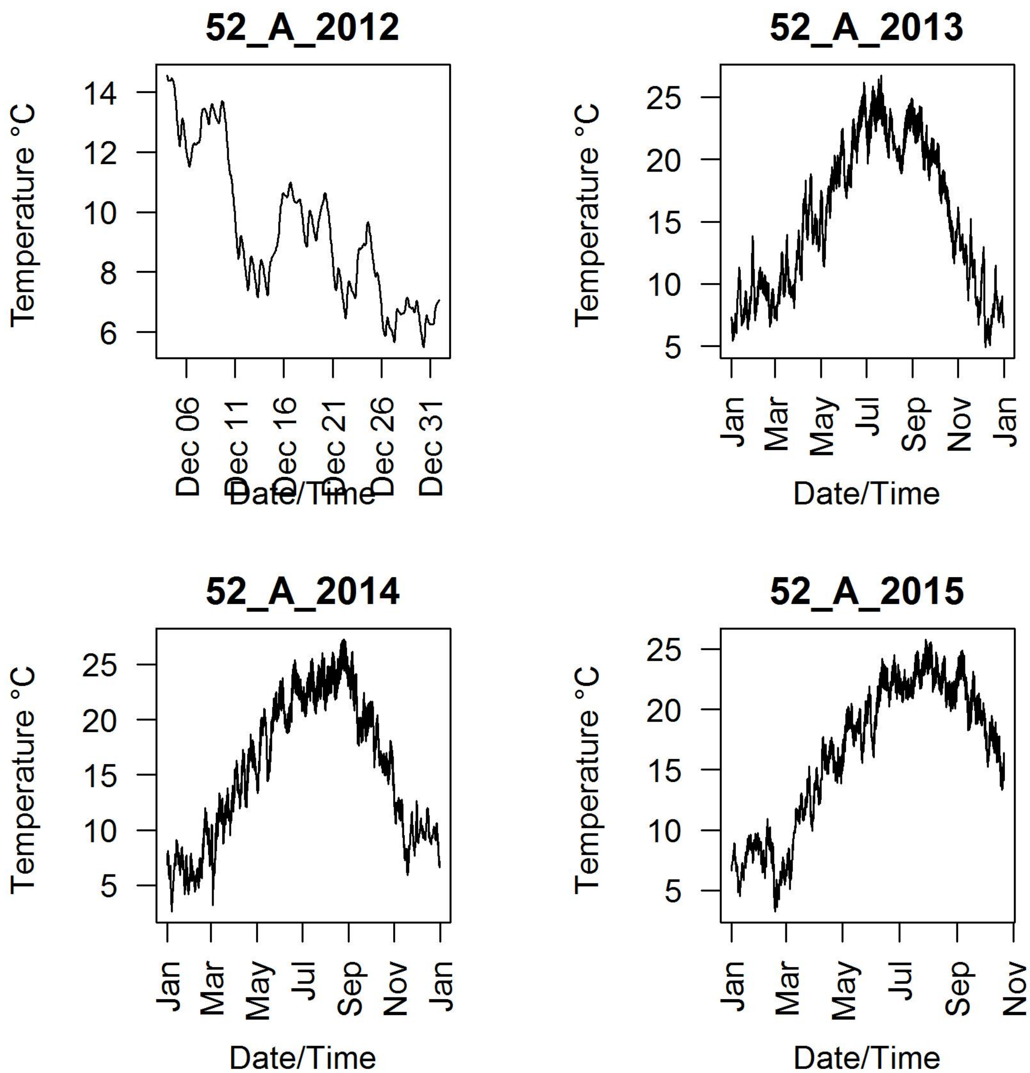


Figure 136. Site 52, Point B: Current River at Doniphan, 2013 – 2015.

Decision: used all records.

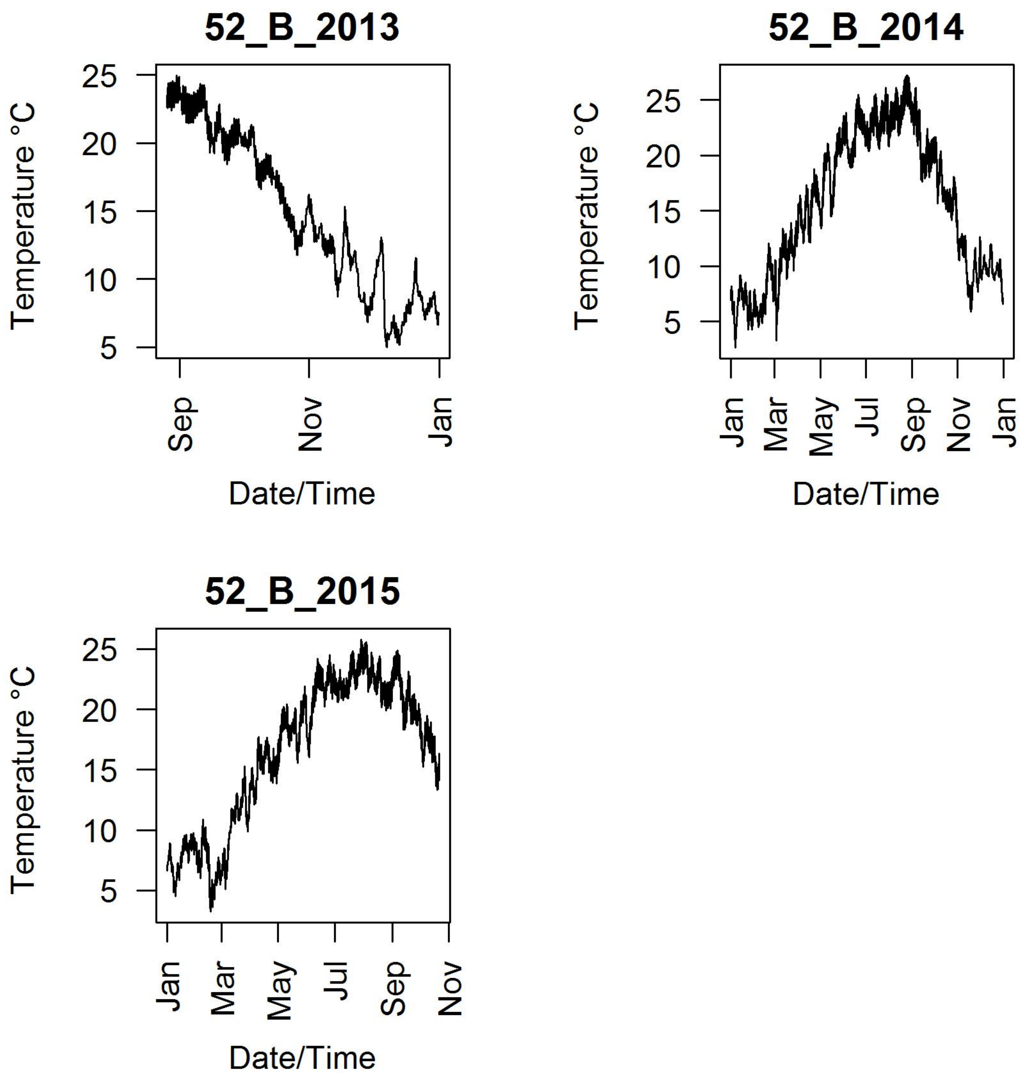


Figure 137. Site 53, Point A: Eleven Point River Near Bardley, 2012 – 2014.
Decision: used all records.

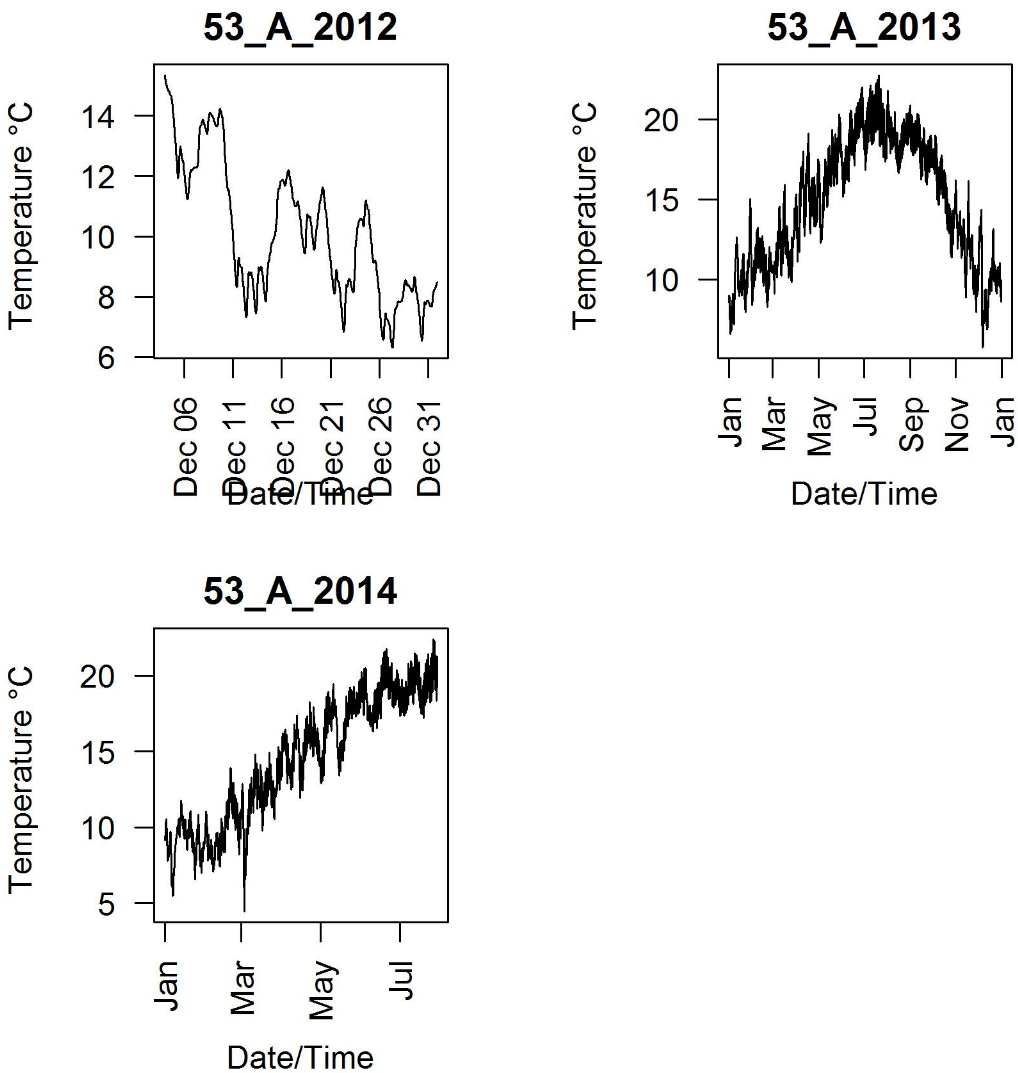


Figure 138. Site 53, Point B: Eleven Point River Near Bardley, 2012 – 2013.
Decision: used all records.

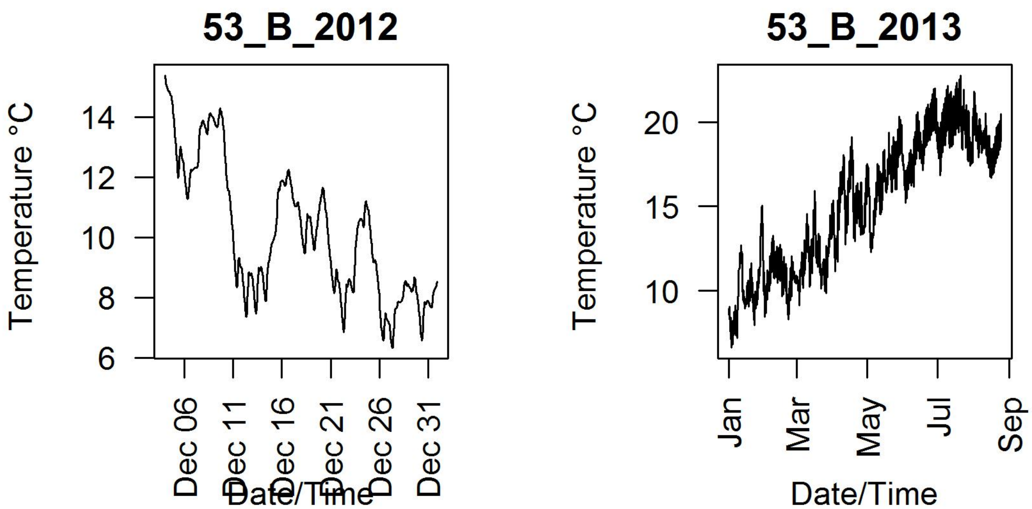


Figure 139. Site 54, Point A: Spring River at La Russell, 2011 – 2012.
Decision: used all records.

