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Hydro-Climatological Summer Trends in the Continental United States

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Abstract

We investigated trends in air temperature, stream temperature and discharge for rivers across the continental United States from the summer months of 1996 to 2016. Using GAGES II from USGS and PRISM and programming language R we analyzed specific hydrological trends in Mann-Kendall's tests. After collecting the slope values whether they were negative or positive and the P-Values, the significance of that slope, we mapped slopes of trends in GIS. Stream temperature increased 12% of stations across the summer, while air temperature increased 22% of stations, and discharge decreased 15% of stations, respectively. Seven day moving average of daily maximum stream temperature increased and other basin characteristics such as precipitation, dam storage, latitude, and vegetation coverage were other influences of that increase. Oregon showed the least number of increasing trends for stream temperature.

Introduction

This study will examine daily data of air temperature, stream temperature, and stream discharge for rivers and streams across the continental United States, during the summer (June – September) from the years 1996 to 2016. The purpose of observing this daily data is to identify trends within an extreme amount of data. When reading about other research that has been conducted, it is important to note their results and come to realizations from preexisting information. Similar studies can be useful for improving complicated research questions.

A literature review was completed before this research began. The reason for this is to familiarize myself with what research has been conducted and what needs better refining. This literature search is to better educate my understanding of the subject and to familiarize myself with occurring patterns within the different but similar topics of research. Table 1 shows a summary of literature that was evaluated to help organize thoughts and ideas to better explain this research.

Table 1: Literature Review

Author (Year)	**Study Area**	**Data Period**	**Parameters/Variables & Trend Analysis**	**Model**	**Question/Hypothesis**	**Major Findings**
Arismendi et al. (2012)	Watershed: CA, ID, MT, NV, OR, and WA This region has warm dry summers and cool wet winters.	1950 – 2010 Summer	Stream Temperature Maxima Streamflow Minima Air Temperature Maxima 1-Day Moving Average 7-Day Moving Average	Least-squares linear regression analysis	If streamflow peak happens earlier, there might be a shift in the timing of low flow which would decrease the interval between annual stream temp max and annual flow min and increase potential of them occurring at the same time.	Years with higher stream temp max and high air temp also showed low stream flow min. Increase in synchrony between stream temp max and stream flow min. Decrease in time lag between stream temp max and stream flow min. Time lag shortened by 20-30 days.
Chang et al. (2012)	Pacific NorthWest: OR, WA, ID	1958 – 2008 March and September	Streamflow Stream Temperature Hydrologic Landscape Factors Elevation Seven-Day Low flows Precipitation Ecoregion	SER model GWR model Mann-Kendall Trend Test	Understand hydrologic response to climate variability across the PNW, identifying long-term trends in streamflow, and how trends vary across hydrological landscapes. Most detailed study of streamflow trends for the PNW.	September streamflow decreased 1958 to 2008, these are in the major populated cities.

Arismendi et al. (2012)	CA, NV, OR, ID, WA, AK Least Disturbed Watersheds	1987 - 2009	Air Temperature Stream Temperature (Min, Max, Mean)	Mann-Kendall Trend Test	Find warming trends in min, max, and mean temperatures using observed trends of decreasing summer streamflow and increasing air temperature.	Found less sites with warming trends and twice as many with cooling trends for temp max. There needs to be a better method for understanding the links between climate change, human impacts, and stream temperature. Improve sensor networks for better data in the future.
van Vliet et al. (2013)	Global	1971 - 2000	Stream Temperature Discharge Climate	VIC-RBM model	Assess the impact of climate change on river discharge, and water temp on global scale. Use models	The US, Europe, and eastern China have the largest predicted water temp increase.
Gray et al. (2018)	Upper Mississippi River	Summer 1994 – 2011 (No 2003)	Air Temperature Discharge	Linear Regressio n	How does the changes of air temperature and discharge effect the upper Mississippi river stream temperature? Used models to evaluate changes in water temperature and discharge.	Water temperature and discharge associations were weak. Correlation between water temperatures and air temperatures.
Kaushal1 et al. (2010)	The US (NH, NY, PA, DE, MD, DC, VA, NC, FL, AL, GA, IN, IA, CO, UT, MT, OR, CA)	Time varies by station. Year ranges staring at 1908 - 2007	Daily Stream Temp Monthly Stream Temp	Simple Linear Regressio n Mann-Kendall Trend Test	Analyze long-term trends in the temperature of 40 streams across the US	20 out of 40 streams had significant linear increases from historical stream temp data
Rice et al. (2014)	Mid-Atlantic Region in the USA	1960 - 2010	Water Temperature Air Temperature Discharge	Simple Linear Regressio n	Examine monthly mean air temp and stream temp to find any significant trends.	Water temperature increases are noticed despite increase of discharge

McCabe et al. (2017)	AZ, CA, CO, NM, NV, UT, WY	1906 – 2012 Water-Year (October – September)	Air Temperature Discharge	Multiple Linear Regression Analysis	Increasing air temperatures will likely elevate the risk of reduced water supply in the basin.	The results did find that the warming has had an increasingly negative influence of the upper Colorado river flow over the past three decades.
Arismendi et al. (2014)	Regulated and unregulated streams.	Up to 44 years of data	Stream Temperature Air Temperature	Linear Regression Analysis Non-Linear Regression Model	Test two different models that are often used in many studies that predict stream temperatures from air temperatures.	Models may be used but other factors and attributes must be included.
Luce et al. (2014)	PNW	Summer 1988 - 2010	Stream Temperature Air Temperature		Analyze summer stream temperatures in forested areas of the PNW.	Cold streams are less sensitive to direct temperature increases.
Morrill et al. (2015)	Globally	1996 - 2001	Weekly Air Temperature Daily Stream Temperature Dissolved Oxygen	Simple Linear Model Non-Linear Model	Examine relationship between stream and air temperatures using linear and nonlinear relationships	Showed similar results to other studies that used weekly data for both parameters.
Letcher et al. (2016)	Western Massachusetts	1999 - 2013	Stream Temperature	Hierarchical Linear Autoregressive Model	How missing data of stream temperature can affect results.	Missing data had a small effect on performance.

Previous studies of rivers conducted in the United States can assist with the explanation of the results received at the end of this research. Reduction of stream flows is a concern for the existence of streams. In the southwest region of the US, looking at low stream flow trends in the Upper Colorado River shows that there is possibility of droughts occurring more often in that area (McCabe, Wolock, Pederson, Woodhouse, & McAfee, 2017). These droughts can result to reduced water supply for the states that rely on the Upper Colorado River (McCabe, Wolock, Pederson, Woodhouse, & McAfee, 2017). Warming trends of climate change correlate with the increase of low stream flows, causing an increased potential of droughts to happen if the warming continues (McCabe, Wolock, Pederson, Woodhouse, & McAfee, 2017). In the Midwest region of the US, a study of the Upper Mississippi River during the summer observed air and stream flow trends in effectiveness on the stream temperature (Gray, Robertson, & Rogala, 2018). Stream temperatures are affected by other factors such as precipitation, solar radiation, and the type of location/land (Gray, Robertson, & Rogala, 2018). This makes it difficult to rely on only air temperature and stream flow trends to predict the water temperature.

A comparison of stream temperature and stream flow are important drivers for stream ecosystems (Arismendi, Safeeq, Johnson, Dunham, & Haggerty, 2013). Increasing stream temperature and low stream flow synchrony are dangerous for aquatic life. (Arismendi, Safeeq, Johnson, Dunham, & Haggerty, 2013). Trends that have been observed in western North American streams are that high water temperatures are happening at the same time as low stream flows (Arismendi, Safeeq, Johnson, Dunham, & Haggerty, 2013). Can there be predictions of this to happen more often in the future? It is hypothesized that if the peak flow of rivers happens earlier in the year, it will shift the timing of low flow and causing a chance for high water temperature and low stream flows to occur at the same time (Arismendi, Safeeq, Johnson, Dunham, & Haggerty, 2013). Methods in observing this trend is by looking at the water temperature and stream flow data together during the summer.

