THESIS

# INTER-DAILY TEMPERATURE VARIABILITY

# IN THE SOUTHERN ROCKY MOUNTAINS OF COLORADO

Submitted by

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ABSTRACT

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While daily temperature variability has decreased in northern latitudes, variability across the western United States has increased. Changes in temperature variability can influence hydrological and earth system processes that could have severe ecological impacts. Mountainous areas are more sensitive to warming trends, but daily temperature variability in the Rocky Mountains is unknown. We investigated daily temperature trends across the Yampa and Rio Grande watersheds of the Southern Rocky Mountains in Colorado using 23 Snow Telemetry (SNOTEL) stations at high elevation, snow-covered regions (2521-3536m) and ten Cooperative Observer Program (COOP) stations at lower elevations (1961-2840m). SNOTEL data were homogenized to account for temperature sensor changes in 2003-2006, with five possible bias correction combinations compared. Daily data were detrended using the long-term and annual means, so that the day-to-day variability could be quantified. Trends were analyzed from the mid-1980s to 2022 using the Mann-Kendall significance test and Theil-Sen's rate of change.

Inter-daily temperature variability (ITV) changed over the 30+ year period of evaluation with mixed increases and decreases based on location and time period. Variability in the spring at 26 stations has increased upwards of 0.8°C per 30 years in the spring. Ninety percent of stations have increased in variability up to 1.0°C per 30 years in the fall. In the summer, Yampa area stations decreased in variability while the Rio Grande area stations increased, both significantly. Low elevation COOP stations demonstrated smaller increases in variability than high elevation SNOTEL stations in the Rio Grande watershed throughout all seasons. The Yampa watershed

showed no similar elevational patterns, but rather decreased variability for SNOTEL stations with little change for variability for COOP stations. The scattered decreases in the Yampa area and at lower elevations emphasize the spatiotemporal variability of montane climatology and suggest increased ITV trends across the Rocky Mountain West are watershed and station specific.

## ACKNOWLEDGEMENTS

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In loving remembrance of my grandmother Barbara June Steen, who always believed in the power of education and trying something new.

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# CHAPTER 1: INTRODUCTION

Global mean surface temperatures for the period 2011-2020 were 1.09°C higher compared to the mid-nineteenth century, with a mean increase over land of 1.59°C (IPCC, 2023). While there is a global trend of increasing mean air temperature, the warming pattern exhibits spatial and temporal variations with certain regions experiencing more pronounced extremes than others. The overall warming is associated with a reduction in the diurnal temperature fluctuation, with greater warming of minimum temperatures than maximum temperatures (Easterling et al., 2000). Climate models suggest a reduced diurnal temperature fluctuation could reduce the high-frequency temperature variability and increase the amount of precipitation in extreme events (Karl et al., 1995). Warming intensifies climactic and hydrological processes, including average precipitation and runoff (Labat et al., 2004) as well as timing, intensity and duration of water-related disasters (Yarnal et al., 1997; Reggani and Weerts, 2008; Sang et al., 2010). Temperature variability is not regionally uniform as it is influenced spatially by the seasonal surface energy balance and atmospheric fluctuations, as well as geographical conditions (Gough 2008). Volatility in inter-daily temperature variability (ITV), the extent of temperature fluctuations between two adjacent days, has severe implications for human health, agriculture and ecology (Zhongfeng et al., 2020). These implications range from shifting infectious disease, a decrease in species diversity, and habitat loss (Raffel et al., 2012, Wang et al., 2022).

Increases and decreases in ITV are likely to have strong implications for hydrological processes. Modeling suggests that increased ITV amplifies warming in the extremes, with hottest days warming considerably more than average summer temperatures. Models also suggest decreased ITV in winter, where cold extremes warm more than the average winter temperature (Fisher et al., 2012). Less-cold nights could result in increased ablation and reduced seasonal snow cover (Robeson, 2002), which can lower the albedo and increase solar loading. This can make existing snowpack isothermal and change the onset of snowmelt. Warmer air temperatures could also affect precipitation, leading to increased rain-on-snow events, as well as changes in soil moisture (Musselman et al., 2017).

There are multiple ways to define temperature variability with the most common being the day-to-day temperature range (DTD) which is the absolute difference of the surface air temperature between two adjacent days, and standard deviation (SD) (Karl et al., 1995). The results depend upon the chosen statistic and evaluation time period. Gough (2008) compared DTD and SD methods against three hypothetical climates. SD performed well in orderly and random climates but did not characterize variability as well as DTD in oscillatory climates where temperatures vary in quick succession, such as a cold day followed by warm day, which again is followed by a cold day, etc., where the climate amplifies DTD variability. Variability is commonly compared over discrete time periods, (e.g., daily, weekly, intra-monthly, inter-seasonally, etc.), but large observation windows can allow for overestimates of variance due to seasonal changes creating a seasonal bias. James and Arguez (2015) used SD after removing the daily departure mean from the observation window and estimated variance that was several percent less than the regular SD during seasonal temperature fluctuation.