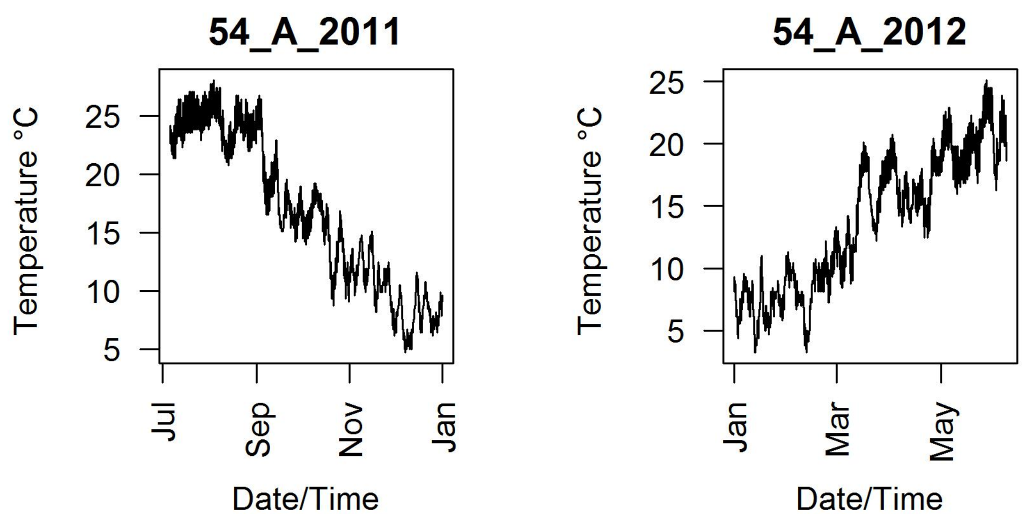
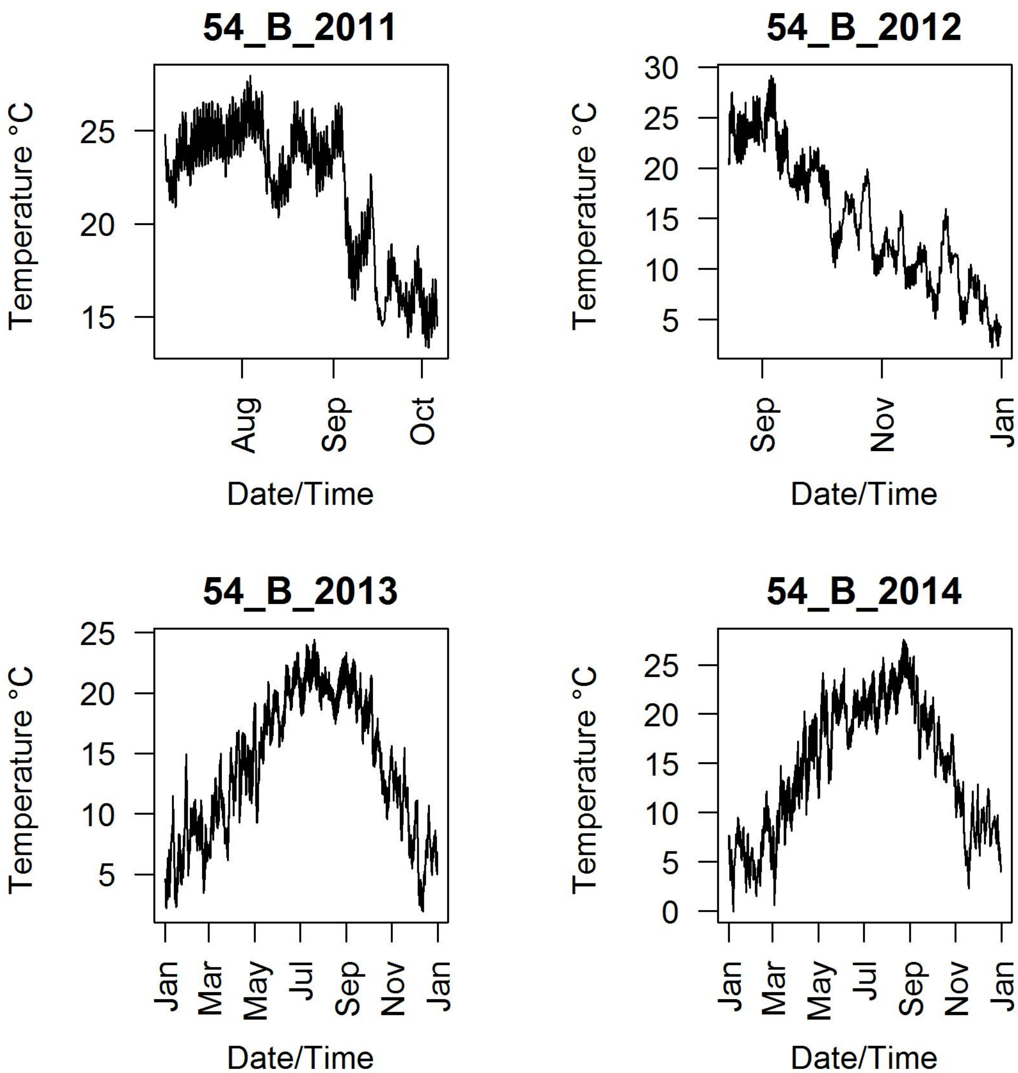
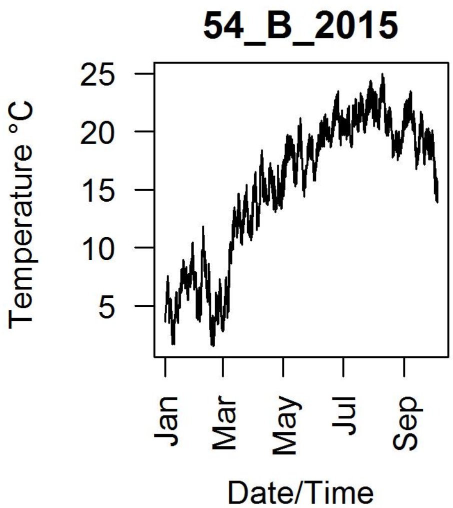


Figure 140. Site 54, Point B: Spring River at La Russell, 2011 – 2013.
Decision: used all records.




54_B_2015
Temperature °C
25
20
15
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5
Jan
Mar
May
Jul
Sep
Date/Time

Figure 141. Site 54, Point C: Spring River at La Russell, 2012 – 2013.
Decision: used all records.

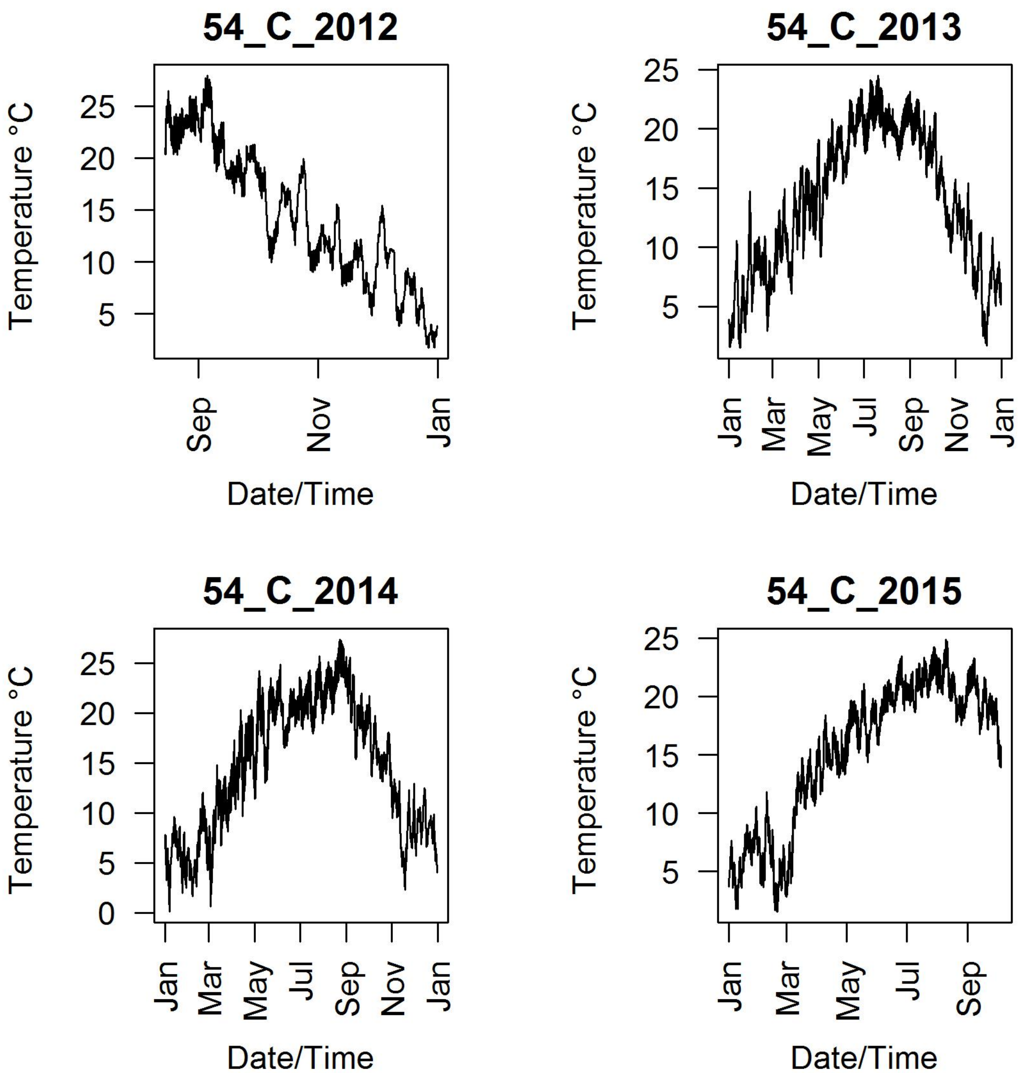
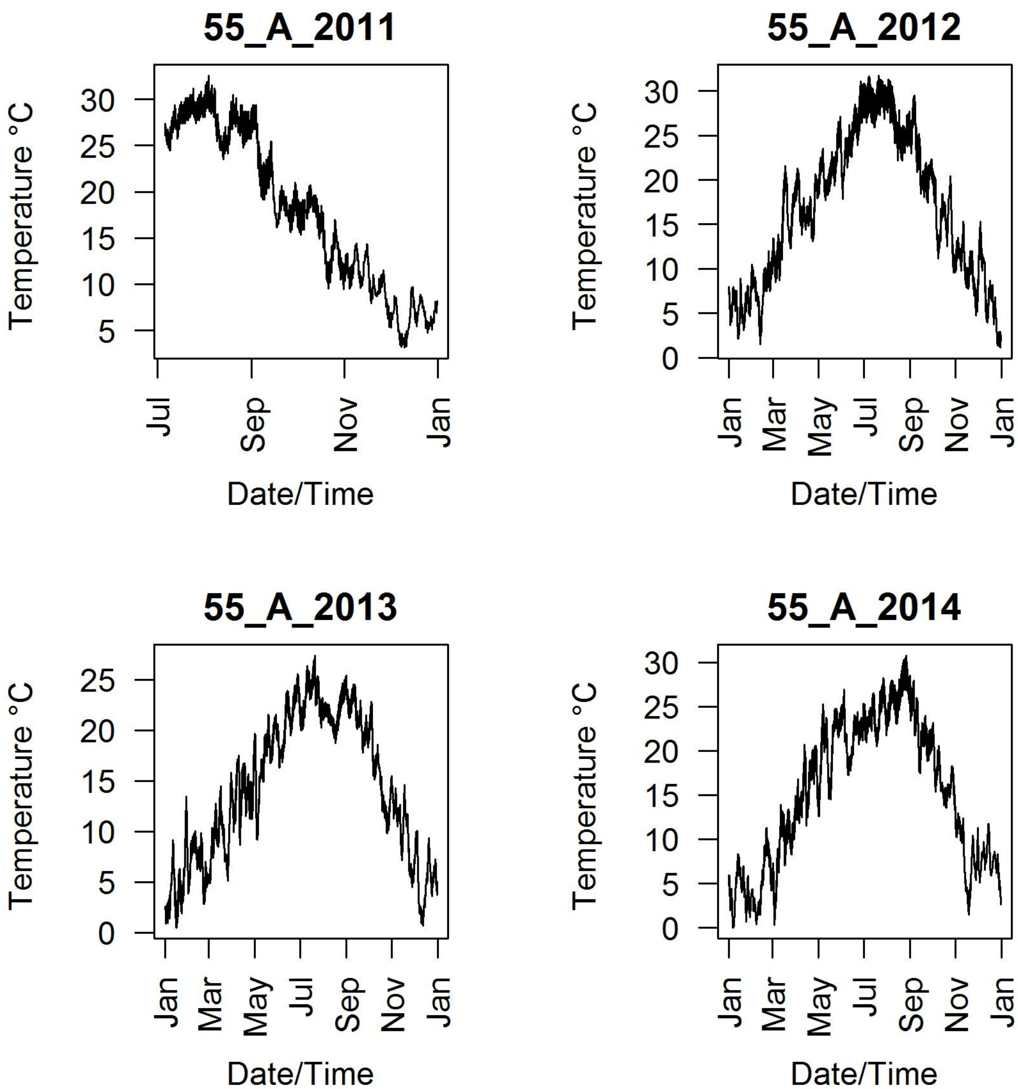


Figure 142. Site 55, Point A: Spring River at Carthage, 2011 – 2015.
Decision: used all records.



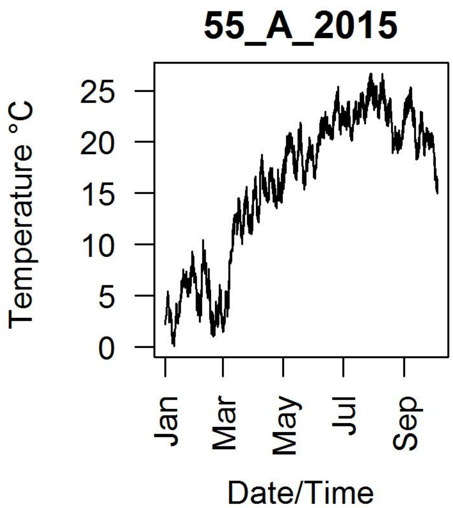
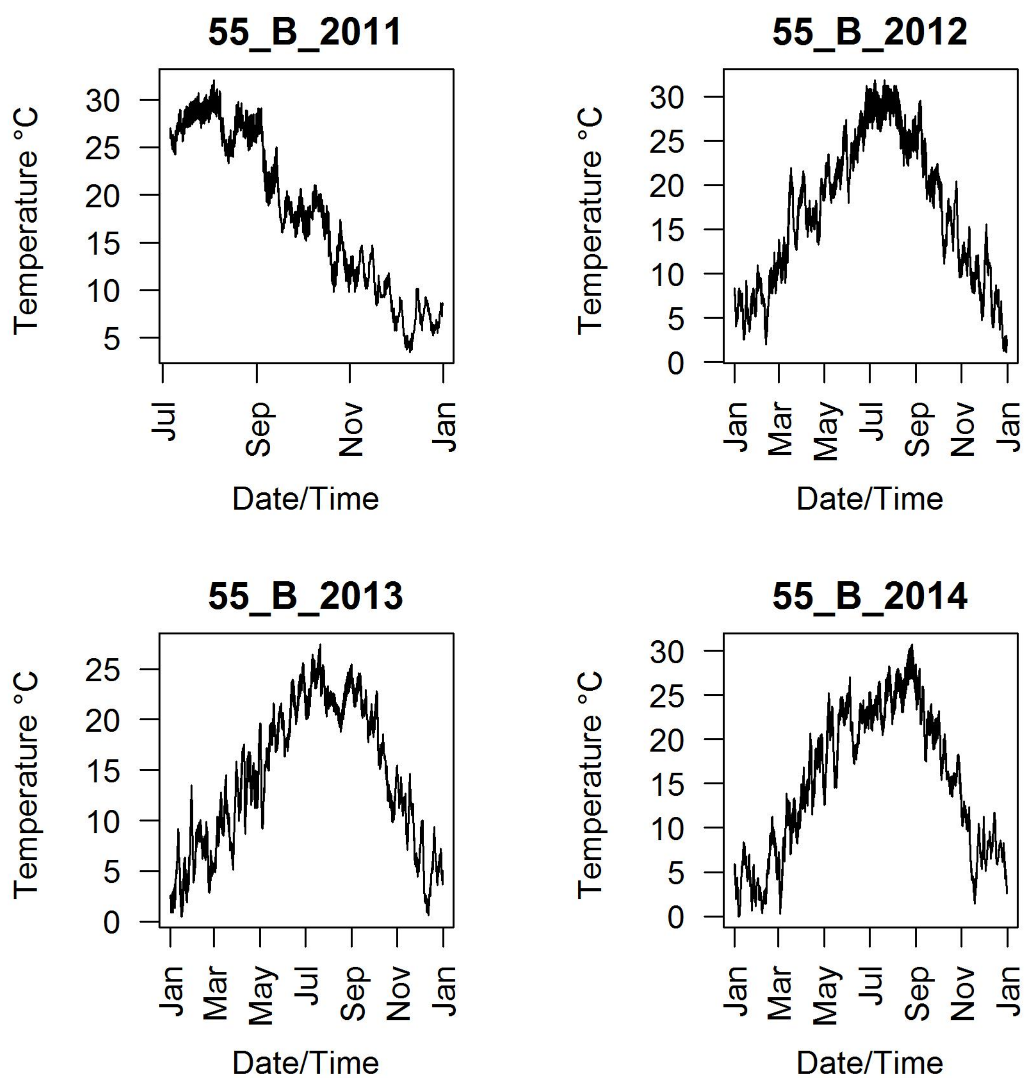

55_A_2015
Temperature °C
25
20
15
10
5
0
Jan
Mar
May
Jul
Sep
Date/Time

Figure 143. Site 55, Point B: Spring River at Carthage, 2011 – 2015.
Decision: used all records.