Claims have been made that predictions of future stream temperatures can be made with data from air temperature (Morrill Jean C., Bales Roger C., & Conklin Martha H., 2005). Using linear and nonlinear models to see the relationship between air temperature and stream temperature concludes that it is possible to predict future stream temperatures with air temperature data (Morrill Jean C., Bales Roger C., & Conklin Martha H., 2005). On the other hand, in a more recent article, it has been argued that using stream temperature predictive models from air temperature trends, have not yet been fully evaluated to be accurate (Arismendi, Safeeq, Dunham, & Johnson, 2014). It turns out that it is difficult to rely on these predictive models because they exclude other important factors, such as, vegetation coverage, urbanization, and elevation, that need to be considered (Arismendi, Safeeq, Dunham, & Johnson, 2014).

A common theme between these sources were that many considered the idea of climate change/climate variability. Climate change is an important factor to many research topics when looking into air temperature, water temperature, and stream flow. This is because the reasoning of climate change is negatively impacting streams and rivers and it must be assessed. Stream sensitivity in response to climate change needs to be evaluated more closely (Luce et al., 2014). When looking at summer, stream temperature data for rivers in the PNW located within forested areas, it is important to notice if any significant trends of water temperature (Luce et al., 2014). It turns out that rivers surrounded within forests were less sensitive to the changes in air temperature due to the vegetation. (Luce et al., 2014). The results of these data trends are important to recognize because it may bring awareness to conservation planning to keep forests safe. (Luce et al., 2014).

Climate change is affecting rivers and streams globally. Specifically, in the United States, rising trends of stream temperatures are due to global warming and urbanization (Kaushal et al., 2010). Temperature data for rivers and streams in the United States haven’t been fully analyzed compared to most countries (Kaushal et al., 2010). The growth of cities interacts with global warming and can ruin the water quality of the rivers and streams (Kaushal et al., 2010). We must be more conscious when deforestation occurs because it has been proven by multiple studies that less vegetation can cause warmer stream temperatures in correlation with climate change (Kaushal et al., 2010).

Methodology

Datasets of air temperature, discharge, and stream temperature were observed throughout 69 stations from 1996 to 2016 in the continental United States. The time frame for observation will be for summer. For our research, summer begins June 1st and ends in September 31st. Stations were decided based on the limitation of available data. A Geography grad student, Junjie Chen, provided a list of 100 stations located in the United States that were selected based on available stream temperature data. This list of stations was filtered down to 75 stations due to limitation of discharge data. Then we ended up with 69 stations due to limited data from Geospatial Attributes of Gages for Evaluating Streamflow version two (GAGES II). Table 2 shows all stations used in research. Latitude and Longitude data was noted for collecting air temperature data and mapping on GIS. Every station in this table has available data for air temperature, discharge, and stream temperature, which will be the three parameters used for trend analysis for the continental United States.

River locations in the United States have sensors set up that are collecting daily data. The data can be accessed through USGS water watch database. Each station is assigned an 8-digit identification number. To access information about a water station you must know the station ID number. These stations have daily water temperature data from 1996 – 2016 located only within the United States. The daily data in USGS includes minimum stream temperature, maximum stream temperature, and mean stream temperature data. The temperatures are measured in degrees Celsius. Discharge daily data is also included within the USGS database which includes only daily discharge mean data. The discharges are measured in cubic feet per second.

Table 2: List of River Stations

Station ID	State	Latitude	Longitude
02423130	AL	33.622325	-86.599431
02423397	AL	33.5345489	-86.5624847
02423496	AL	33.369277	-86.784155
02455980	AL	33.7112127	-86.6961013
02457595	AL	33.597049	-86.868048
02458450	AL	33.5176059	-86.8791584
11074000	CA	33.88334875	-117.6453296
11261100	CA	37.2477186	-120.8521446
11262900	CA	37.26244	-120.9065908
11274550	CA	37.4318795	-121.0138193
11276500	CA	37.93742147	-119.7982326
11276600	CA	37.87936848	-119.9471261
11289650	CA	37.66632102	-120.4421394
11302000	CA	37.85159385	-120.6379816
11303000	CA	37.72965078	-121.1104934
11303500	CA	37.6760406	-121.2663293
11390000	CA	39.7259952	-121.7088643
11390500	CA	39.00989476	-121.82469
11446500	CA	38.6354601	-121.2277262
11530000	CA	41.049852	-123.673668
06711565	CO	39.6649874	-105.004149
07096000	CO	38.4338867	-105.2572128
07099970	CO	38.253614	-104.6060854
07106000	CO	38.6016647	-104.6702503
07106500	CO	38.2877801	-104.6010849
07109500	CO	38.248058	-104.3991356
07124000	CO	38.0808399	-103.2196523
07130500	CO	38.06639635	-102.9324228
09041400	CO	40.1085963	-106.4139212
09095500	CO	39.2391463	-108.2661946
09105000	CO	39.1836111	-108.2683333
09152500	CO	38.9833158	-108.4506446
09163500	CO	39.1327605	-109.0270546
09169500	CO	38.3102675	-108.8853805
09171100	CO	38.3569337	-108.8334347
09251000	CO	40.5027467	-108.0334152
09371492	CO	37.3127716	-108.6612067
09371520	CO	37.3266601	-108.7006527
02337170	GA	33.6566667	-84.6736111
13340000	ID	46.4783333	-116.2575
13340600	ID	46.8405556	-115.621111
13341050	ID	46.5002778	-116.3925

13342500	ID	46.4483333	-116.8275
03353611	IN	39.7144889	-86.2005434
03354000	IN	39.4975477	-86.40054952
06041000	MT	45.49020577	-111.6341382
06054500	MT	46.14604028	-111.42052
12363000	MT	48.3618111	-114.18495
10351700	NV	39.77737222	-119.3375222
01463500	NJ	40.2216667	-74.7780556
01417500	NY	42.02480929	-75.11988987
01421000	NY	41.9730556	-75.1741667
01425000	NY	42.07480591	-75.39600945
01426500	NY	42.0030556	-75.3836111
01428500	NY	41.5089782	-74.98572346
02077200	NC	36.3977778	-79.1966667
02077303	NC	36.5225	-78.9975
14138850	OR	45.4981743	-122.0123049
14138870	OR	45.4801189	-122.0256385
14138900	OR	45.4942856	-122.0359167
14139800	OR	45.444564	-122.1095292
14150000	OR	43.9456815	-122.8372967
14338000	OR	42.6787364	-122.7419867
01481000	PA	39.8698328	-75.5932623
02156500	SC	34.5951393	-81.4212089
02160105	SC	34.5354163	-81.548158
02160700	SC	34.5093039	-81.5981594
03428200	TN	35.90284234	-86.4299923
08049500	TX	32.7987406	-97.02973015
08062500	TX	32.42652988	-96.46304152
08065350	TX	31.33851319	-95.65634069
08123850	TX	32.05374399	-100.762052
09379500	UT	37.1506778	-109.8666889
02011800	VA	37.9484583	-79.9492237
12181000	WA	48.5337306	-121.4298499

Air temperature data was collected from the Precipitation Regression on Independent Slopes Model (PRISM) database from Oregon State University (Daly, Neilson, & Phillips, 1994). The air temperature data that is included is daily minimum air temperature, daily maximum air temperature, and daily mean air temperature. The air temperature is measured in degrees Celsius. To retreat the data from PRISM it is required to use the coordinate locations instead of the station IDs that USGS provides. USGS provides coordinates for each station but they are in DMS (Degrees, Minutes, and Seconds) units. The coordinates were converted to decimal units to correspond with the PRISM database. When entering the coordinate locations into PRISM, the interactive map highlights a square outline in red for that specific location. The location inside the red square corresponds with the coordinated entered and the data that will be downloaded will be for that specific area. This process was done 75 times to collect the air temperature data from 1996 – 2016 for all the stations. The data from PRISM was downloaded as CSV files. Every file is renamed to have the station ID, state, and type of data. This keeps each station organized and easier to access when ran through the program in R.