Regardless of their chosen method, previous studies have examined ITV either in limited regions or using specific stations. Karl et al. (1995) analyzed temperature in China, the former Soviet Union, and the USA using several absolute value differences between two adjacent discrete times (1-day, 2-day, 5-day, 10-day and 30-day, and interannually). The ITV had decreased in the Northern Hemisphere with significant decreases across the USA. Moberg et al. (2000) compared statistical measures and used the intramonthly SD of daily temperature anomalies to find an increase of ITV in southwestern Europe, and a decrease of ITV in northeastern Europe. Rebetez (2001) examined long term temperature records at two different elevations (487m & 1590m) using SD. The ITV for mean temperatures had decreased at the low-elevation site, while only winter saw negative trends for the higher elevation site. For all seasons at the higher elevation station, minimum temperature variability decreased while maximum temperatures increased. At the lower elevation station, increases in both minimum and maximum temperatures were observed for the summer, with decreasing trends in the other seasons. In their study of the Yangtze River Basin, Sang et al. (2012) concluded rugged topography of the basin impacts daily temperature variability, with decreases in the headwaters of the basin due to increased daily minimum temperatures. Most studies using stations in the United States (e.g., Karl et al., 1995; Moberg et al., 2000; Robeson, 2002) show seasonal fluctuation in ITV with overall annual decreases. At present, there are few studies beyond Rebetez (2001) examining ITV elevational differences beyond 1590m using observed temperature data.

*1.1 ITV using the SNOTEL dataset*

The Natural Resources Conservation Service (NRCS) Snow Telemetry (SNOTEL) network <*wcc.nrcs.usda.gov*> was initially designed in the 1970's to measure snow water equivalent in winter snowpack to forecast summer water supply in the western United States (Julander et al.2007). In the mid-1980's, thermistors were added to measure and report daily minimum, average and maximum air temperatures, and these data provide an opportunity to study ITV at higher elevations that develop persistent winter snowpack. However, the thermistors were initially installed without consistency in mounting or measurement protocol, so in the late 1990s through mid-2000s the NRCS implemented a standardized sensor placement with a linear YSI Extended Range thermistor (Julander et al., 2007). This change shows a temperature shift typical in many time series analyses and affects temperature trends (Julander et al., 2007; Oyler et al., 2015; Ma et al., 2019).

Although there are issues with data bias due to the sensor changes, SNOTEL datasets are commonly used to analyze temperature at higher elevations throughout the western United States (Diaz and Eischeid, 2007; Clow, 2010; Pederson et al., 2011). A pairwise homogenization algorithm reduced the overall warming trend observed at higher elevation SNOTEL stations. While there is a global trend of increasing mean air temperature, the warming pattern exhibits spatial and temporal variations, with certain regions experiencing more pronounced extremes than others from a gridded dataset comparing minimum and maximum SNOTEL observations to nearby U.S. Historical Climatological Network (USHCN) station data (Oyler et al., 2015). However, the gridded dataset (henceforth, the "Oyler dataset"), did not match trends observed on the Colorado Front Range and were too spatially uniform (Ma et al., 2019). In examining 68 SNOTEL stations in the Southern Rockies of Colorado, Ma at al. (2019) compared the original SNOTEL dataset, a bias correction based on co-located new and old sensors in Idaho, and the Oyler dataset. Employing a temperature-index Snow Water Equivalent (SWE) model, the authors compared various homogenization methods alongside the original SNOTEL dataset to identify the most effective approach for simulating SWE at each station (Ma et al., 2019).  In 2016, the Snow Survey discovered a bias causing a shift in YSI Extended Range thermistors and in 2023 released bias corrections to be applied to SNOTEL datasets while using those thermistors (Atwood et al., 2023).

*1.2 Question and Objectives:*

For this study, our overarching research question was: Has the ITV changed at high elevation across two study watersheds in Colorado, and if so, how? To address this question, we established the following objectives: 1) Determine the temperature bias correction for individual SNOTEL stations within the study sites. 2) Compute ITV after removing seasonal and long-term climate change-induced trends. 3) Examine the elevational, seasonal, and spatial distribution of ITV across the two study watersheds. There are three bias correction methods to address the first objective: the National Oceanic and Atmospheric Administration (NOAA) $9^{th}$ order polynomial correction (or "NOAA9") recommended by the Snow Survey (Atwood et al., 2023), the 4th order polynomial correction based on the co-located new and old sensor sites in Idaho (referred to as the "Morrisey" method) (Ma et al., 2019), and the Oyler et al., (2015) dataset.