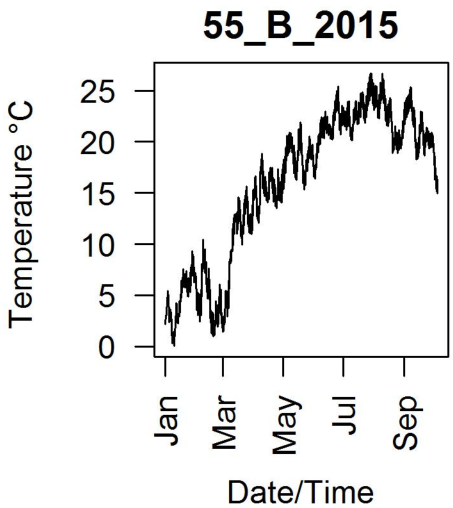

55_B_2015
Temperature °C
25
20
15
10
5
0
Jan
Mar
May
Jul
Sep
Date/Time

Figure 144. Site 56, Point A: North Fork Spring River near Purcell, 2011.
Decision: used all records.

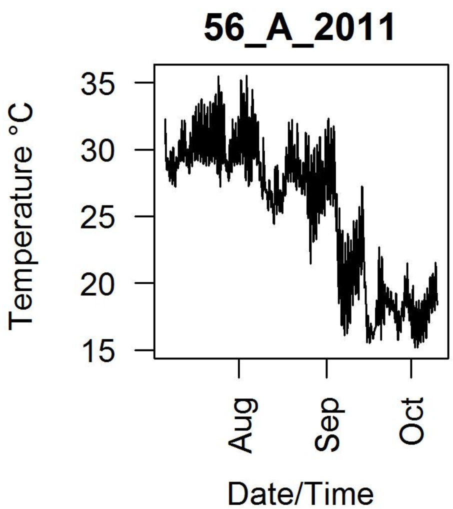
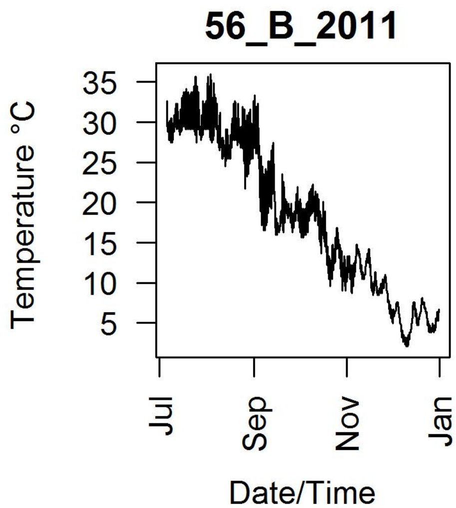
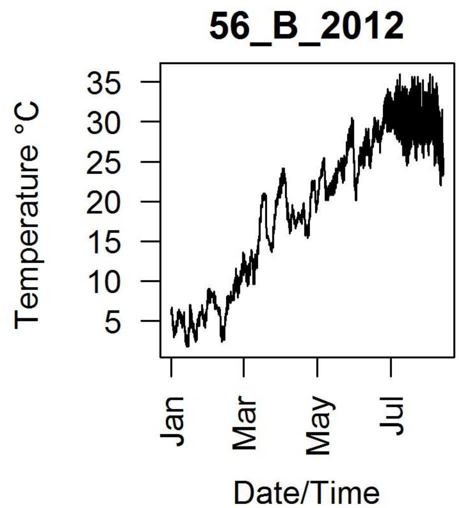


*Figure 145. Site 56, Point B: North Fork Spring River near Purcell, 2011 – 2012.***

Note: logger was found exposed on 14 Aug 2012. Based on change in daily variation, did not use records after 26 June 2012.

Decision: Based on change in daily variation, did not use records after 26 June 2012. Used remaining records.





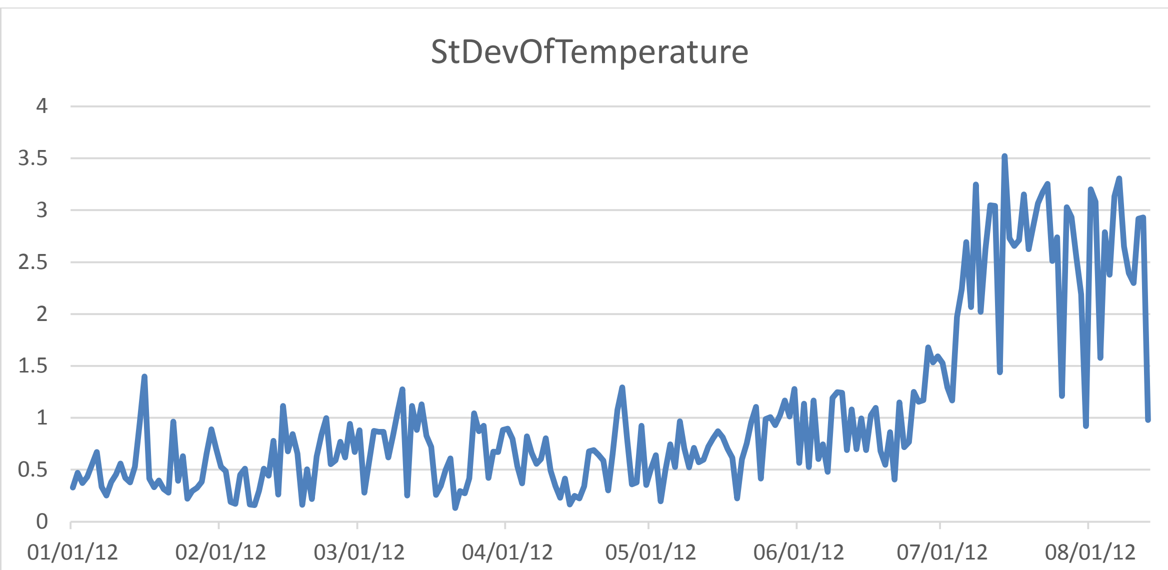


Figure 146. Site 56, Point C: North Fork Spring River near Purcell, 2012 – 2015.
Decision: used all records.

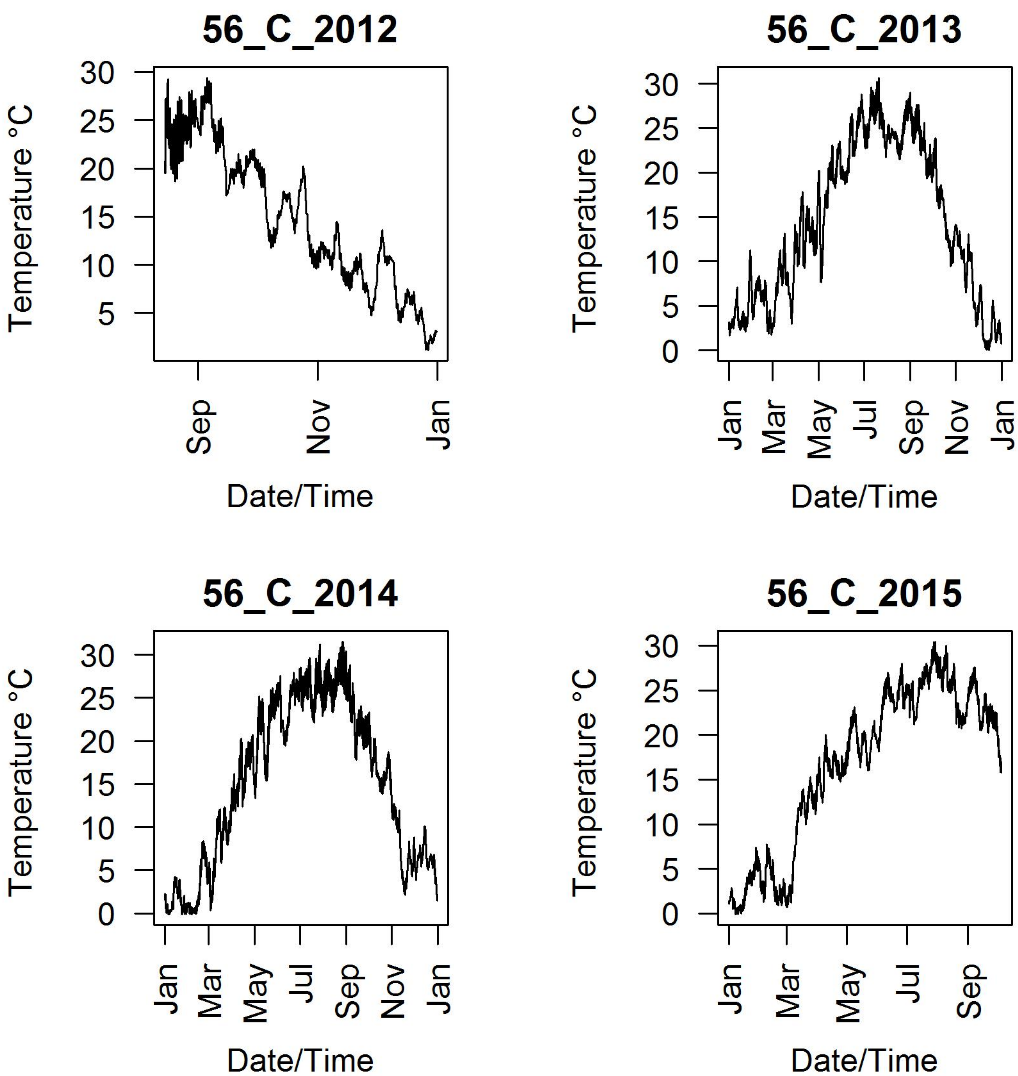


Figure 147. Site 56, Point D: North Fork Spring River near Purcell, 2012 – 2013.
Decision: used all records.

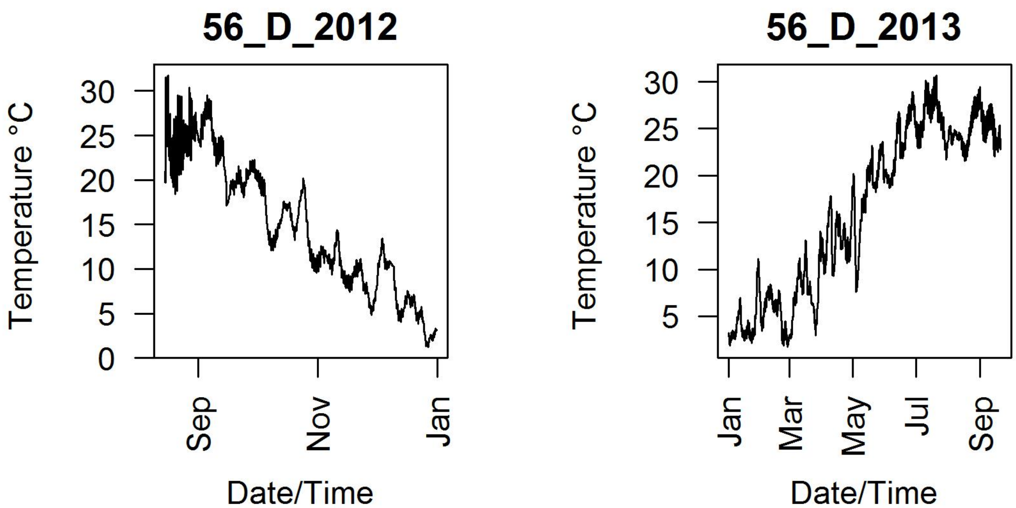


Figure 148. Site 57, Point A: Spring River near Waco, 2011 – 2012.
Decision: used all records.

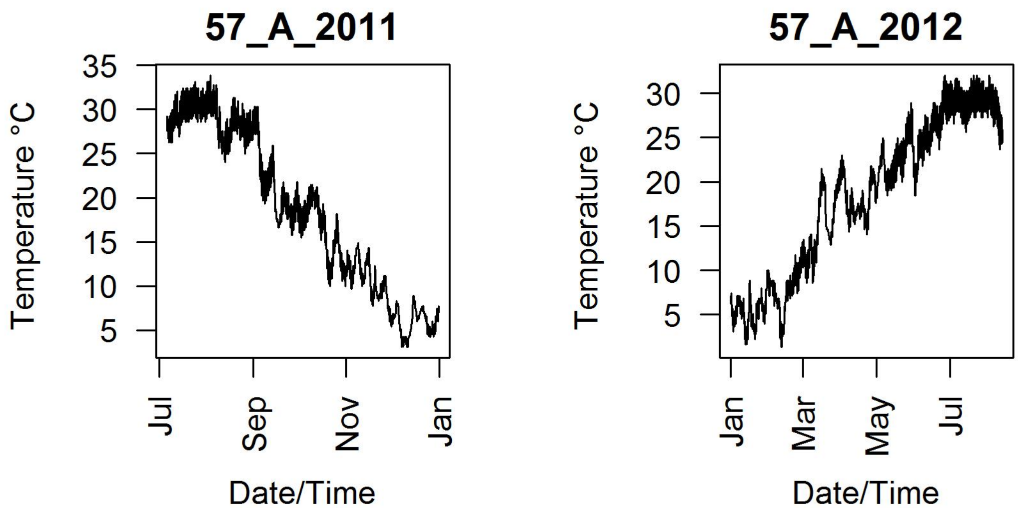
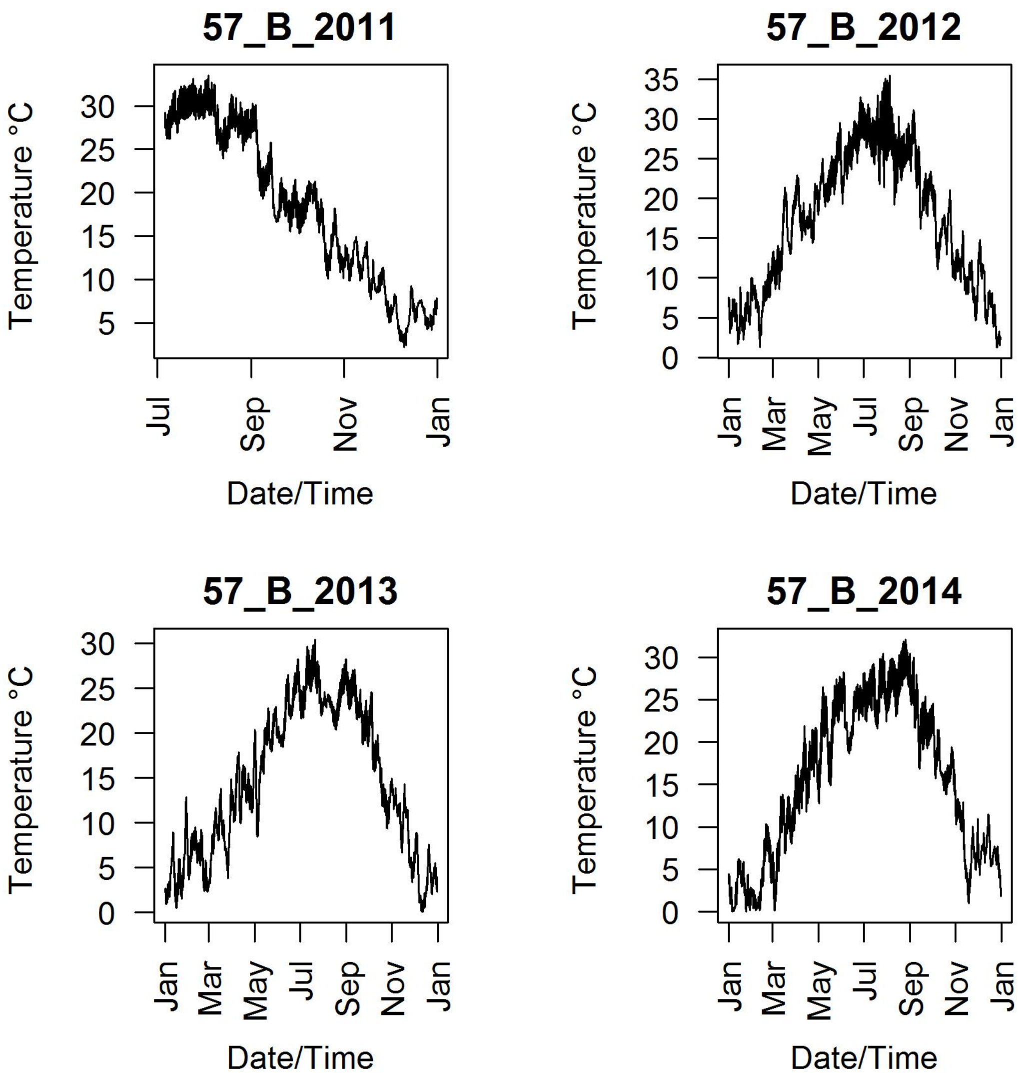
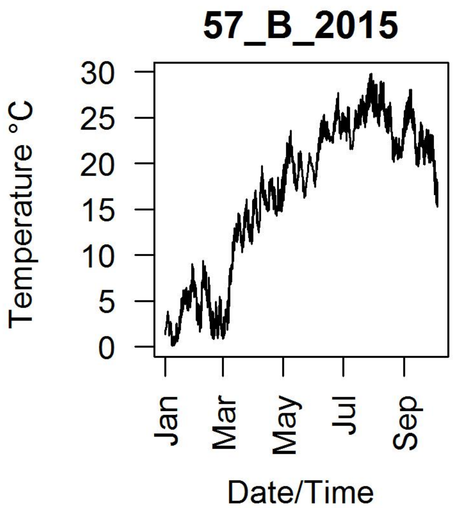