Each parameter will correspond with a trend analysis. The trend analysis for air temperature is; monthly average of daily air temperature minimum (MA_ATmin), monthly average of daily air temperature maximum (MA_ATmax), monthly average of daily air temperature mean (MA_ATmean), monthly max of 7-day moving average of daily temperature maximum (7dATmax), and coefficient of variation of 7-day moving average of air temperature maximum (CV_7dATmax). The trend analysis for discharge is; monthly average of daily discharge mean (MA_Qmean), monthly min of 7-day moving average of the discharge mean (7dQmin), and coefficient of variation of 7-day moving average of the discharge mean (CV_7dQmin). The trend analysis for water temperature are; monthly average of daily stream temperature max (MDA_STmax), monthly max of 7-day moving average of daily temperature maximum (7dSTmax), and coefficient of variation of the 7-day moving average of daily temperature max (CV_7dSTmax). Table 3 show the trend analysis abbreviations for organization.

Table 3: Trend Analysis

Parameter	Monthly Average	7-Day Moving Average	Coefficient of Variation
Air Temperature	MA_ATmin, MA_ATmax, MA_ATmean	7dATmax	CV_7dATmax
Discharge	MA_Qmean	7dQmin	CV_7dQmin
Stream Temperature	MA_STmax	7dSTmax	CV_7dSTmax

The programming language R was used for statistical computing and manipulating data. It is more efficient to program in R rather than sorting through data in excel. The environment used to create the programs for this data is R Studio. Junjie Chen supplied a program that he created for a similar research project. The previous program is referenced to create codes to create the specific data analysis needed. R programming language includes downloadable packages that carry useful functions such as the package titled “waterData”. This package includes functions that corresponds with USGS. The functions, importDVs() and fillMiss() are used for trend analysis (Karen R. Ryberg, Aldo V. Vecchia, 2017). The function importDVs() imports selected data directly from the USGS website. The function requires the site identification number, the parameter code, the statistic code, the start date, and the end date (Karen R. Ryberg, Aldo V. Vecchia, 2017). The function is assigned to a variable that is named accordingly to the data that it retrieves. The function fillMiss() fills in data for stations that have gaps of missing data. The daily data collected by USGS may likely have missing gaps of data. The fillMiss() function is used to fill up the gaps of missing data that would cause a problem during the trend analysis. The function requires the data frame that was imported by the importDVs() function, the block size of the largest block of missing data that will be filled in, the maximum percentage of the amount of data that can be missing for the fill-in procedure to be performed, the type of structural time series model (we used “trend”). (Karen R. Ryberg, Aldo V. Vecchia, 2017). Importing the air temperature data from PRISM required different steps. The PRISM data that was downloaded manually and organized was imported into R studio with the function read.csv(). This function only requires the name of the file but the work directory in R must be set to the folder where the files are located.

The general idea for the programs, for all the trend analysis, are similar. Each program takes in the daily data into a data frame variable and then uses the fillmiss() function (only for data from USGS). Using the new data frame (that ran through fillMiss()), the data is subset by using a format function and created into new variables that are separated by four months (June, July, August, and September). Each value that is essential for the trend analysis uses a specific function based on the functionality of the trend analysis. The plot() function is used to graph each variable that is labelled by month. The lm() function stands for “linear model”. The linear model creates the closes fitting line of each graph per month of all the data points based on that trend analysis. The summary() function is used for the linear model value. We end up with an output of the summary for the linear model of the graph. Each time the program runs, there are four separate summaries, one for each graph of the month. The important values to be noted down is the slope value of the linear model line, the p-value of the significance of the slope, and the t-value (shown highlighted in figure 1).

Figure 1: Example of a Summary from the Linear Model

```
Coefficients:
                                Estimate Std. Error      t value   Pr(>|t|)
(Intercept)                     2.727e+02     2.346e+02   1.162    0.259
jun.Mean_dMean.14138850$dates 1.523e-03     1.738e-02    0.088     0.931

Residual standard error: 176.2 on 19 degrees of freedom
(42 observations deleted due to missingness)
Multiple R-squared:  0.0004037,   Adjusted R-squared:  -0.05221
F-statistic: 0.007674 on 1 and 19 DF,  p-value: 0.9311
```

The P-Value is a statistical measurement of the significance. In our programs, the P-Value is measured on the linear regression slope of the trend analysis plot point graphs. Table 4 is a ranking system of the P-Values based on their significance and the sign of the slope (negative or positive). This makes it easier to identify the trends when mapped. Every single P-value is analyzed and ranked based on the following ranking system in Table 4.

Table 4: P-values Key for Mapping

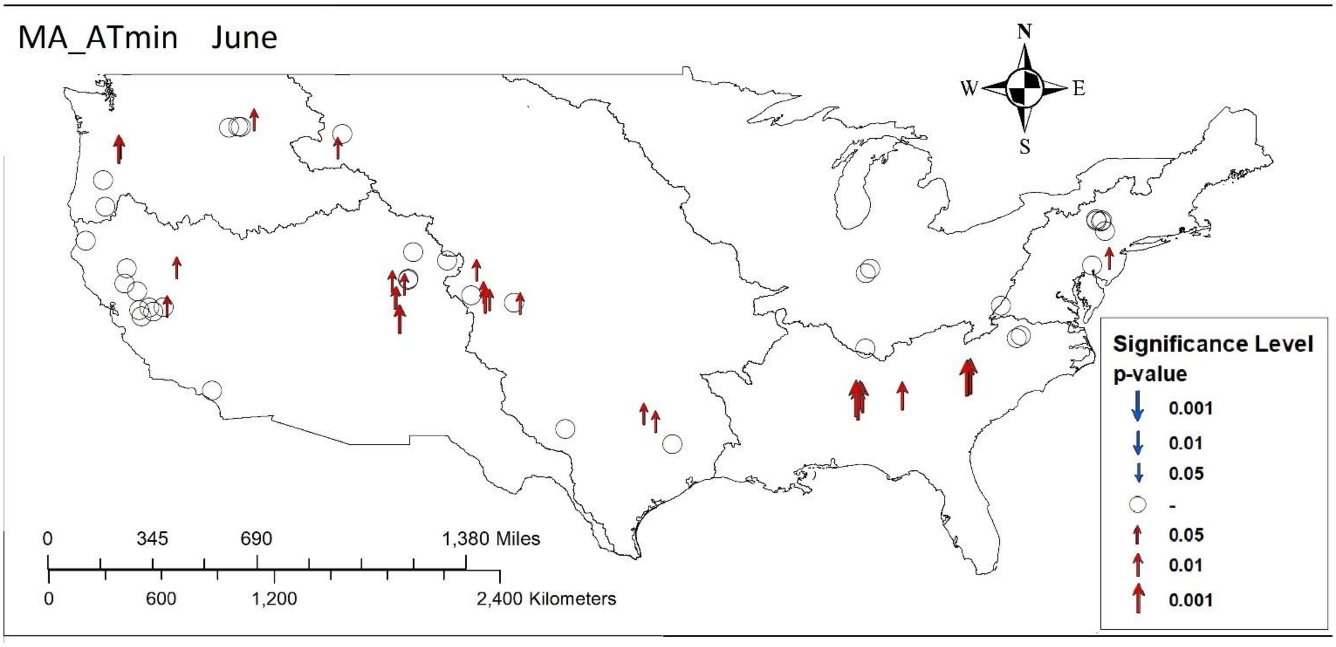
P-Value	Slope	Rank	Symbol
P < 0.001	-	1	Large Blue Arrow
P < 0.01	-	2	Medium Blue Arrow
P < 0.05	-	3	Small Blue Arrow
P ≥ 0.05	- / +	4	Hollow Circle
P < 0.05	+	5	Small Red Arrow
P < 0.01	+	6	Medium Red Arrow
P < 0.001	+	7	Large Red Arrow