# CHAPTER 2: DATA AND METHODS

## *2.1. Study Sites*

This study focuses on the Yampa and Rio Grande watersheds in the Southern Rocky Mountains in Colorado. The two study sites were chosen due to their long-term SNOTEL and COOP data availability and their previous SNOTEL temperature trend analysis by Ma et al. (2019) based on station selection by Fassnacht and Records (2015) (Table 2-1). COOP stations were chosen to reflect rain-dominated lower elevations whereas SNOTEL stations are more seasonal snow-dominated higher elevation stations above 2300m (Fassnacht et al., 2012). Some COOP and SNOTEL stations are outside of the respective watershed basins; these were chosen due to their proximity to the basins (Fassnacht et al., 2003) and should be representative of spatial variability within and around the basins themselves (Figure 2-1).

### *2.1.1 Yampa River Study Watershed*

The Yampa watershed is mostly a semi-arid plateau in the northwestern corner of Colorado and southern Wyoming. The basin drains 19,800 km$^2$ to the Green River and is bounded by the Park Range and Flat Top mountains. Five SNOTEL and three COOP stations are within the basin itself while five SNOTEL and two COOP stations are in neighboring Colorado River and North Platte River basins (Figure 2-1 and Table 2-1a). In the Yampa watershed, the Hayden COOP is the western-most station at 107.6° W and the northern-most station is Elk River SNOTEL at 40.85° N. Walden COOP is the eastern-most station at 106.28° W in the North Platte watershed, while the southern-most station is Burro Mountain at 39.88° N in the Colorado River watershed. Craig COOP station is the lowest elevation station at 1885m, while Tower SNOTEL station at 3237m is the highest.

### 2.1.2 Rio Grande Study Watershed

The watershed of the upper Rio Grande headwaters subregion is the headwaters for the river of its namesake flowing through 19,600 km$^2$ of the San Luis valley. Most stations of this study fall outside of the western boundary the San Juan mountains into the Gunnison River or Dolores River watersheds, leaving only three stations within the Rio Grande watershed itself (Figure 2-1 and Table 2-1a). Slumgullion SNOTEL station is the furthest north at 38° N while the Pagosa Springs COOP station at 37.24° N is the furthest south. Del Norte COOP at 106.32° W is the eastern-most station, while Cascade #2 SNOTEL is the furthest west. Beartown SNOTEL is the highest elevation station at 3536m; Pagosa Springs COOP is the lowest at 2172m.

## 2.2 Datasets

### 2.2.1 SNOTEL Time Series and Their Adjustment

We downloaded maximum, mean, and minimum temperatures for the 22 SNOTEL stations from the NRCS through the snotelr R package (Hufkins, 2022; Table 2-1). Temperature sensor installation at each station varied from the late 1970s to the early 1980s, but the early data were inconsistent. For most stations, reliable average temperature records begin in water year (WY) 1985 (October 1, 1984 to September 30, 1985); water year 2022 marked the end of the analysis. Exact dates of temperature sensor changes (2002- 2006) were extracted from individual station metadata <*http://www.wcc.nrcs.usda.gov/snow/*>. For each station's period of temperature record, any abnormally high or low values (> three standard deviations) were removed, and any year with more than 15 observations missing (constituting >5% of annual observations) was eliminated. While Ma et al. (2019) interpolated missing observations using neighboring station datasets (also see Morán-Tejeda et al., 2022), we did not interpolate as the presence of missing data should not bias the results with a sufficient sample of years in our analysis.

For this analysis, temperatures were adjusted using the Morrisey method for stations identified by Ma et al. (2019), with the adjustment applied to pre-sensor change mean temperature data at station-specific dates (Table 2-2). It should be noted that the online version of the Oyler et al. (2015) dataset only extends to 2016. Ma et al. (2019) used a temperature index-based SWE model and compared the original SNOTEL data, the gridded temperature dataset created by Oyler et al. (2015), and method used by Morrisey to correct pre-sensor change data (2019). The Morrisey method attempts to correct biases by applying a fourth order polynomial to adjust the pre-sensor dataset:

$$5.3 * 10 - 7\, {T_{old}}^4 + 3.72E * 10^{-5} {T_{old}}^3 - 2.16 * 10^{-3} {T_{old}}^2 - 7.32 * 10^{-2} T_{old} + 1 = T_{adjusted}$$

*(Equation 2-1)*

where $T_{old}$ is the original average temperature from the period before the sensor change, in degrees Celsius (°C), and $T_{adjusted}$ is the adjusted original temperature. For this analysis, we used Ma et al.'s recommended dataset based on the greatest NSE and smallest bias result for each respective SNOTEL station (2019).

Since the Ma et al. (2019) analysis, the NRCS announced the YSI extended range thermistor requires a bias correction of its own. The original thermistor calculated air temperature using a linear least-squares regression algorithm and sensor output voltage, which resulted in a bias when compared to NOAA satellite and, as a result, NRCS recommends correcting all YSI extended range data with a ninth order polynomial equation (2-2) (Atwood et al., 2023).

$$610558.226380138 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^9 - 2056177.65461394 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^8 + 2937046.42906361 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^7 - 2319657.12916417 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^6 + 1111854.33825836 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^5 - 337069.883250001 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^4 + 66105.7015922199 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^3 - 8386.78320604513 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right)^2 + 824.818021779729 * \left(\frac{(T_{(bias-c)}+65.929)}{194.45}\right) - 86.7321006757439 = T_c$$

*(Equation 2-2)*

Between the different pre- and post-sensor corrections, there were five possible dataset combinations that might be representative of the actual temperature (Table 2-2).