Figure 149. Site 57, Point B: Spring River near Waco, 2011 – 2015.
Decision: used all records.





57_B_2015
Temperature °C
30
25
20
15
10
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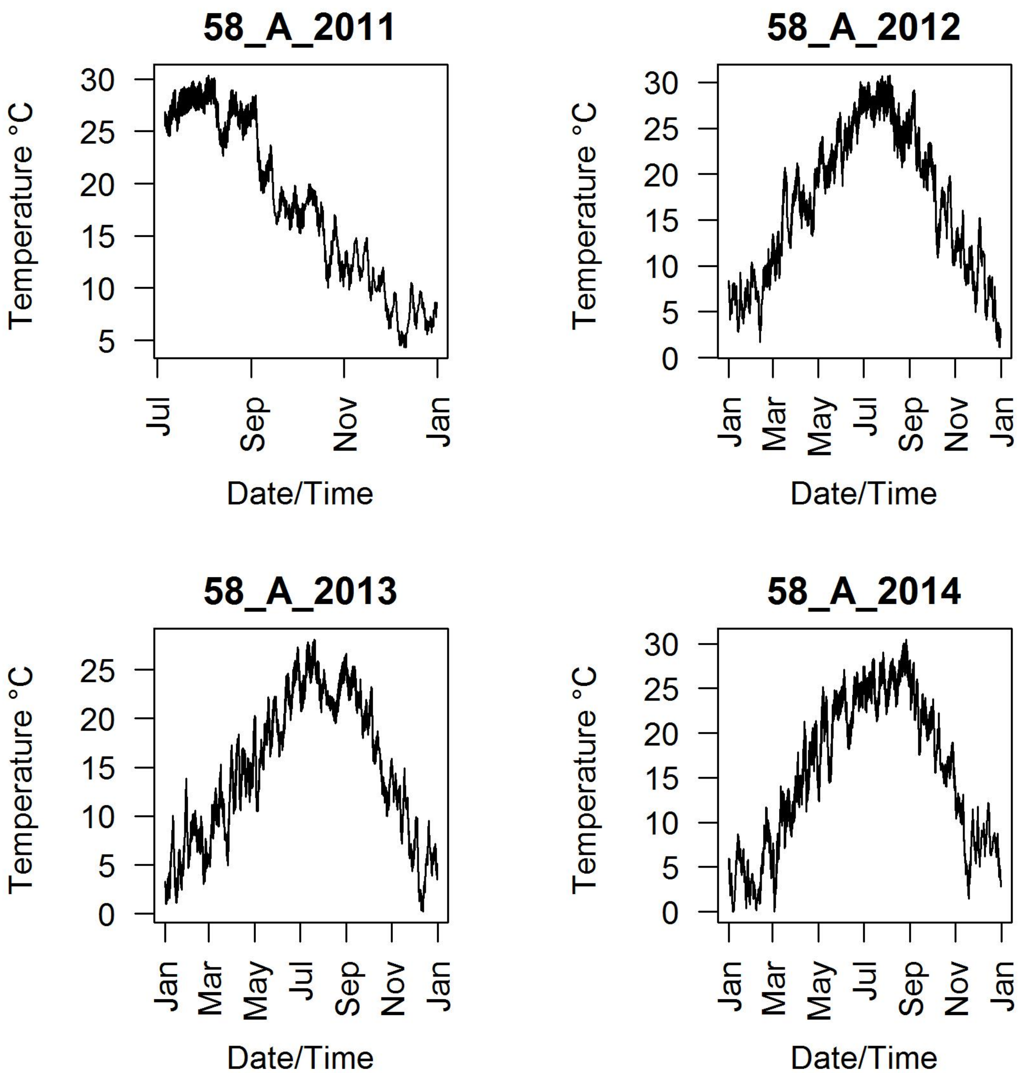
0
Jan
Mar
May
Jul
Sep
Date/Time

Figure 150. Site 58, Point A: Shoal Creek above Joplin, 2011 – 2015.
Decision: used all records.



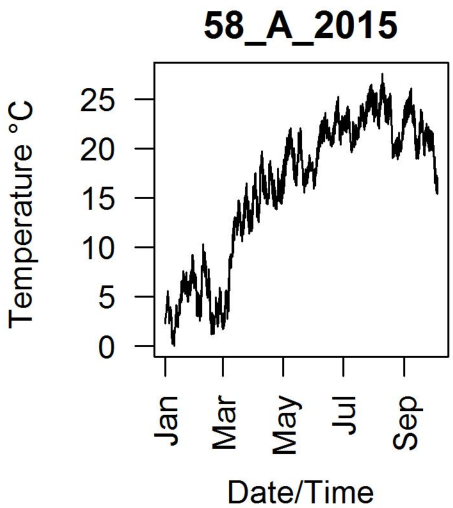
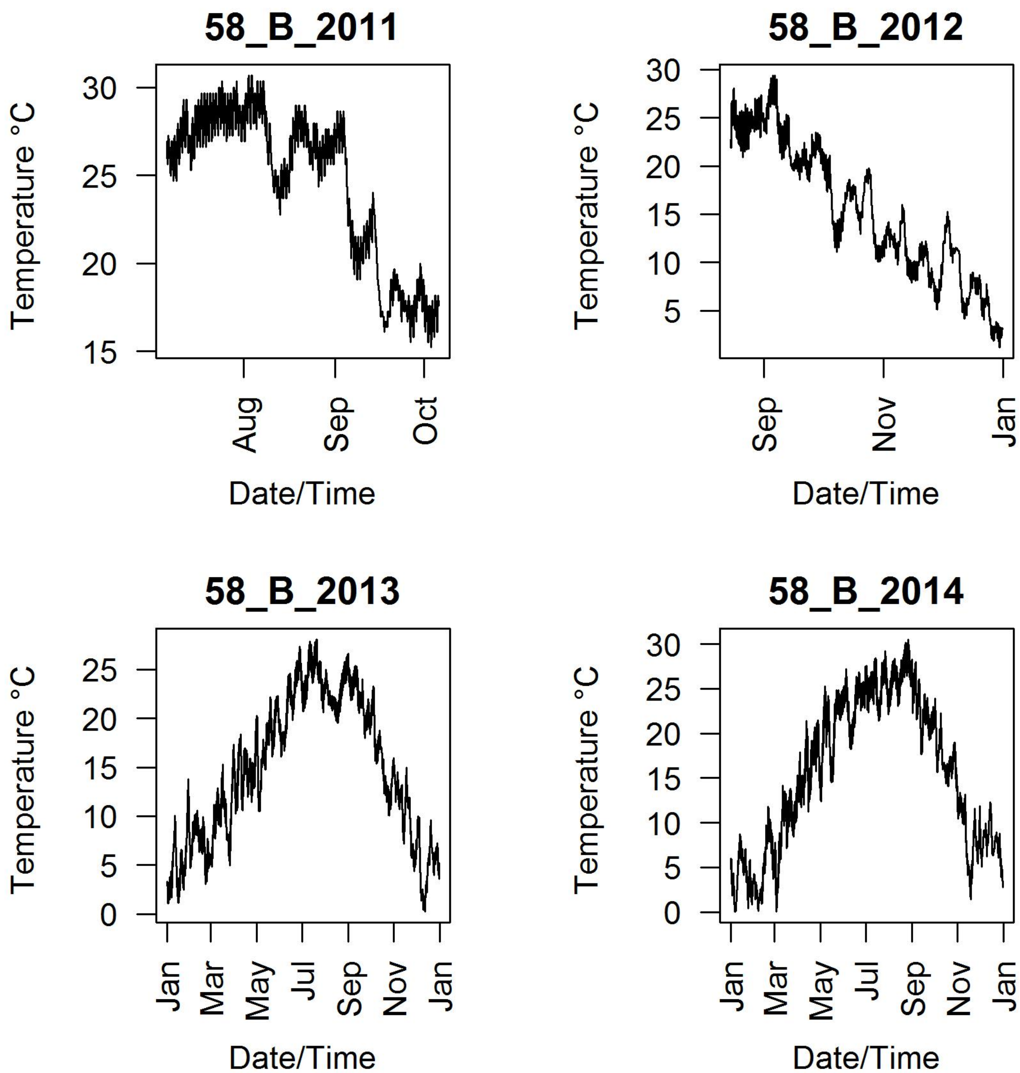

58_A_2015
Temperature °C
0
5
10
15
20
25
Jan
Mar
May
Jul
Sep
Date/Time

Figure 151. Site 58, Point B: Shoal Creek above Joplin, 2011 – 2015.
Decision: used all records.



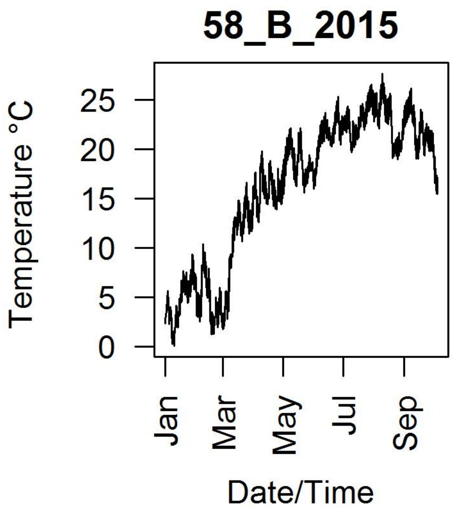

58_B_2015
Temperature °C
0
5
10
15
20
25
Jan
Mar
May
Jul
Sep
Date/Time

Figure 152. Site 59, Point A: Big Sugar Creek near Powell, 2011 – 2013.
Decision: used all records.

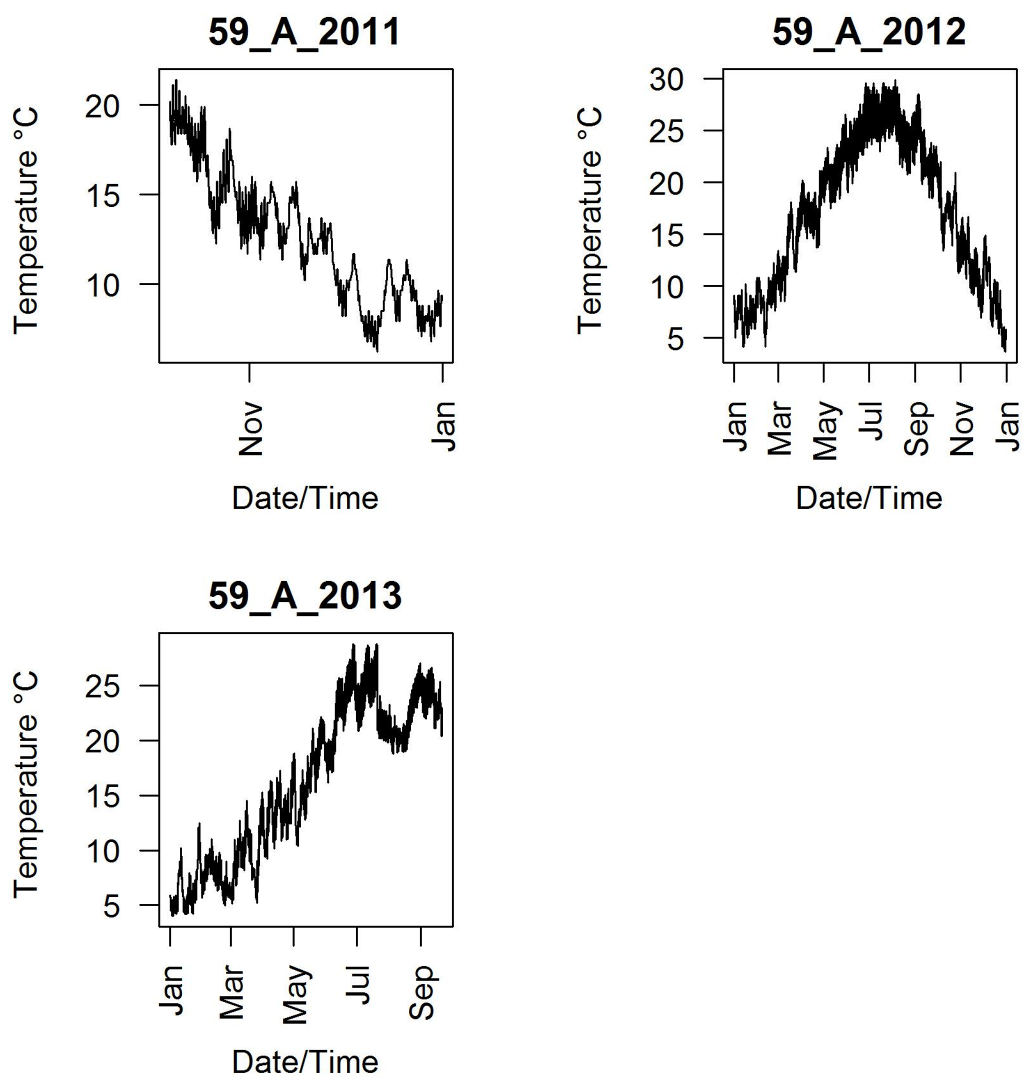
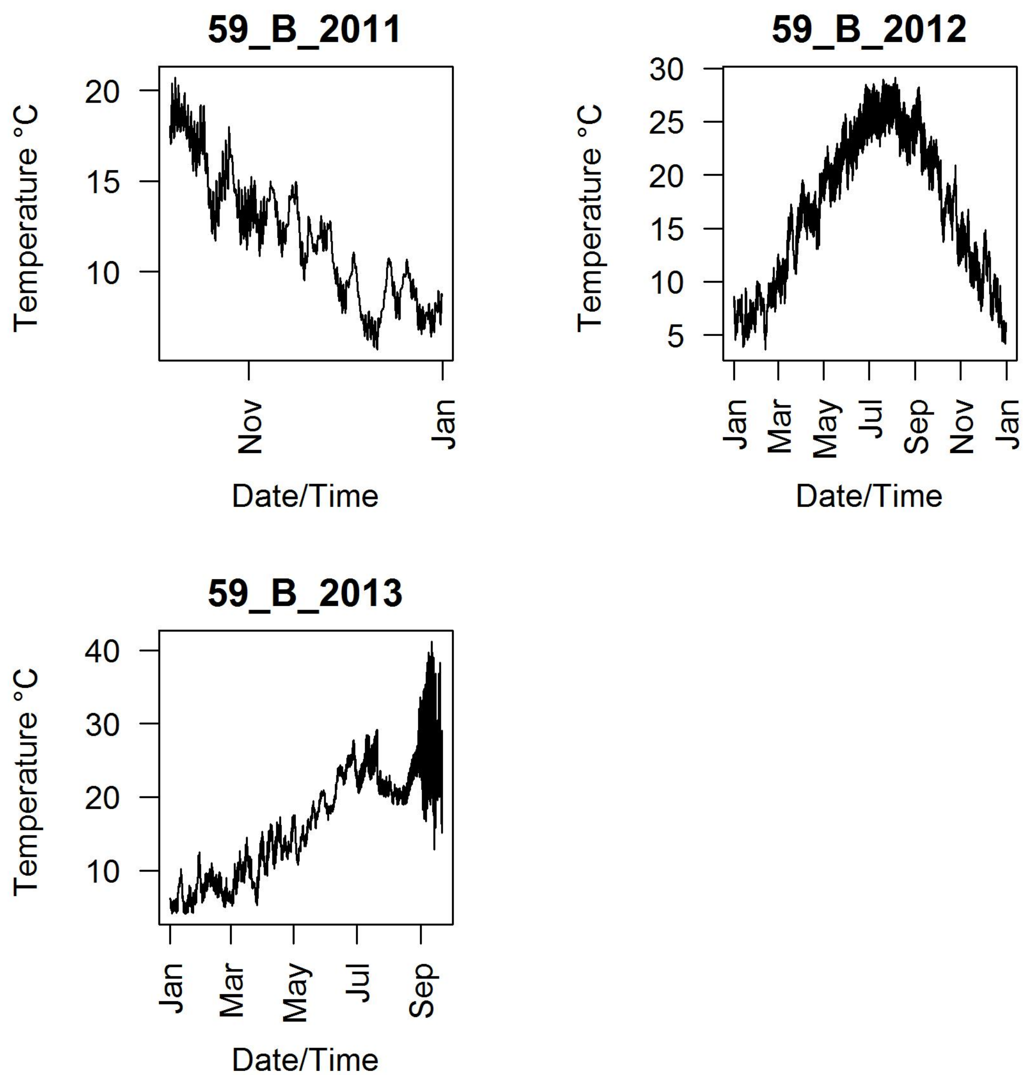