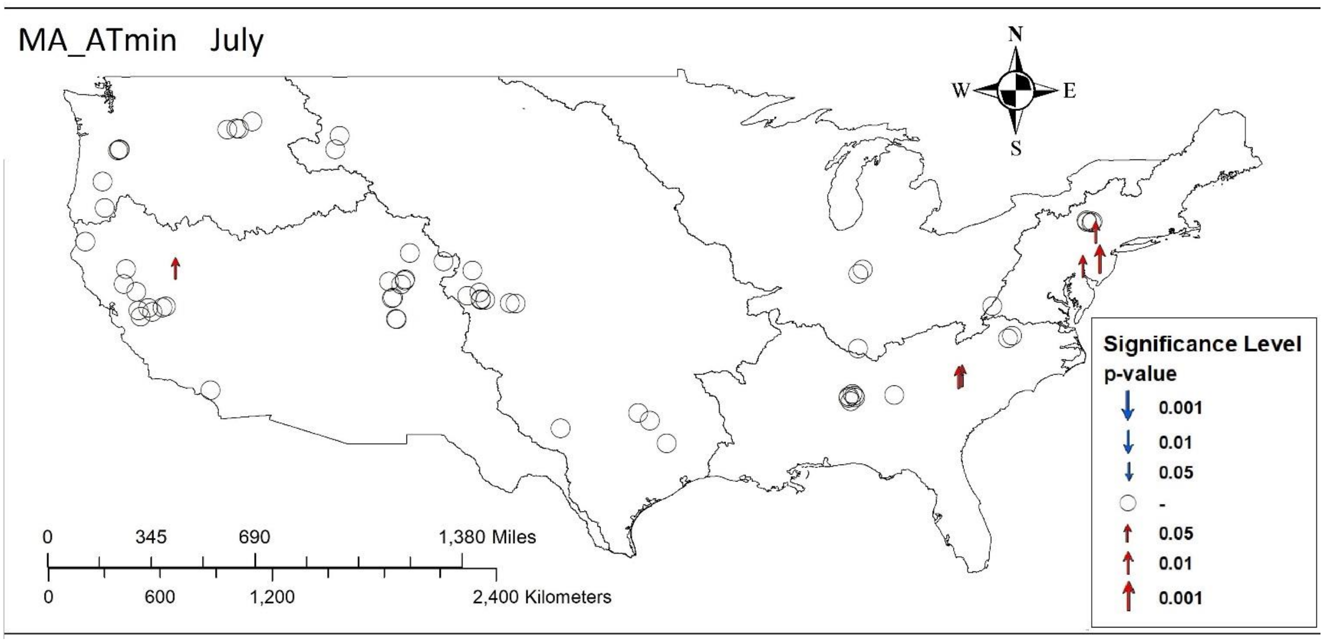
Results

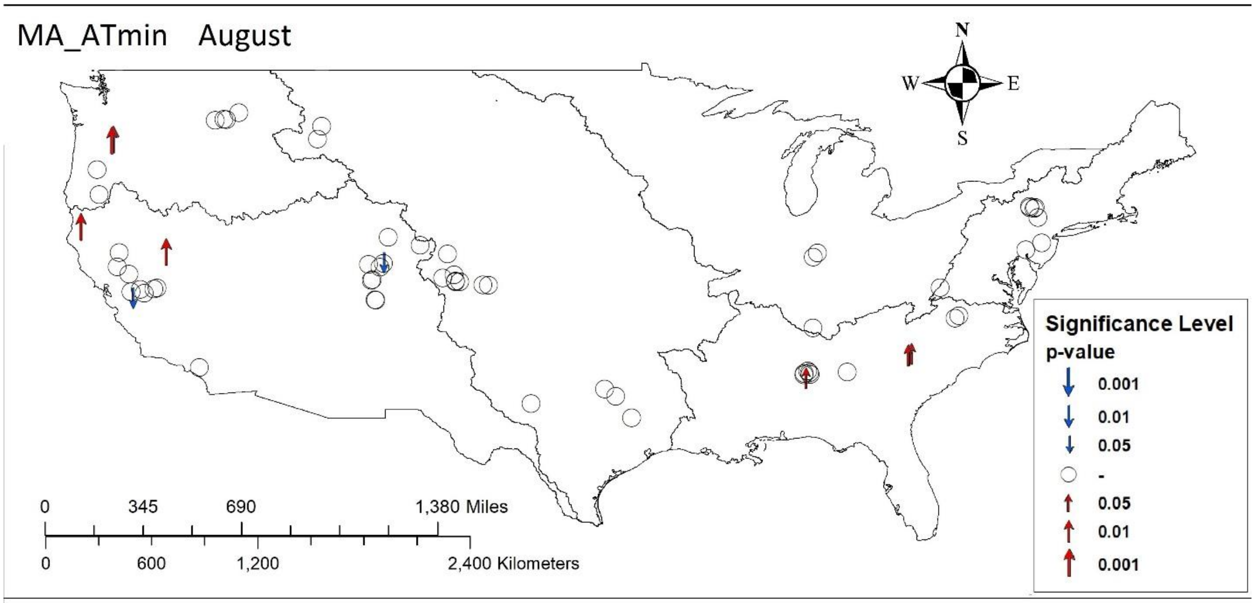
The maps in Figures 2, 3, and 4, show the P-values plotted for each station. Each map is one month for the continental United States. Positive P-values for MA_ATmin and 7dSTmax determine an increase in temperature for that region and the more significant the P-value is, the more significant of an increase. Negative P-values for MA_ATmin and 7dSTmax determine a decrease in temperature for that region and the more significant the P-value, the more significant the air temperature decrease is. The positive values for 7dQmin determine an increase of streamflow and the negative values determine and decrease of streamflow.

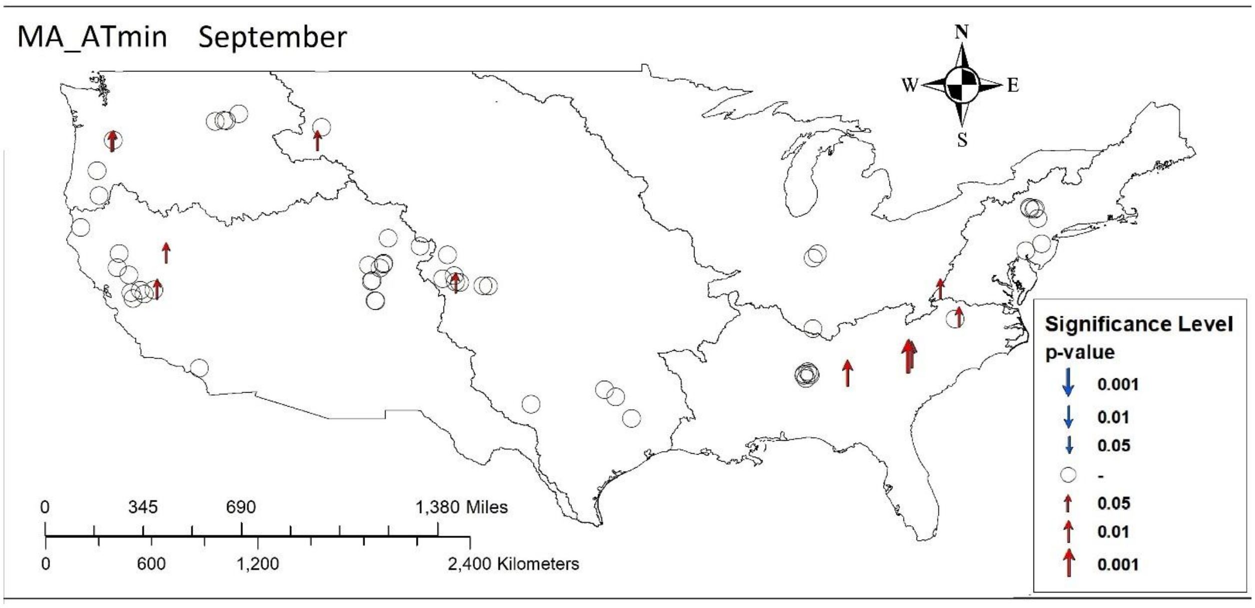
MA_ATmin for June had 33 stations with significance. 19 stations with positive $p < 0.05$ were in CA, CO, ID, MT, NV, NJ, OR, and TX. Eight stations with positive $p < 0.01$ were in AL, CO, GA, and OR. Six stations with positive $p < 0.001$ were in AL and SC. MA_ATmin for July had nine stations with significance. Six stations with positive $p < 0.05$ were in NV, NY, PA, SC. One station with a positive $p < 0.01$ located in NJ. Two stations with negative $p < 0.05$ were both in CA. MA_ATmin for August had 15 stations with significance. Four stations with positive $p < 0.05$ were in AL and SC. Six stations with $p < 0.01$ located in CA, NV, and OR. Three stations with negative $p < 0.05$ were in CA and CO and two stations with negative $p < 0.01$ were in CA and CO. MA_ATmin for September had 14 stations with significance. Nine stations with positive $p < 0.05$ were in CA, CO, MT, NC, OR, and VA. Two stations with positive $p < 0.01$ were in GA and SC and two stations with positive $p < 0.001$ were both in SC. One station with negative $p < 0.05$ was in CA.