*2.2.2 COOP*

Temperature data for low elevations are from the National Weather Service (NWS) Cooperative Observer Program (COOP) < *https://www.weather.gov/coop/Overview*>. COOP stations were chosen because of their long-term datasets and spatial relationships within or near the Yampa and Rio Grande study watersheds. Data were accessed through Iowa State University Iowa Environmental Mesonet <*https://mesonet.agron.iastate.edu*>. It was assumed that any protocol changes in the COOP temperature collection met the data quality measures required by the NWS (Table 2-1).

*2.3 Data Analysis*

*2.3.1 Detrending Temperature Data*

Daily mean temperature observations were detrended to determine whether values were increasing or decreasing from the entire time series trend (Figures 2-2 and 2-3). Daily mean temperatures were first averaged by water year, with all water year means then averaged by day of water year. The mean temperature by day for the period of record was averaged. To find the standard deviation, the daily mean temperatures by water year were subtracted from the averaged mean temperature by day for the period of record. All water year means averaged by day of water year were subtracted from the temperature mean. The resulting values were then added together to find the "residual" of the daily mean temperatures by water year. Since the residuals approach a normal distribution, standard deviation is appropriate for this analysis (Appendix B).

*2.3.2 Variability Analysis*

To understand variability in the daily mean temperature for each SNOTEL and COOP station, the standard deviation was then computed from the residual absolute value subtracted from the previous day (Figures 2-2 and 2-3). The significance of the trends was computed from the Mann-Kendall non-parametric test (Mann, 1945; Kendall and Gibbons, 1990; Gilbert, 1987). Although significance is typically accepted with p-values of 0.05, we included moderately significant trends, identified with p-values <0.10. The rate of change was computed as the Theil-Sen's slope (Theil, 1950; Sen, 1968; Gilbert, 1987), the value of which was then multiplied by 30 to represent the amount of temperature (°C) change per 30 years. The ITV was assessed annually. Seasons were based on monthly time periods to consider snow accumulation as "winter," snowmelt as "spring," snow-all-gone as "summer," and potential snow fall as "fall." (Table 2-3).

*2.3.3 Dataset Comparison*

The assumed "least incorrect" or "assumed truth" SNOTEL temperature dataset (henceforth "reference dataset") was a station-dependent, pre-sensor change original SNOTEL data or Morrisey method correction combined with the NOAA9 post sensor change. The mean temperature and Theil-Sen's slope of the SD from the five different bias correction combinations (Table 2-2) were compared using Crosho (426) and Ripple Creek (717) SNOTEL station data (Table 2-1). Results were evaluated using Nash-Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE) tests (Nash and Sutcliffe, 1970; Gutpa et al., 2009).

**Table 2-1**. Station metadata for (a) Yampa and (b) Rio Grande watershed basin COOP and SNOTEL stations with station number, elevation, latitude and longitude.

| **Station Name** | **Number** | **Elevation (meters)** | **Latitude (degrees)** | **Longitude (degrees)** |
|---|---|---|---|---|
| (a) Yampa River | | | | |
| Steamboat | CO7936 | 2052 | 40.49 | -106.82 |
| Hayden | CO3867 | 1961 | 40.49 | -107.25 |
| Walden | CO8756 | 2469 | 40.74 | -106.28 |
| Kremmling | CO4664 | 2229 | 40.06 | -106.37 |
| Craig | CO1932 | 1885 | 40.45 | -107.59 |
| Burro Mountain | 378 | 2840 | 39.88 | -107.6 |
| Columbine | 408 | 2794 | 40.24 | -106.36 |
| Crosho | 426 | 2735 | 40.17 | -107.06 |
| Dry Lake | 457 | 2521 | 40.53 | -106.78 |
| Elk River | 467 | 2664 | 40.85 | -106.97 |
| Lynx Pass | 607 | 2719 | 40.08 | -106.67 |
| Rabbit Ears | 709 | 2868 | 40.37 | -106.74 |
| Ripple Creek | 717 | 3155 | 40.11 | -107.29 |
| Tower | 825 | 3237 | 40.54 | -106.68 |
| Trapper Lake | 827 | 2975 | 40 | -107.24 |
| (b) Rio Grande | | | | |
| Del Norte | CO2184 | 2403 | 37.67 | -106.32 |
| Hermit 7 ESE | CO3951 | 2743 | 37.77 | -107.11 |
| Pagosa Springs | CO6258 | 2172 | 37.24 | -107.02 |
| Silverton | CO7656 | 2840 | 37.81 | -107.66 |
| Valencito | CO8582 | 2377 | 37.38 | -107.58 |
| Beartown | 327 | 3536 | 37.43 | -107.31 |
| Cascade #2 | 387 | 2747 | 37.66 | -107.8 |
| Idarado | 538 | 2991 | 37.93 | -107.68 |
| Middle Creek | 629 | 3435 | 37.85 | -107.73 |
| Molas Lake | 632 | 3240 | 37.75 | -107.69 |
| Red Mountain Pass | 713 | 3377 | 37.89 | -107.71 |
| Slumgullion | 762 | 3523 | 37.99 | -107.2 |
| Spud Mountain | 780 | 3253 | 37.7 | -107.78 |
| Stump Lakes | 797 | 3428 | 37.48 | -107.63 |
| Upper Rio Grande | 839 | 2859 | 37.43 | -107.16 |
| Upper San Juan | 840 | 3091 | 37.49 | -106.84 |
| Vallecito | 843 | 3286 | 37.49 | -107.51 |
| Wolf Creek Summit | 874 | 3340 | 37.29 | -106.48 |