*Figure 153. Site 59, Point B: Big Sugar Creek near Powell, 2011 – 2013.***

Decision: logger was found exposed on 22 Sept 2013. Did not use records from 28 Aug – 22 Sept 2013. Used remaining records.



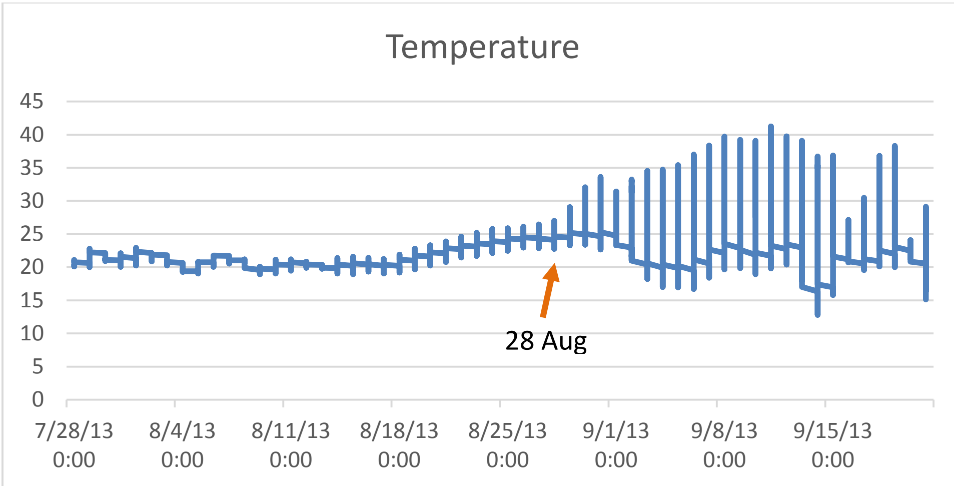
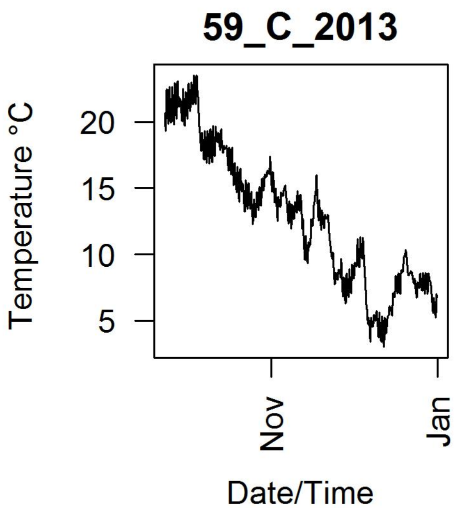
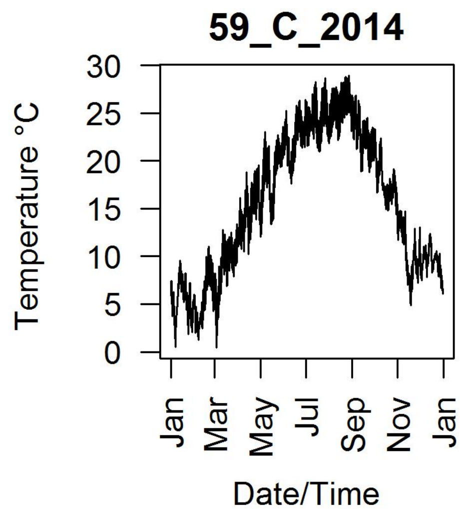

Temperature
45
40
35
30
25
20
15
10
5
0
28 Aug
7/28/13 0:00
8/4/13 0:00
8/11/13 0:00
8/18/13 0:00
8/25/13 0:00
9/1/13 0:00
9/8/13 0:00
9/15/13 0:00

Figure 154. Site 59, Point C: Big Sugar Creek near Powell, 2013 – 2015.

Decision: used all records.





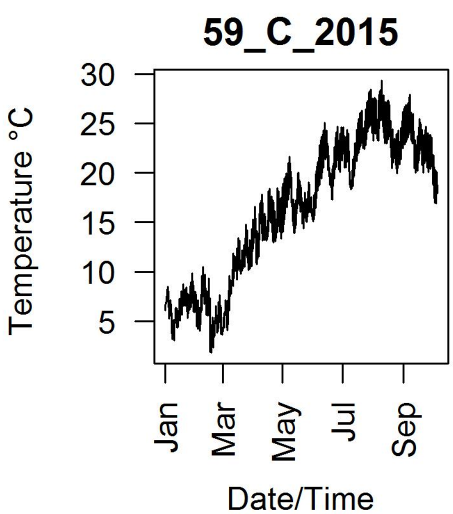


Figure 155. Site 59, Point D: Big Sugar Creek near Powell, 2013 – 2015.
Decision: used all records.

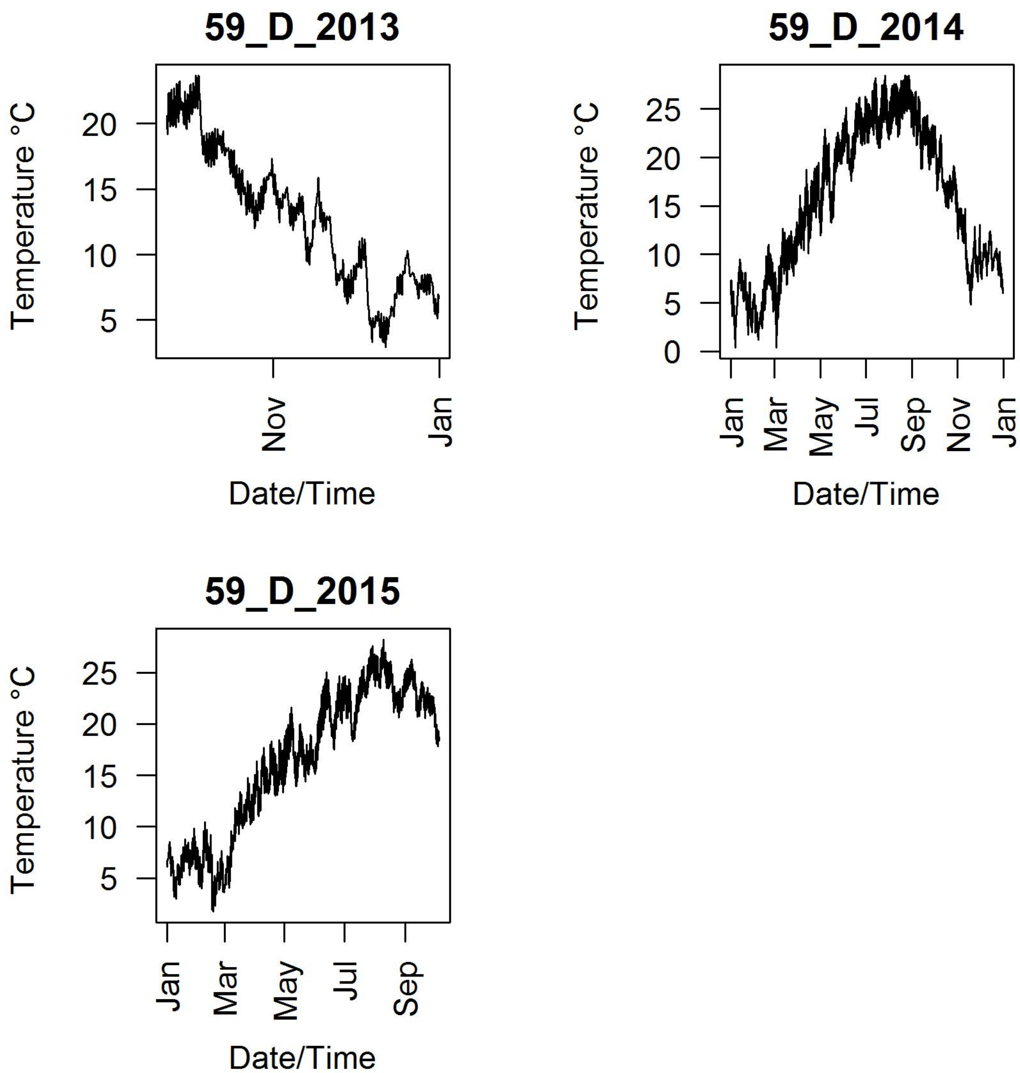


Figure 156. Site 61, Point C: Indian Creek near Lanagan, 2014 – 2015. NEED TO IMPORT MISSING DATA
Decision: used all records.

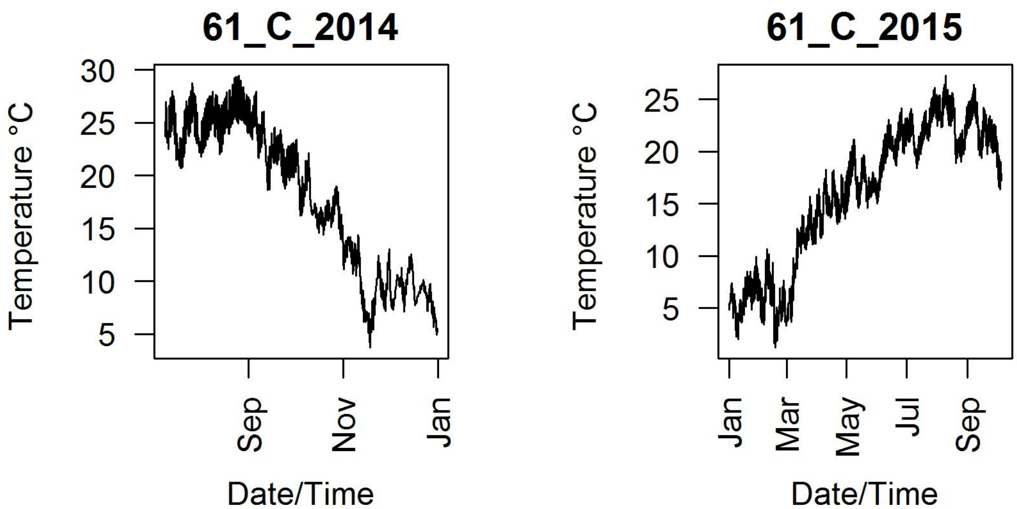


Figure 157. Site 61, Point D: Indian Creek near Lanagan, 2014 – 2015.
Decision: used all records.

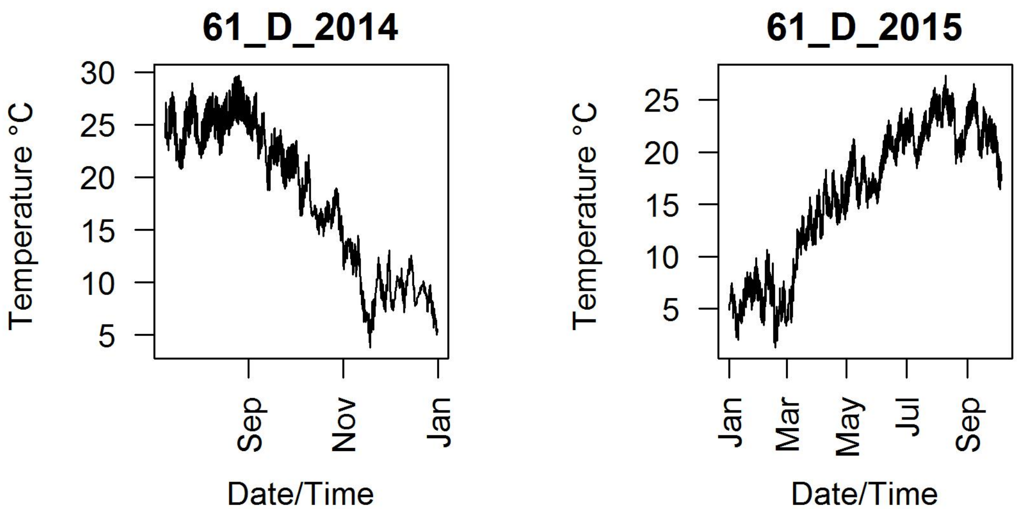


Figure 158. Site 62, Point C: Elk River near Tiff City, 2013 – 2015.
Decision: used all records.