Figure 2: United States Map with MA_ATmin P-values Plotted



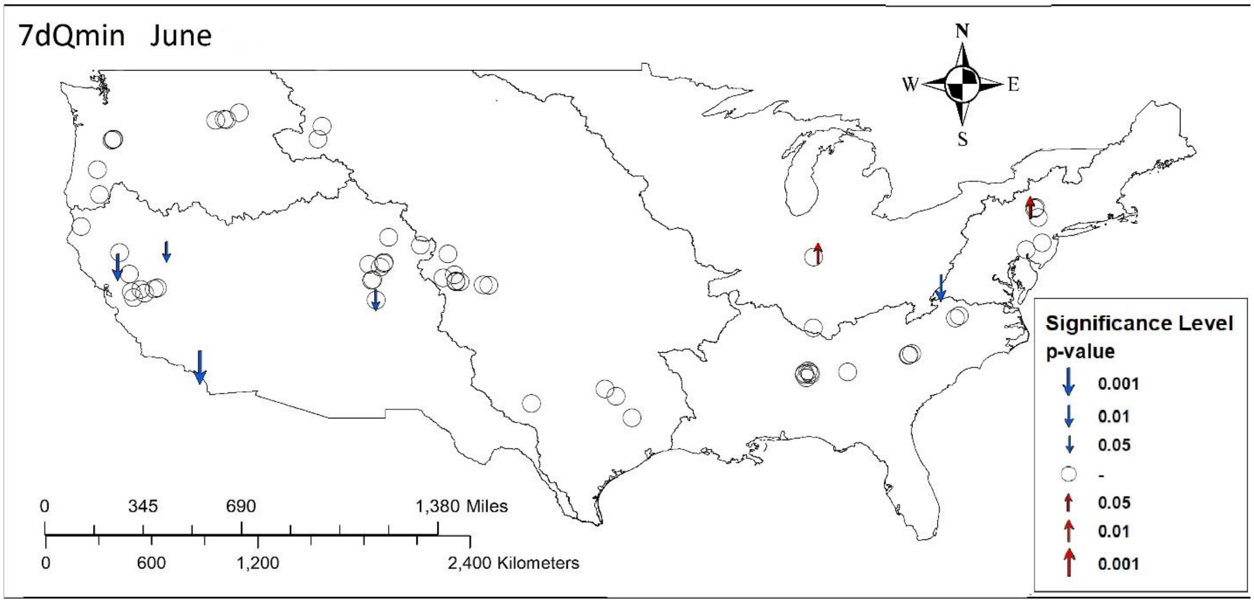


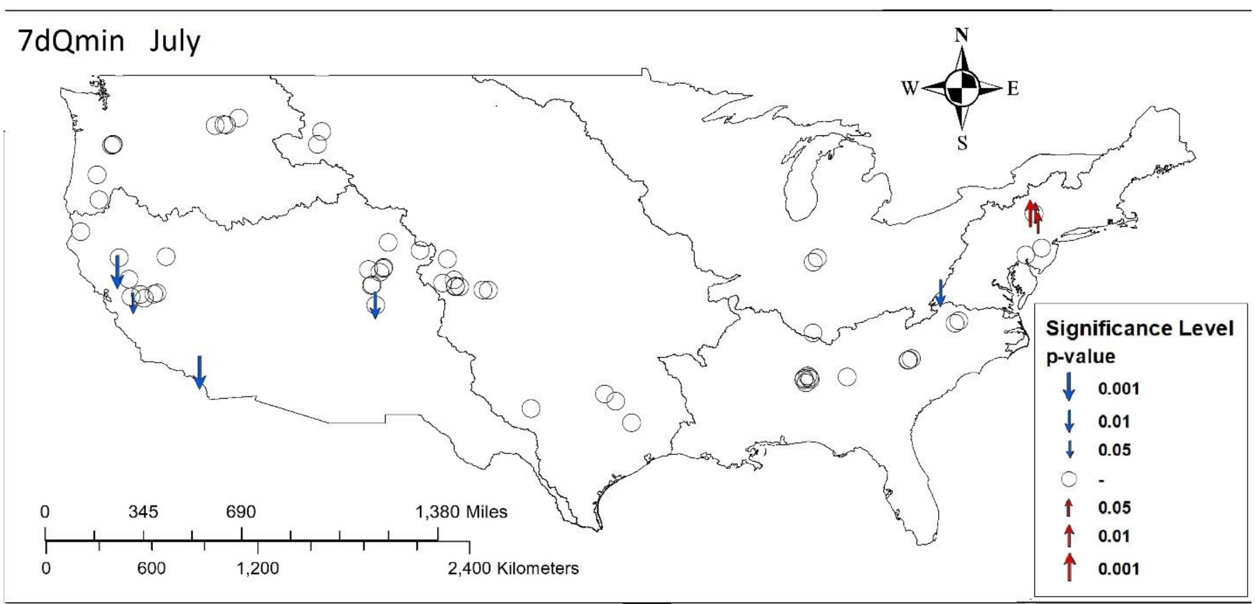

MA_ATmin August
N
W
E
S
Significance Level
p-value
0.001
0.01
0.05
-
0.05
0.01
0.001
0 345 690 1,380 Miles
0 600 1,200 2,400 Kilometers

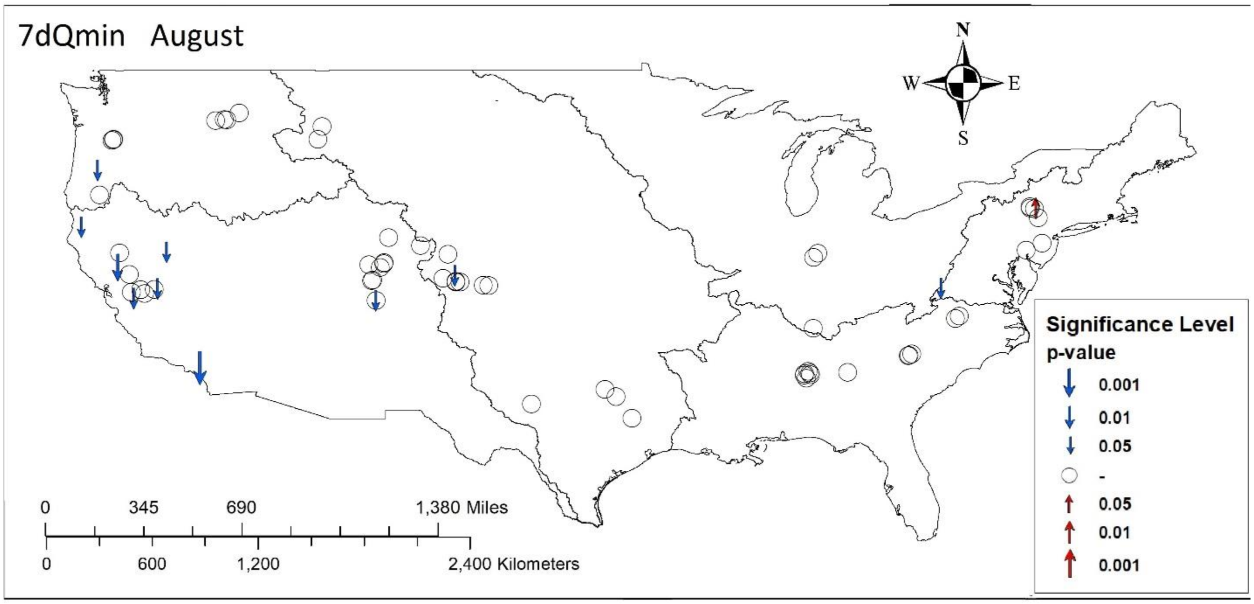

MA_ATmin September
N
W
E
S
Significance Level
p-value
0.001
0.01
0.05
-
0.05
0.01
0.001
0 345 690 1,380 Miles
0 600 1,200 2,400 Kilometers