**Table 2-2**. Possible pre-sensor and post sensor SNOTEL bias correction combinations.

| Pre-sensor dataset | Post-sensor dataset |
|---|---|
| original SNOTEL | original SNOTEL |
| Oyler | Oyler |
| Morrisey | original SNOTEL |
| original SNOTEL | NOAA9 |
| Morrisey | NOAA9 |

**Table 2-3**. Seasonal time periods used in the data analysis.

| Season | Calendar Period | Water Year day start | Water Year day end |
|---|---|---|---|
| Spring | Apr 1 to May 31 | 183 | 243 |
| Summer | Jun 1 to Aug 31 | 244 | 335 |
| Fall | Sept 1 to Oct 31 | 336 | 31 |
| Winter | Nov 1 to March 31 | 32 | 182 |

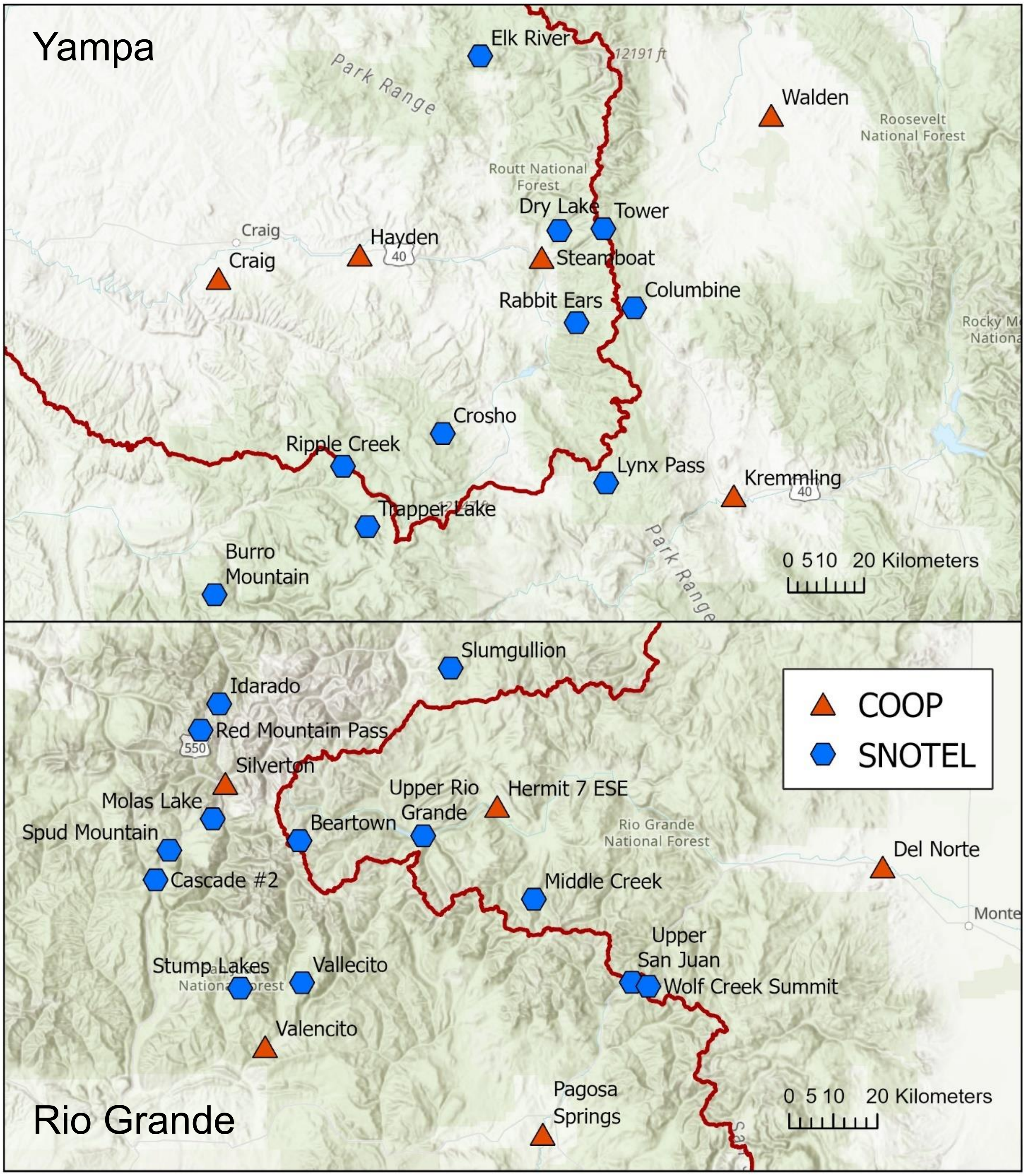


**Figure 2-1**. Site map of the Yampa (north) and Rio Grande (south) watershed study basins.

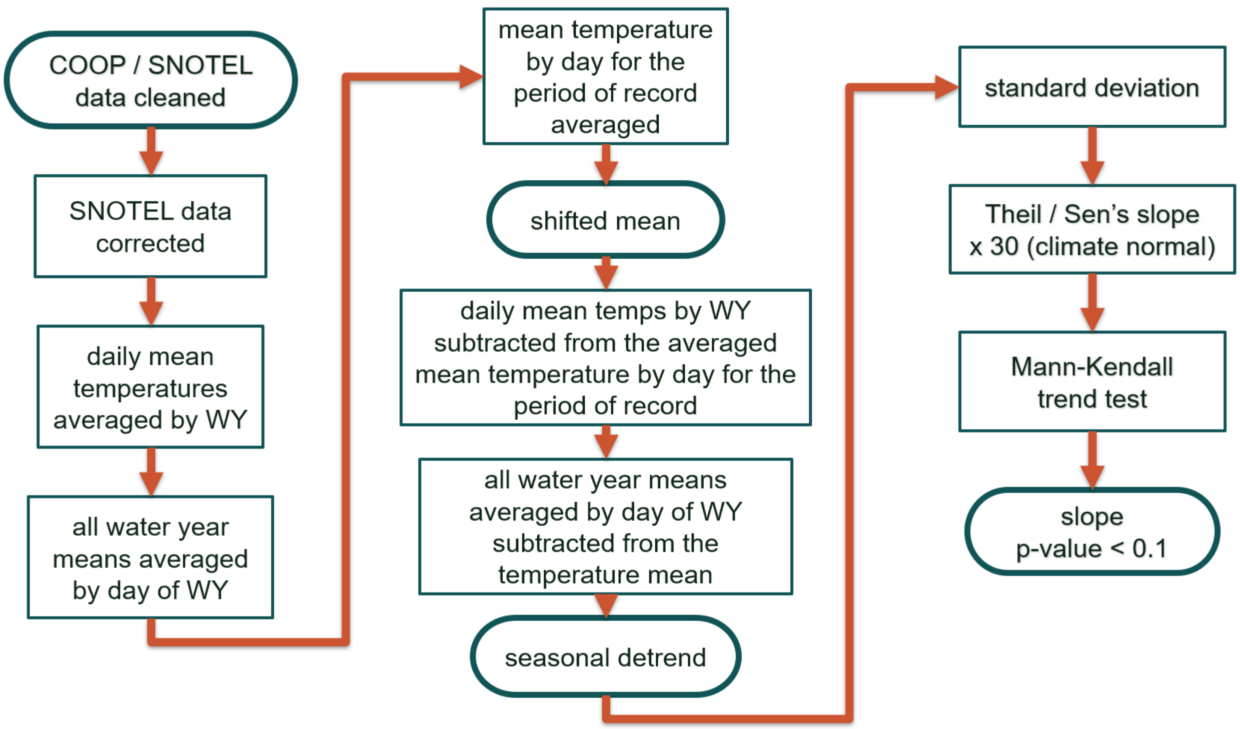


**Figure 2-2**. Schematic of detrending process and analysis.

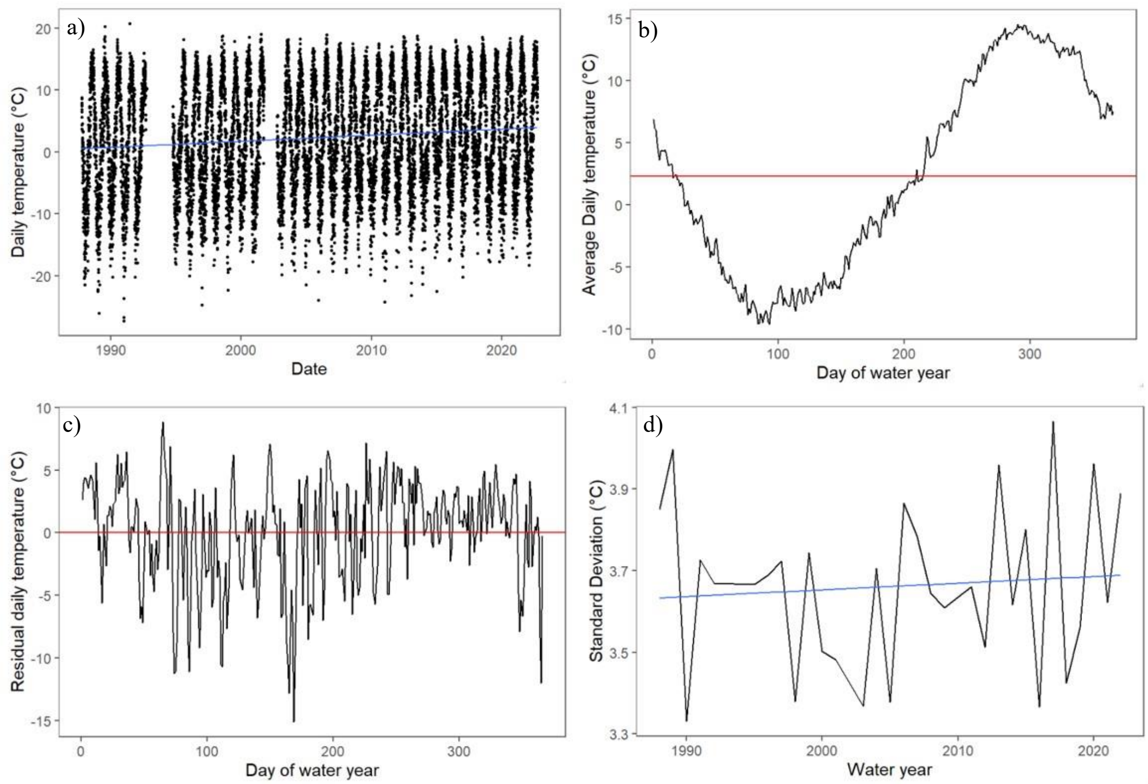


**Figure 2-3**. Example data analysis for Columbine SNOTEL, station 408. Daily temperature data (a) were cleaned (and corrected for sensor changes at relevant SNOTEL stations), with (b) the warming trend removed by shifting the mean. Annual seasonal trends (c) were removed, with the standard deviation (d) taken by water year.

# CHAPTER 3: RESULTS

## *3.1 SNOTEL Bias Correction Comparison*

For the Crosho SNOTEL station, all bias corrections had significant warming trends with the original dataset trending 1.2°C warmer per climate normal than the reference dataset (Morrisey/NOAA9) (Figure 3-1a, Table 3-1). The