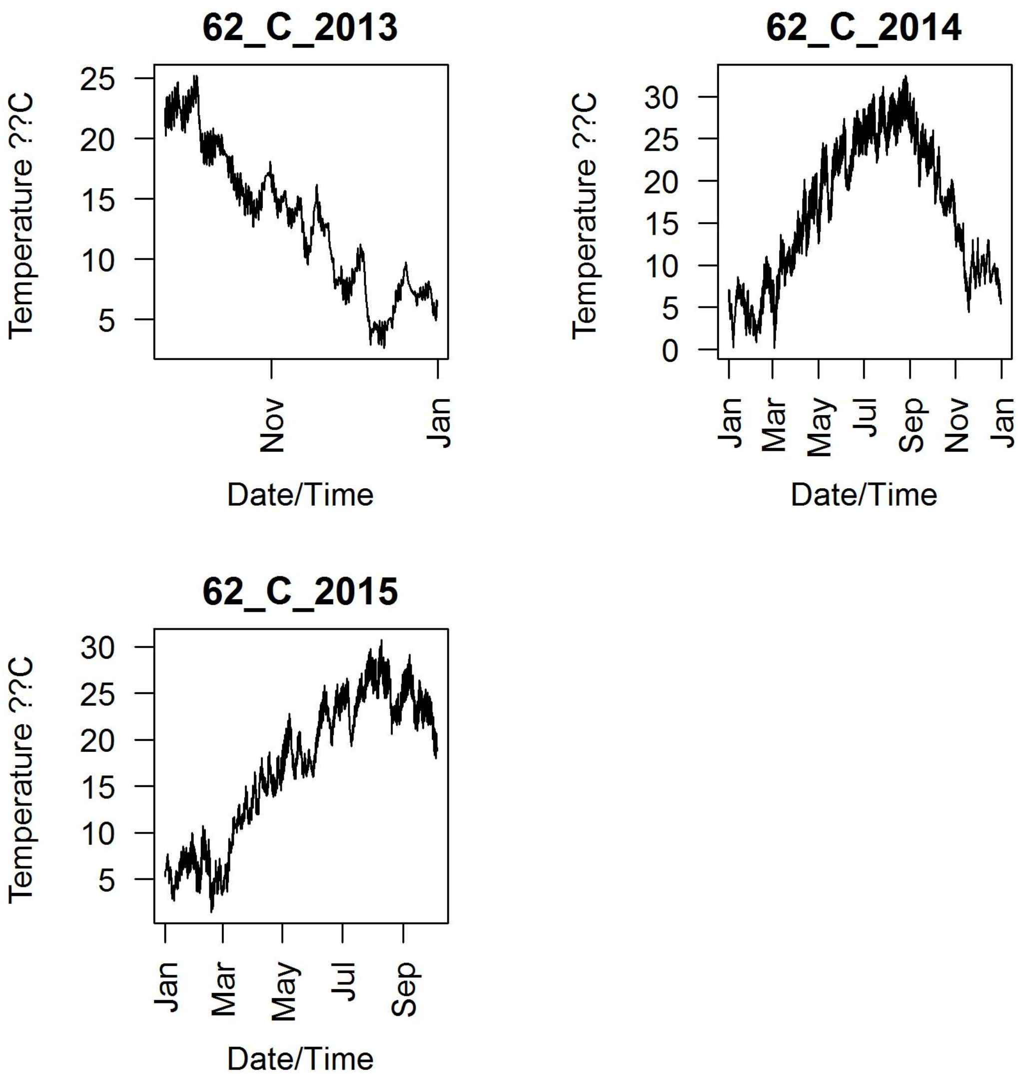


Figure 159. Site 62, Point D: Elk River near Tiff City, 2013 – 2015.
Decision: used all records.

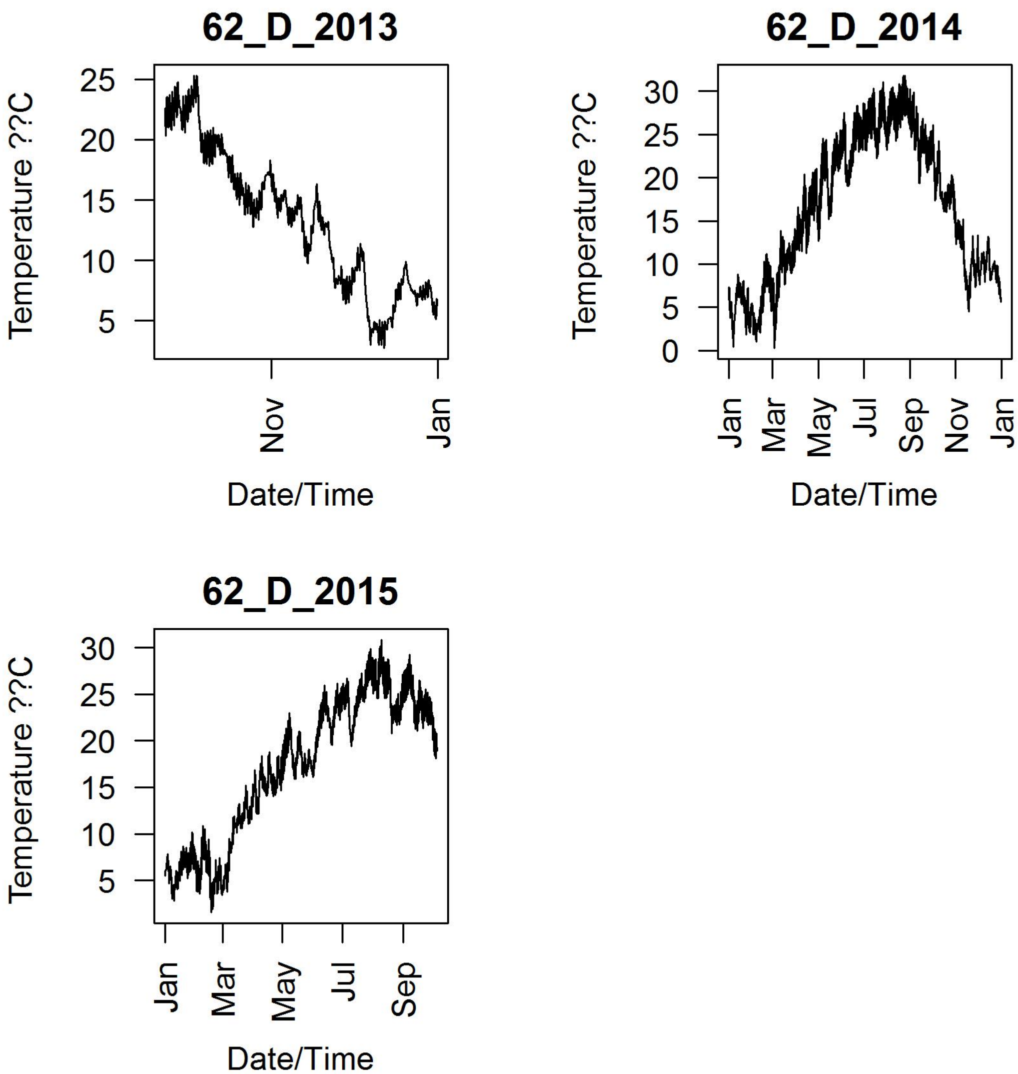


Figure 160. Site 63, Point B: Buffalo Creek at Tiff City, 2012 – 2013.
Decision: used all records.

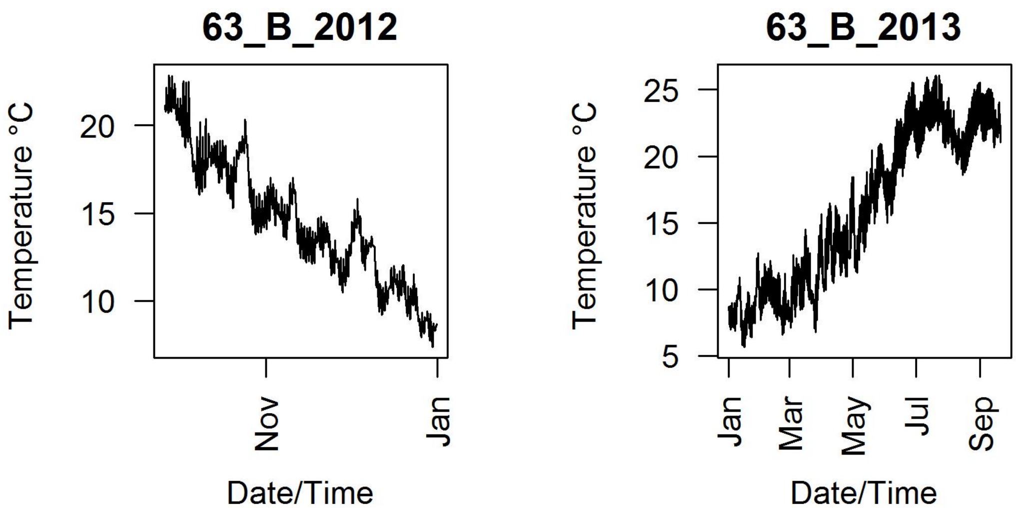


Figure 161. Site 64, Point A: Big Piney River near Big Piney, 2012 – 2015.
Decision: used all records.

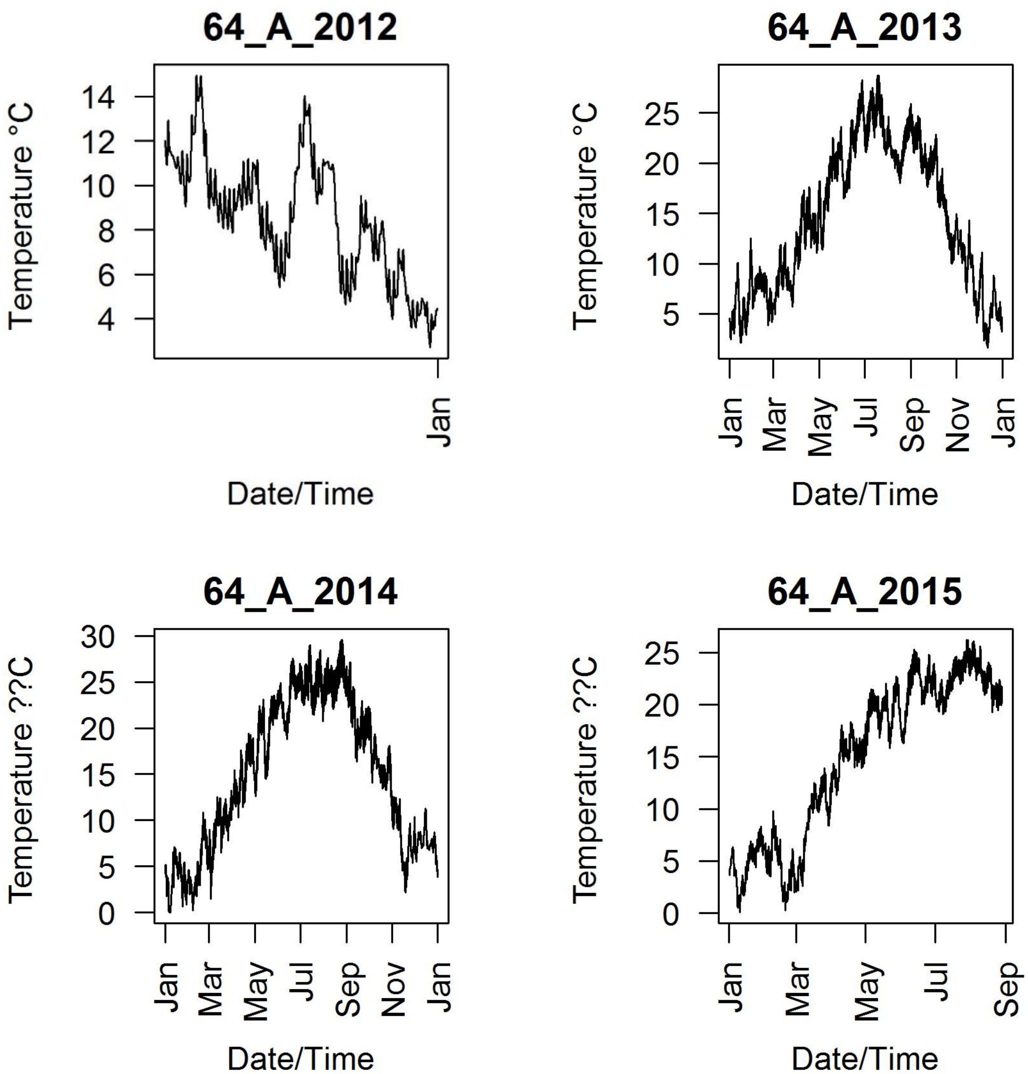


Figure 162. Site 64, Point C: Big Piney River near Big Piney, 2013 – 2015.
Decision: used all records.

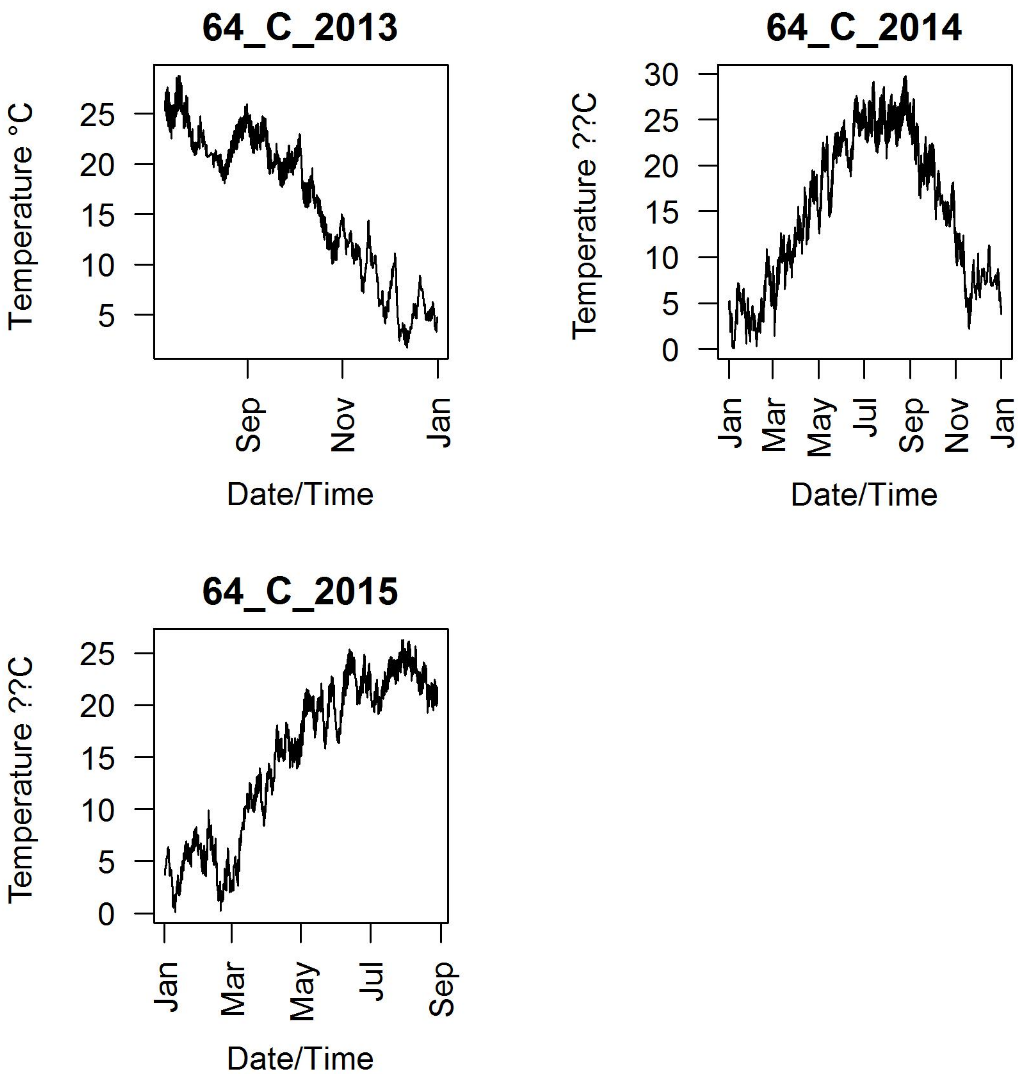


Figure 163. Site 65, Point A: Big Piney below Fort Leonard Wood, 2012 – 2014.
Decision: used all records.