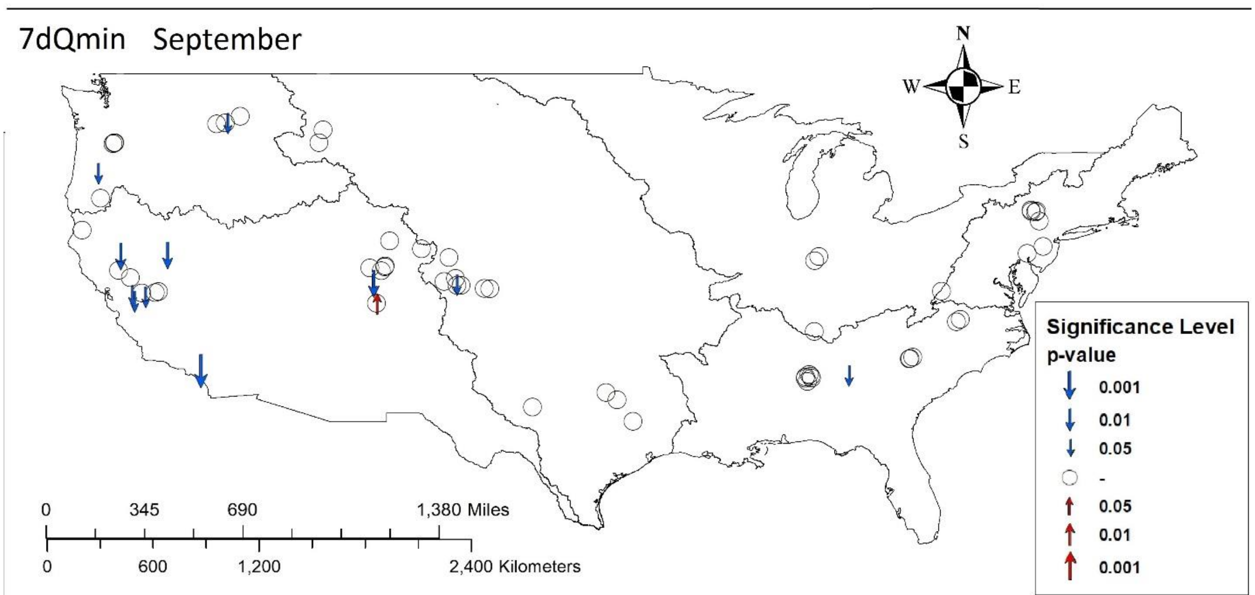
7dQmin for June had 10 stations with significance. Three stations with positive $p < 0.05$ were in IN and NY. Two stations with negative $p < 0.05$ were in CO and NV. Three stations with negative $p < 0.01$ were in CA and VA. Two stations with negative $p < 0.001$ were in CA. 7dQmin for July had 12 stations with significance. Three stations with positive $p < 0.05$ were in NY. One station with positive $p < 0.01$ is in NY. Two stations with negative $p < 0.05$ is in CA. Two stations with negative $p < 0.01$ is in CO and VA. Four stations with negative $p < 0.001$ were in CA. 7dQmin for August had 13 stations with significance. One station with positive $p < 0.05$ was in NY. Eight stations with negative $p < 0.05$ were in CA, CO, NV, OR, and VA. Two stations with negative $p < 0.01$ were in CA and two stations with negative $p < 0.001$ were in CA. 7dQmin for September had 16 stations with significance. One station with positive $p < 0.05$ was in CO. Nine stations with negative $p < 0.05$ were in CA, CO, GA, ID, OR. Five stations with negative $p < 0.01$ were in CA, CO, and NV and one station with negative $p < 0.001$ was in CA.

Figure 3: United States Map with 7dQmin P-values Plotted



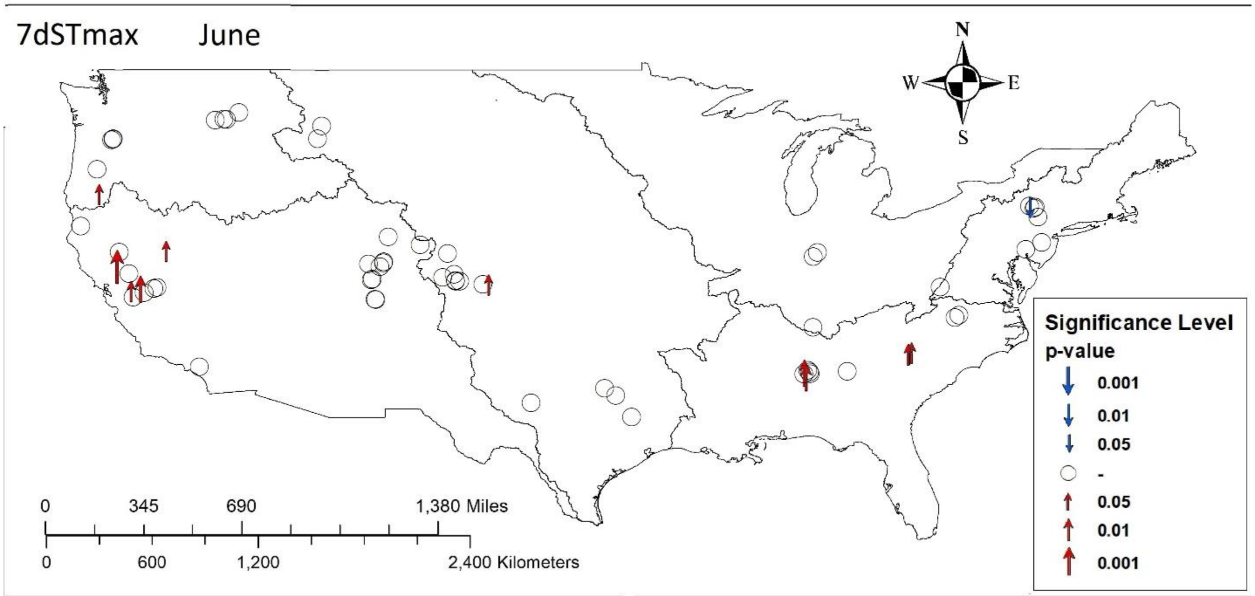


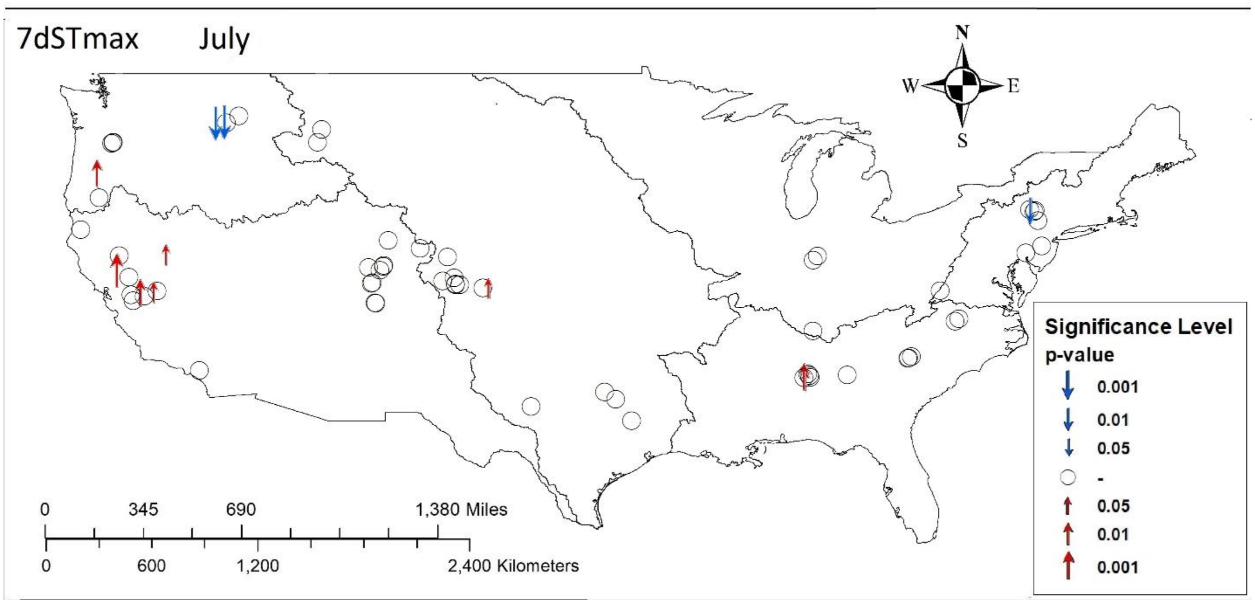

7dQmin August
N
W
E
S
Significance Level
p-value
0.001
0.01
0.05
-
0.05
0.01
0.001
0
345
690
1,380 Miles
0
600
1,200
2,400 Kilometers