Morrisey and Oyler corrections yielded the largest increase and decrease, respectively for Crosho mean temperatures from the reference dataset at ±0.8°C. The original/NOAA9 correction had the closest mean temperature and the highest NSE and KGE values in comparison to the reference dataset. Both Oyler and Morrisey correction methods' NSE values of were similar to the reference dataset, however both had lower KGE values. The warming trends computed from the Theil-Sens slope were nearly the same at 0.3°C per 30 years for Morrisey/NOAA9, Morrisey and original/NOAA9, with significant p-values. The original and Oyler datasets yielded a negative and smaller trend respectively; neither were significant (Figure 3-1c). The slope of original/NOAA9 was the closest to the reference dataset as reflected by NSE and KGE values, whereas the other methods had low or negative NSE values (Table 3-1).

The mean temperatures for all methods at Ripple Creek SNOTEL exhibited warming trends, although only original/NOAA9 and Oyler methods were significant (Figure 3-1b, Table 3-1). The Oyler method yielded nearly a 3°C warmer mean temperature at Ripple Creek than the assumed reference dataset. The original/NOAA9 dataset was 0.1°C cooler while the original and Morrisey were 0.4 and 1.0°C warmer respectively. The NSE of 1 for the original/NOAA9 method highlighted the similarity of the mean temperature of the reference dataset, although this was not reflected by the KGE value. Morrisey and the original had high