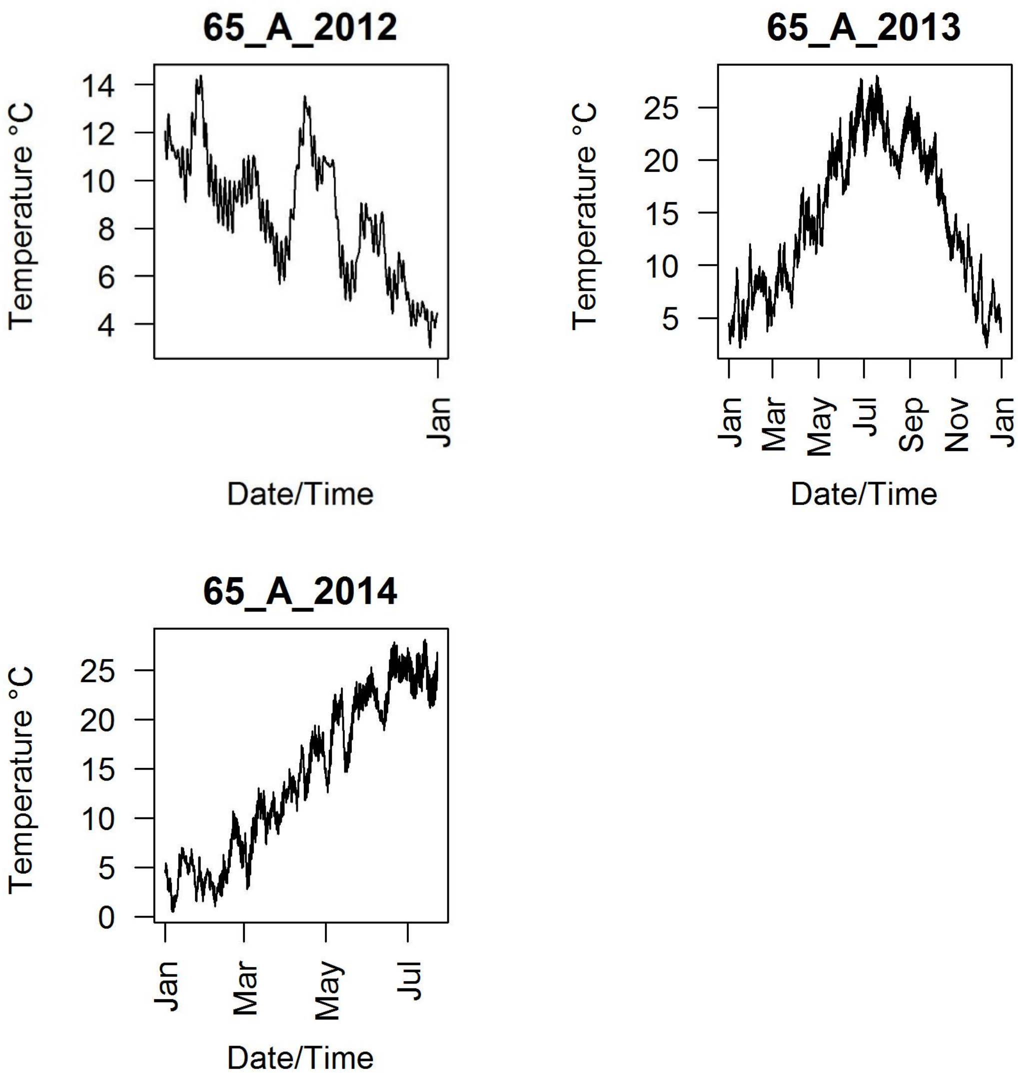


Figure 164 Site 65, Point B: Big Piney below Fort Leonard Wood, 2013 – 2014.

Decision: used all records

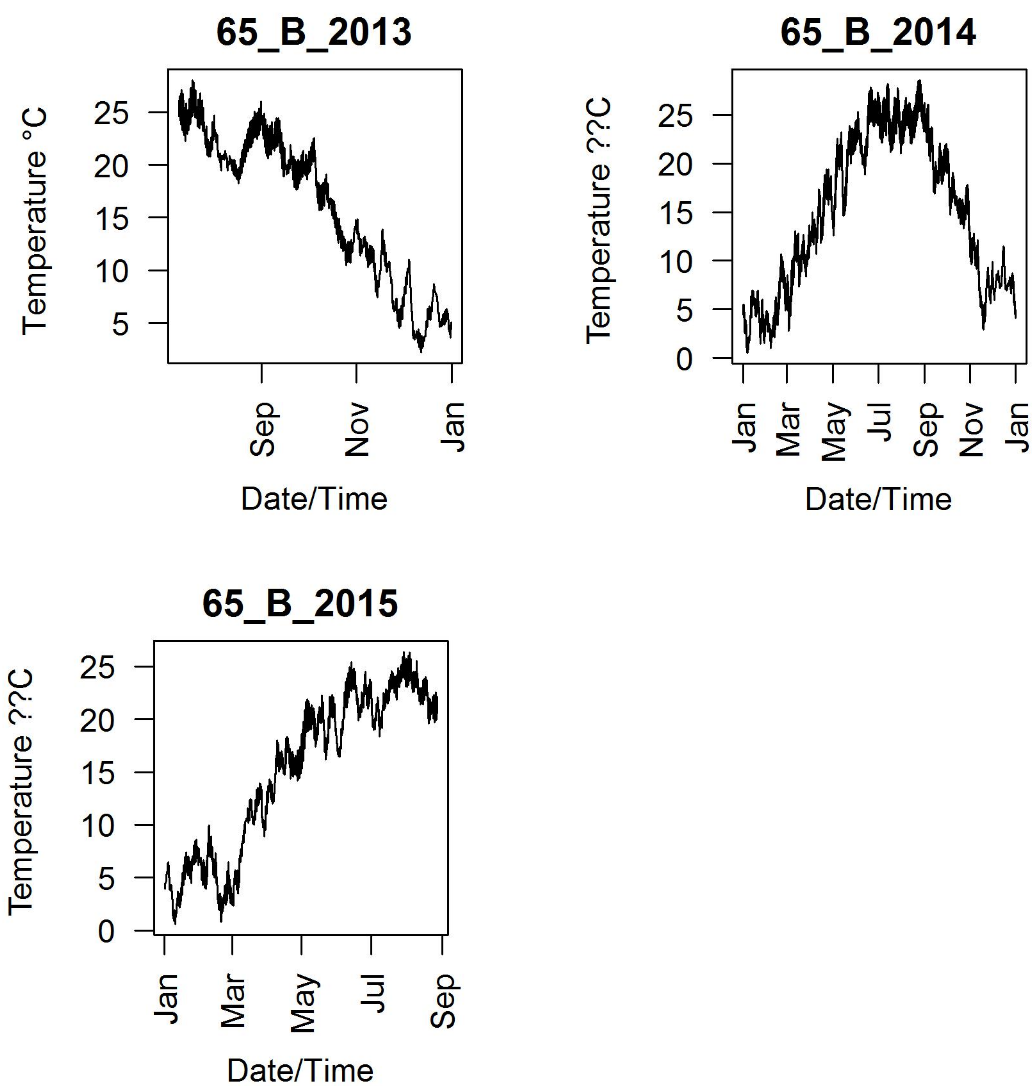


Figure 165. Site 66, Point A: Gasconade River near Hazelgreen, 2012 – 2015.
Decision: used all records.

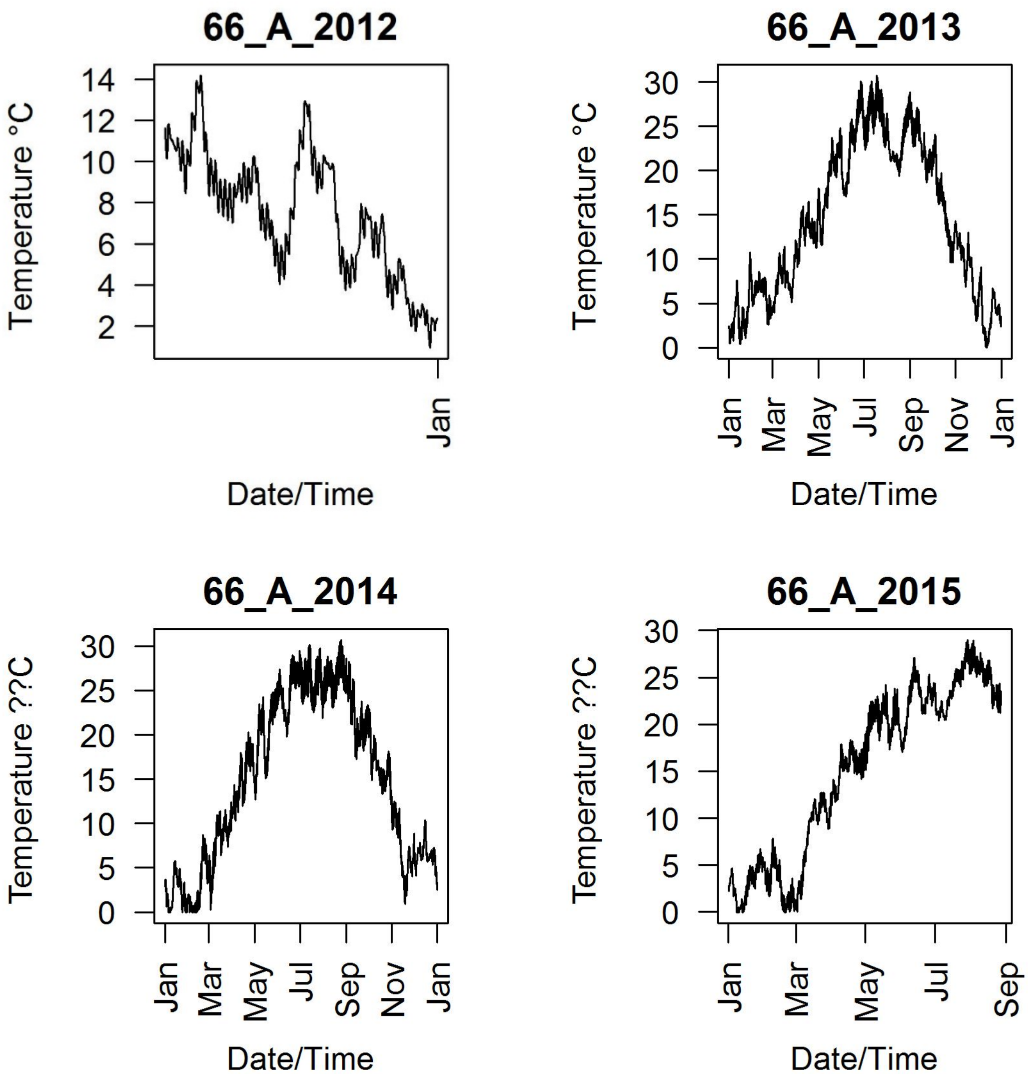


Figure 166. Site 66, Point C: Gasconade River near Hazelgreen, 2013 – 2015.

Decision: used all records.

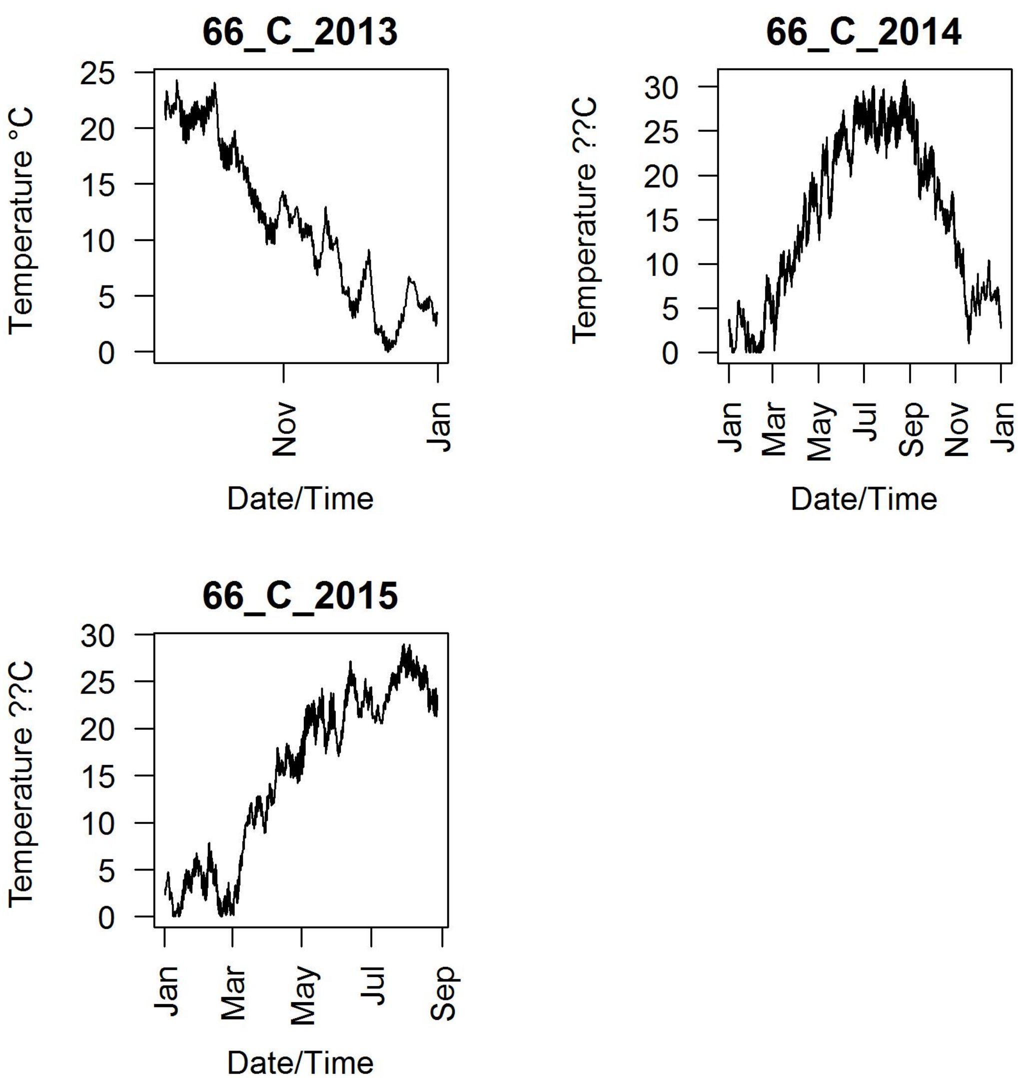


Figure 167. Site 67, Point A: Gasconade River at Jerome, 2012 – 2015.
Decision: used all records.