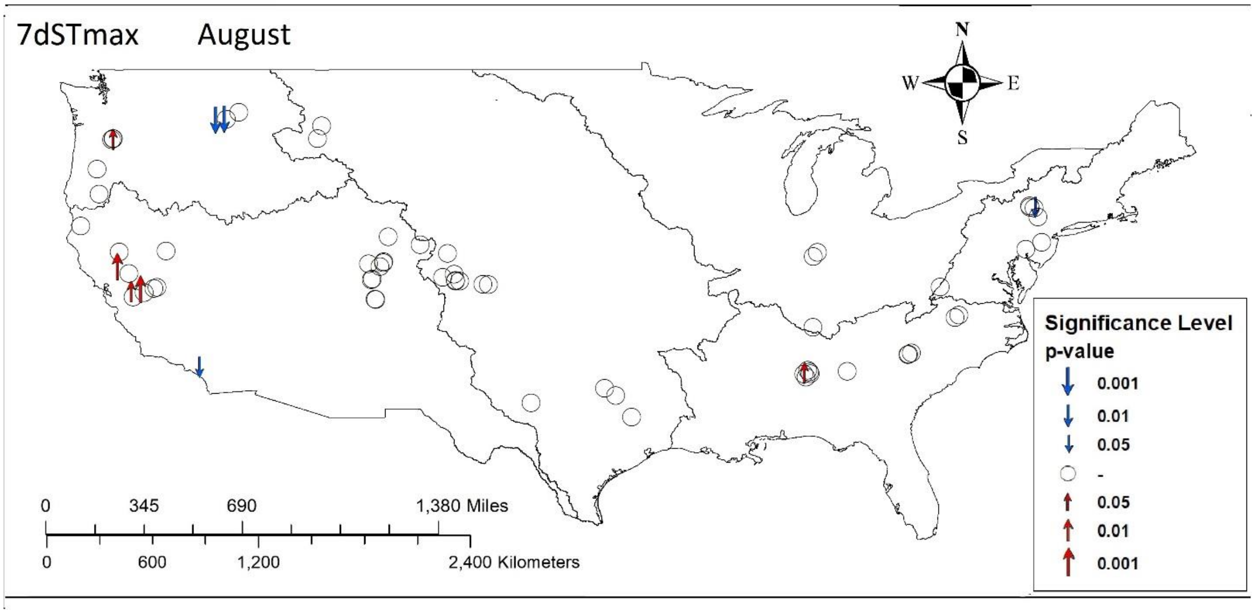

7dQmin September
N
W
E
S
Significance Level
p-value
0.001
0.01
0.05
-
0.05
0.01
0.001
0
345
690
1,380 Miles
0
600
1,200
2,400 Kilometers

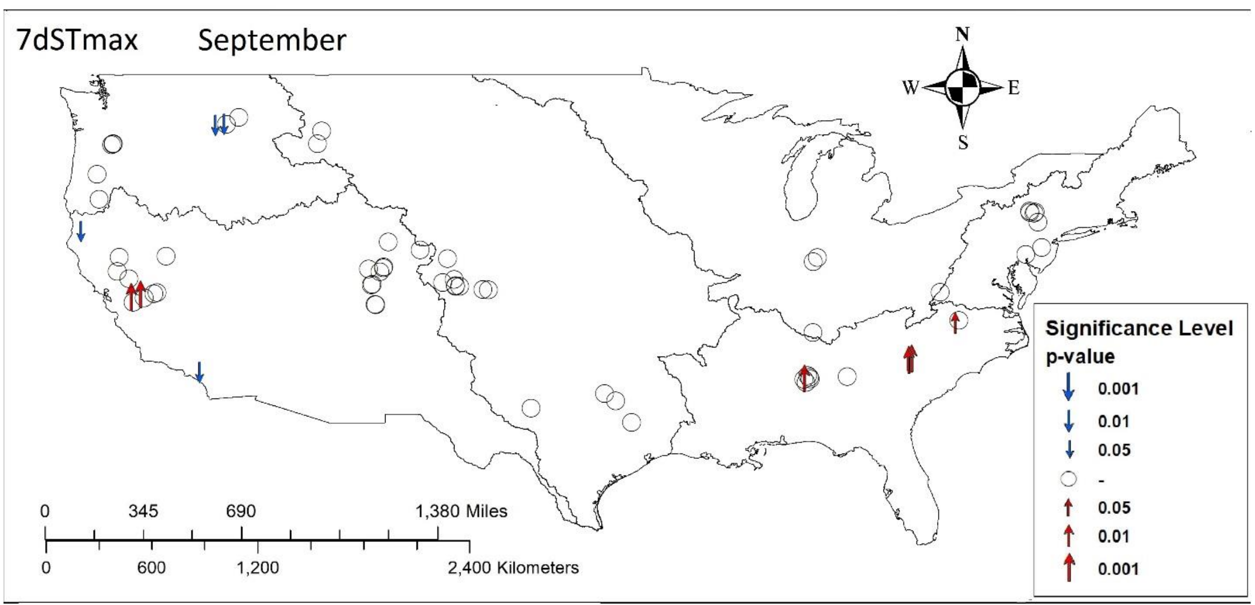
7dSTmax for June had a total of 13 stations with significance. Seven stations with positive $p < 0.05$ were in CA, CO, NV, OR, and SC. Three stations with positive $p < 0.01$ were in AL and CA. Two stations with positive $p < 0.001$ were in CA. One station with negative $p < 0.001$ was in NY. 7dSTmax for July has a total of 11 stations with significant trends. Four stations with positive $p < 0.05$ were in AL, CA, CO, and NV. Three stations with positive $p < 0.01$ were in AL, CA, and OR. One station with positive $p < 0.001$ was in CA. One station with negative $p < 0.05$ was in NY and two stations with negative $p < 0.001$ were both in ID. 7dSTmax for August had a total of 10 stations with significant trends. Four stations with positive $p < 0.05$ were in AL, CA, OR, and WA. Two stations with positive $p < 0.01$ were both in CA. Two stations with negative $p < 0.05$ were in CA and NY and two stations with negative $p < 0.01$ were both in ID. 7dSTmax for September had a total of 12 stations with significant trends. Three stations with positive $p < 0.05$ were in NC, SC, and WA. Five stations with positive $p < 0.01$ were in AL, CA, and SC. There were four stations with negative $p < 0.05$ in CA and ID.

Figure 4: United States Map with 7dSTmax P-values Plotted






7dSTmax August
N
W
E
S
Significance Level
p-value
0.001
0.01
0.05
-
0.05
0.01
0.001
0
345
690
1,380 Miles
0
600
1,200
2,400 Kilometers


7dSTmax September
N
W
E
S
Significance Level
p-value
0.001
0.01
0.05
-
0.05
0.01
0.001
0
345
690
1,380 Miles
0
600
1,200
2,400 Kilometers

A statistical program called Statistic Package for the Social Science (SPSS) was used to model the linear regression of all trend analysis variables and geospatial attributes for all stations. The t-values collected for every single trend analysis were used. To identify other variables that may be affecting the stream temperature, data from GAGES-II is used to apply attributes to the trend analysis results (Falcone, 2011). There were 47 different variables also included that were provided from GAGES II. Examples of some of the included attribute values were elevation, precipitation, and vegetation coverage. The dependent variable used for modelling was the 7dSTmax t-values per month. The independent variables were all the rest of the variables mentioned. The R squared value is the coefficient of determination. The higher the percentage of the R squared, the more accurate the model explains the trend of stream temperature. The regression equation is created with the linear regression model using the variables. The equation for June shows that the increasing of 7dSTmaxJun is caused by MA_STmaxJun, CV_7dSTmaxJun, PPTAVG_BASIN. A decrease of 7dSTmaxJun is caused by 7dQminJun. PPTAVG_BASIN is the mean annual precipitation value. The equation for July shows that and increasing of 7dSTmaxJul is caused by MA_STmaxJul, CV_7dSTmaxJul, MA_STmaxJun, LAT, and STOR_NOR_2009. LAT is the latitude value and STOR_NOR_2009 is the dam storage in watershed. The equation for August shows that the increase of 7dSTmaxAug is caused by MA_STmaxAug and CV_7dSTmaxAug. A decrease of 7dSTmaxAug is caused by MAINS100_43. MAINS100_43 is mainstem percentage of mixed forest. The equation for September shows that an increase of 7dSTmaxSep is caused by MA_STmaxSep, CV_7dSTmaxSep, and CV_7dQminSep. A decrease of 7dSTmaxSep is caused by MAINS100_42. MAINS100_42 is mainstem percentage of evergreen forest. Table 5 shows each regression equation and the R squared value.