NSE values but low or negative KGE values while the Oyler method had low values for both tests. Theil-Sens slope warming trends for the assumed reference dataset, Morrisey and original/NOAA9 were all nearly 0.1°C per 30 years. The original and Oyler methods had negative Theil-Sens slope cooling trends of 0.2 and 0.1°C per 30 years respectively; of all the methods, only the original's trend was significant. Similar to Crosho, the NSE and KGE of original/NOAA9 was closest to the reference dataset for Ripple Creek. Morrisey and the original had larger KGE values but low and negative NSE values respectively, while the Oyler method showed no similarity to the reference dataset in its slope trends (Figure 3-1d, Table 3-1).

*3.2 Spatial Inter-daily Temperature Variability*

Annualized trends in ITV at both study sites were variable (Figure 3-2a). Walden COOP and nearby Tower SNOTEL in the Yampa area had the largest increase at 0.7°C and largest decrease at -0.5°C in ITV over the 30-year timeframe. Both were significant, as was an increase of 0.2°C at Crosho SNOTEL station. 33% of Yampa area stations (one COOP, four SNOTEL) decreased in ITV over the previous 30 years while the remaining stations warmed. In the southern Rio Grande area, 15% of SNOTEL stations decreased in ITV; of the remaining stations 72% had significant warming trends of 0.2 to 0.5°C per 30 years. Three of the five COOP stations decreased in ITV with Pagosa Spring station decreasing significantly at -0.3°C per 30 years.