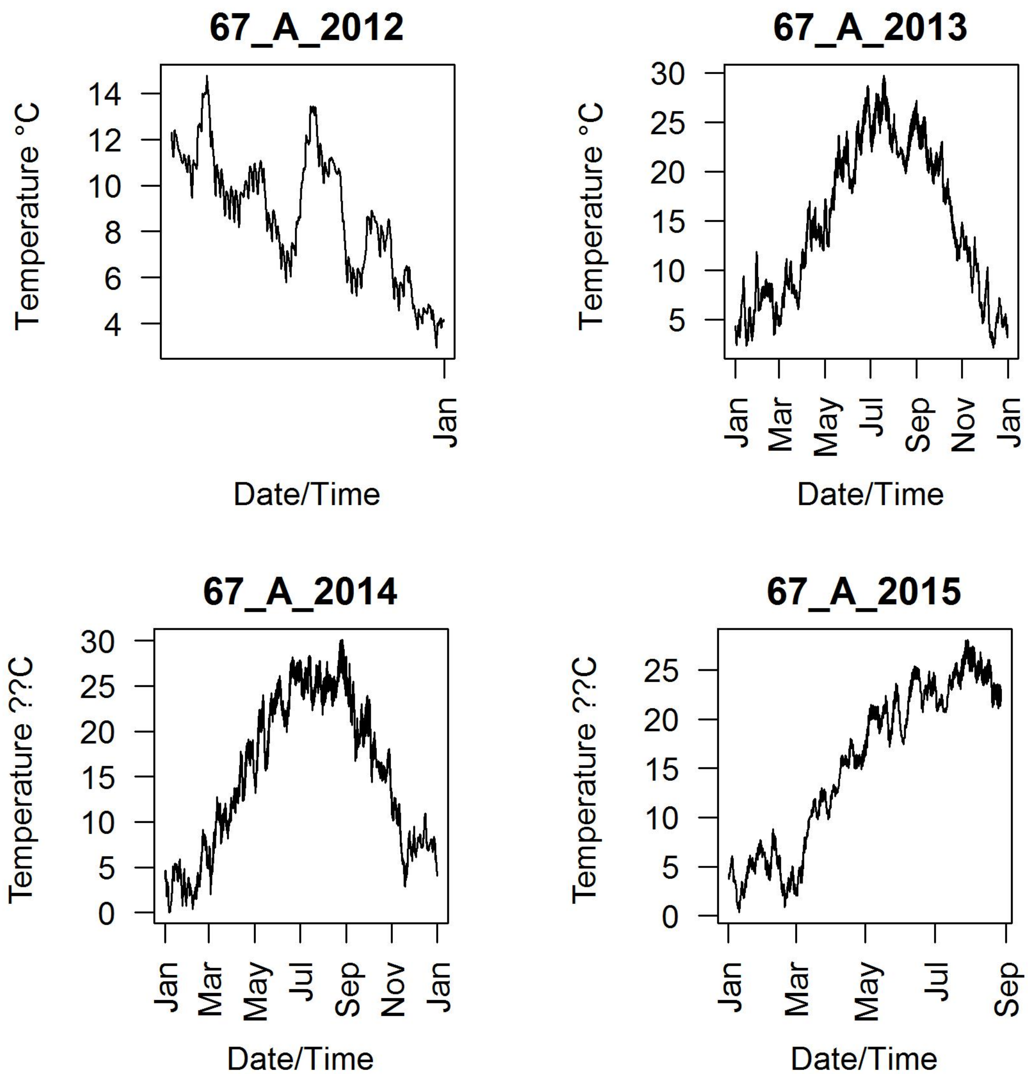


Figure 168. Site 67, Point B: Gasconade River at Jerome, 2012 – 2014.
Decision: used all records.

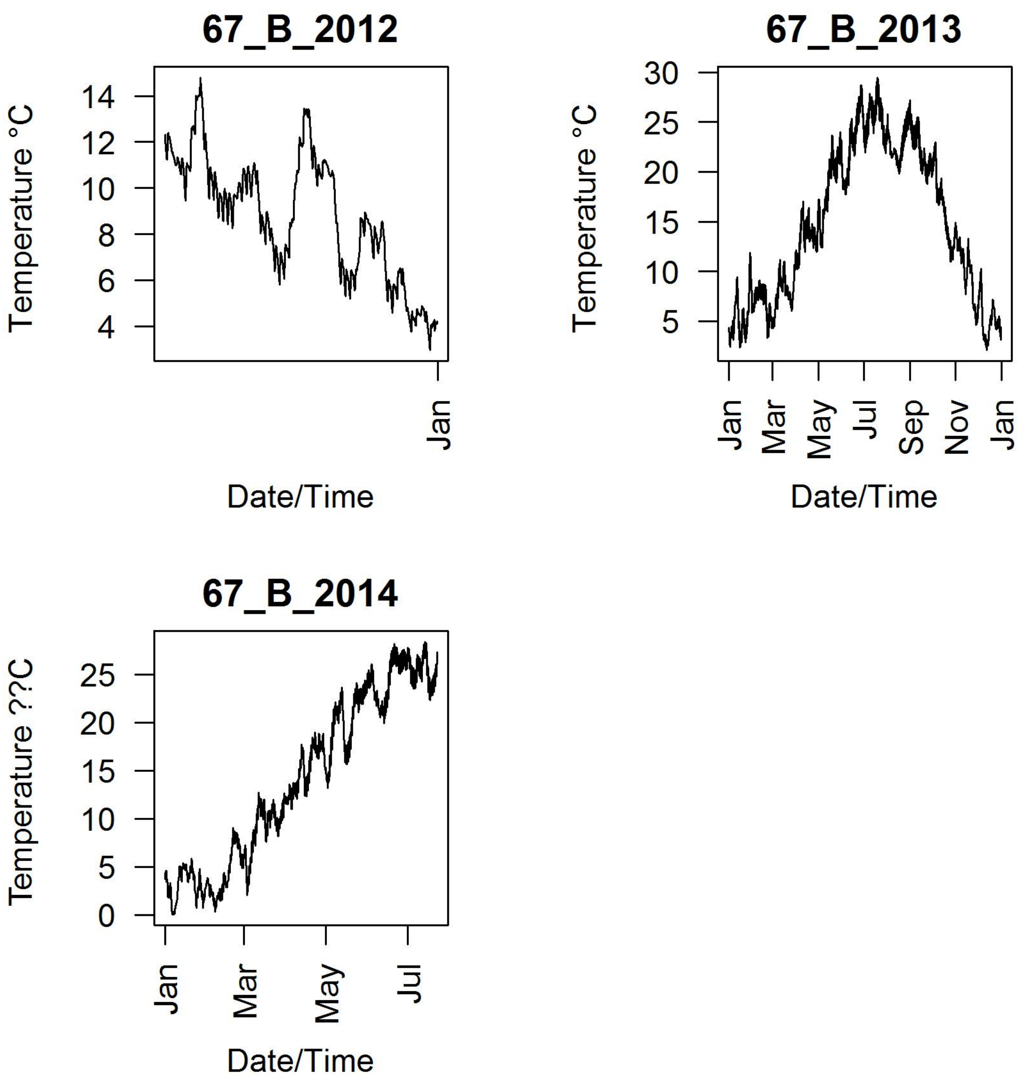


Figure 169. Site 68, Point A: North Fork River near Tecumseh, 2013 – 2015.

Decision: used all records

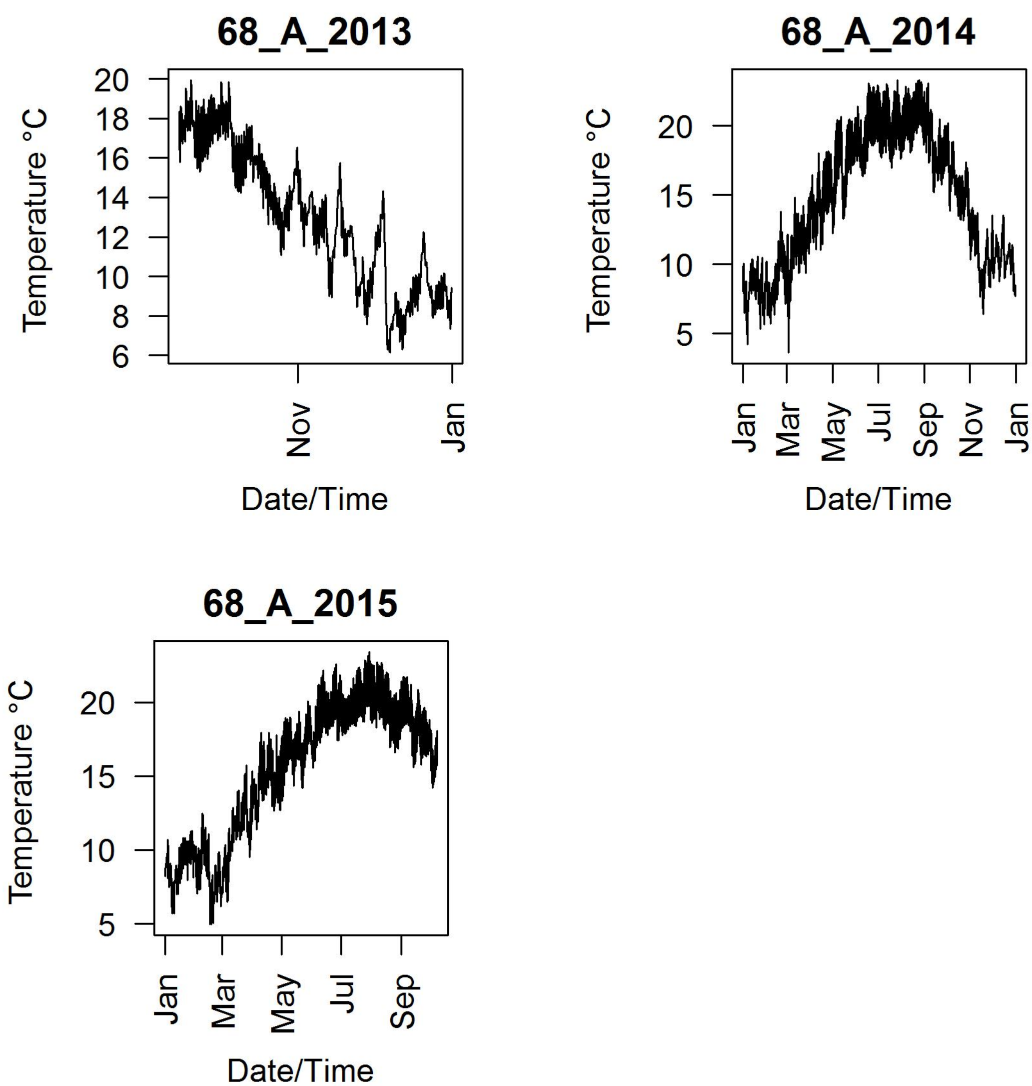
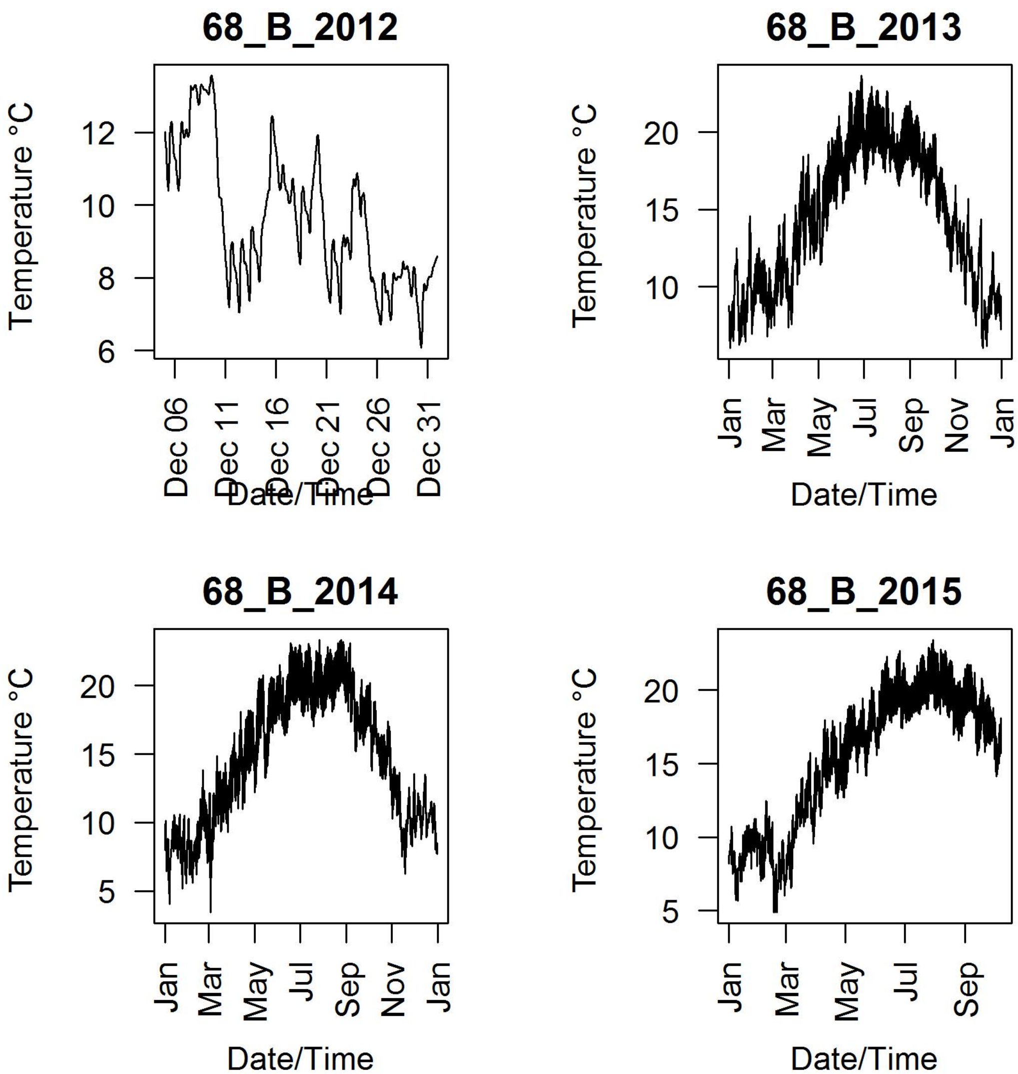


Figure 170. Site 68, Point B: North Fork River near Tecumseh, 2012 – 2015.
Decision: used all records.



Appendix L. QA/QC process to test precision of stream temperature loggers.

Prior to deploying loggers for the first time or after being retrieved, all loggers were tested for precision of recorded temperatures to identify any malfunctioning loggers. Testing was accomplished by submerging loggers in a water bath containing an air bubbler to keep the water circulating. Initial water temperature was approximately 35°C and cooled to approximately 10°C over a 2 hour period. Loggers were set to record temperature at one minute intervals. Recorded temperatures from each logger were plotted and compared among loggers to identify any logger that recorded erroneous data. We never had a logger out of sync or with temperature records offset from the other loggers by more than the specifications indicated. If we had found one that did this, we would have sent it back to Onset for recalibration.