Table 5: Regression Model Equation by Month

Month	Regression Equation	R^2
June	1.022(MA_STmaxJun) + 0.531(CV_7dSTmaxJun) + 0.003(PPTAVG_BASIN) – 0.125(CV_7dQminJun) - 0.281	0.939
July	0.785(MA_STmaxJul) + 0.263(CV_7dSTmaxJul) + 0.146(MA_STmaxJun) + 0.039(LAT) + 0.00001(STOR_NOR_2009) - 1.550	0.962
August	0.873(MA_STmaxAug) + .367(CV_7dSTmaxAug) - .074(MAINS100_43) + 0.169	0.932
September	0.875(MA_STmaxSep) + 0.314(CV_7dSTmaxSep) - 0.007(MAINS100_42) + 0.12(CV_7dQminSep) + 0.315	0.937

Discussion

It was difficult to come to the conclusion of specific trends in certain areas of the continental United States, due to most stations having no significance in P-values. Noticing the significant trends for each month within the maps of the continental United States seemed to explain some of the reasonings of increasing stream temperatures. There is a correlation in June between air temperature increase for 33 stations, decrease of discharge in 7 stations, and increase of stream temperature in 12 stations. There is a correlation in July between air temperature increase 7 stations, decrease of discharge for 8 stations, and increase of stream temperature for 8 stations. There is a correlation in August between air temperature increase for 10 stations, discharge decrease of 12 stations, and stream temperature increase of 7 stations. There is a correlation in September between air temperature increase of 13 stations, discharge decrease of 15 stations, and stream temperature incease of 8 stations. An example is seen within the California stations. The discharge of these stations have a consistent significant decrease of streamflow throughout the summer months. These discharge trends in California correlate to the significan trends of increase of the stream temperatures. The stations that showed trends opposite of what was hypothesized were not able to be explained. This was because mapping only the P-values of trends was not enough. There needs to be an in depth observation of these stations to explain the trends they show.

For Oregon, there were six stations. In June there was an air temperature increase of four stations, zero stations with discharge trends, and one station with stream temperature increase. In July there was zero air temperature trends, zero discharge trends, and one stream temperature increase. In August there were four stations with temperature increase, one station with discharge decrease, and one station with stream temperature increase. The station with stream temperature increase is different from the station with the discharge decrease. In September there were three stations with air temperature increase, one station with discharge decrease, and zero stream temperature increase. The insufficiency of trends in river stations in Oregon doesn't explain our hypothesis. There needs to be research that looks more closely at river in Oregon and how they may be effected in the future. The reasoning for this may be due to the limited data on these river stations in Oregon.

The regression equations could be used for future research. These equaions include other landscape variables and hydroclimatological factors that could explain the warming trends of stream temperatures. These equations may assist in predicting future river stream temperatures for the summer months.

References

Arismendi, I., Safeeq, M., Dunham, J. B., & Johnson, S. L. (2014). Can air temperature be used to project influences of climate change on stream temperature? *Environmental Research Letters*, *9*(8), 084015. https://doi.org/10.1088/1748-9326/9/8/084015

Arismendi, I., Safeeq, M., Johnson, S. L., Dunham, J. B., & Haggerty, R. (2013). Increasing synchrony of high temperature and low flow in western North American streams: Double trouble for coldwater biota? *Hydrobiologia*, *712*(61). https://doi.org/10.1007/s10750-012-1327-2

Arismendi, I., Johnson, S. L., Dunham, J. B., Haggerty, R., & Hockman-Wert, D. (n.d.). The paradox of cooling streams in a warming world: Regional climate trends do not parallel variable local trends in stream temperature in the Pacific continental United States. *Geophysical Research Letters*, *39*(10). https://doi.org/10.1029/2012GL051448

Chang, H., Jung, I.-W., Steele, M., & Gannett, M. (n.d.). Spatial Patterns of March and September Streamflow Trends in Pacific Northwest Streams, 1958–2008. *Geographical Analysis*, *44*(3), 177–201. https://doi.org/10.1111/j.1538-4632.2012.00847.x

Daly, C., Neilson, R. P., & Phillips, D. L. (1994). A Statistical-Topographic Model for Mapping Climatological Precipitation over Mountainous Terrain. *Journal of Applied Meteorology*, *33*(2), 140–158. https://doi.org/10.1175/1520-0450(1994)033<0140:ASTMFM>2.0.CO;2

Gray, B. R., Robertson, D. M., & Rogala, J. T. (n.d.). Effects of air temperature and discharge on Upper Mississippi River summer water temperatures. *River Research and Applications*, *34*(6), 506–515. https://doi.org/10.1002/rra.3278

Kaushal, S. S., Likens, G. E., Jaworski, N. A., Pace, M. L., Sides, A. M., Seekell, D., … Wingate, R. L. (n.d.). Rising stream and river temperatures in the United States. *Frontiers in Ecology and the Environment*, *8*(9), 461–466. https://doi.org/10.1890/090037

Letcher, B., J Hocking, D., O'Neill, K., Whiteley, A., Nislow, K., & O'Donnell, M. (2015). A robust hierarchical model of daily stream temperature using air-water temperature synchronization, autocorrelation, and time lags. https://doi.org/10.7287/PEERJ.PREPRINTS.1578V1

Luce, C., Staab, B., Kramer, M., Wenger, S., Isaak, D., & McConnell, C. (2014). Sensitivity of summer stream temperatures to climate variability in the Pacific Northwest. *Water Resources Research*, *50*(4), 3428–3443. https://doi.org/10.1002/2013WR014329

McCabe, G. J., Wolock, D. M., Pederson, G. T., Woodhouse, C. A., & McAfee, S. (2017). Evidence that Recent Warming is Reducing Upper Colorado River Flows. *Earth Interactions*, *21*(10), 1–14. https://doi.org/10.1175/EI-D-17-0007.1

Morrill Jean C., Bales Roger C., & Conklin Martha H. (2005). Estimating Stream Temperature from Air Temperature: Implications for Future Water Quality. *Journal of Environmental Engineering*, *131*(1), 139–146. https://doi.org/10.1061/(ASCE)0733-9372(2005)131:1(139)

Rice, K. C., & Jastram, J. D. (2015). Rising air and stream-water temperatures in Chesapeake Bay region, USA. *Climatic Change*, *128*(1–2), 127–138. https://doi.org/10.1007/s10584-014-1295-9

Ryberg, K. R., & Vecchia, A. V. (2012). *waterData--An R package for retrieval, analysis, and anomaly calculation of daily hydrologic time series data, version 1.0* (USGS Numbered Series No. 2012–1168) (p. 16). Reston, VA: U.S. Geological Survey. Retrieved from http://pubs.er.usgs.gov/publication/ofr20121168

van Vliet, M. T. H., Franssen, W. H. P., Yearsley, J. R., Ludwig, F., Haddeland, I., Lettenmaier, D. P., & Kabat, P. (2013). Global river discharge and water temperature under climate change. *Global Environmental Change*, *23*(2), 450–464. https://doi.org/10.1016/j.gloenvcha.2012.11.002