Spring (April through May) ITV had largely increased in both the Yampa and Rio Grande study areas (Figure 3-2b). Of the 33 stations, 26 showed an increase in ITV greater than 0.05°C, with a maximum increase of 0.8°C per 30 years. Five showed decreases less than -0.05°C, with a maximum decrease of -0.3°C per 30 years. 27% of the Yampa and 28% of the Rio Grande area stations had significant increases in temperatures, all of which were 0.4°C increases or greater.

The Walden COOP station and the Middle Creek SNOTEL showed the greatest ITV increases, both at 0.8°C per 30 years, in the Yampa and Rio Grande areas.

Summer (June through August) ITV was mixed compared to the spring season. 72% of the southern Rio Grande area stations exhibited increased variability with 62% of those stations having significant increases, with an average increase in ITV of 0.2°C per 30 years (Figure 3-2c). Four of the five COOP stations showed decreasing ITV with a significant decrease at Pagosa Springs COOP station. Only one SNOTEL station in the area demonstrated any decrease. In the Yampa area, the trends were reversed with an average of -0.1°C per 30 years; only four stations exhibited increases in ITV. Rabbit Ears SNOTEL showed the largest increase at 0.9°C over the climate normal, which is anomalous to the rest of the study areas' stations. Walden COOP again exhibited significant increases in variability. 11 of the remaining areas showed decreases up to -0.7°C per 30 years; 45% of those were significant.

Much like spring, fall (September through October) variability had increased in both study areas. Of the 30 stations with greater or less than ±0.05°C, 90% had increased in variability (Figure 3-2d). ITV had increased mostly in the Rio Grande area, with an average of 0.3°C per 30 years and a maximum of 1.0°C per 30 years at the Wolf Creek Summit SNOTEL. All Rio Grande SNOTEL stations showed increased ITV with seven SNOTEL stations having significant increases in temperature, whereas only two of the three Rio Grande COOP stations had increased in temperature. In the Yampa area, all COOP stations exhibited an increase in temperature, the greatest of which was Walden station at 1.0°C per 30 years. The Yampa area SNOTEL stations had a wider range of variability, with three stations showing a decrease in variability and the remaining exhibiting an increase at a smaller magnitude than the Rio Grande SNOTEL stations.

Winter (November through March) ITV demonstrated relatively little change in temperature variability in the Rio Grande area, with an average of -0.01°C per 30 years and only Pagosa Spring COOP station demonstrated a significant decrease (Figure 3-2e). Wolf Creek Summit SNOTEL station had the largest increase in ITV at 0.3°C per 30 years, but neither it nor the other SNOTEL stations in the area had any significant variability. In the northern Yampa area, Walden COOP again showed significant increases in variability at 0.7°C. Only 33% of stations in the Yampa area showed increases in variability, although only two were significant. Trapper Lake SNOTEL had the largest decrease at -0.6°C per 30 years, although it was the only significant decrease in the area. The remaining 90% of the stations had an average of -0.04°C per 30 years.

### *3.3 Inter-daily Temperature Variability at Elevation*

Over the annual time series, no obvious trend in elevational components was observed in the Yampa watershed for either SNOTEL or COOP stations (Figure 3-3a). In the Rio Grande area, 83% of SNOTEL stations exhibited increases in ITV ranging from 0.14°C to 0.49°C per 30 years, while COOP stations in the area showed no uniformity. Seven SNOTEL stations in the Rio Grande had significant increasing trends (Figure 3-3a).

During the spring season, SNOTEL stations in the Yampa area demonstrated both increases and decreases in variability, whereas in the Rio Grande area, only the lowest SNOTEL station (Cascade #2) exhibited decreased variability. Among the 10 stations located above 2991m, five stations showed significant increases in variability ranging from 0.46°C to 0.79°C per 30 years. All COOP stations in the Yampa area exhibited increased variability, with significant increases observed above 2000m. Conversely, Rio Grande COOP stations showed no discernible elevational patterns (Figure 3-3b).

In the summer season, only one SNOTEL station in the Yampa area (Rabbit Ears SNOTEL) exhibited an increase in ITV (0.89°C per 30 years), while the remaining nine stations demonstrated decreases ranging from -0.12°C to -0.67°C, with five of them being significant. In the Rio Grande area, 83% of SNOTEL stations above 2990m showed increased variability, with 70% demonstrating significant increases ranging from 0.16°C to 0.65°C per 30 years. None of the COOP stations in either watershed exhibited any elevational influence on variability.

The largest increases in variability were observed during the fall season (Figure 3-3d). In the Yampa area, all COOP stations showed increased ITV, with two stations between 2000m and 2500m demonstrating significant increases of 0.55°C and 0.96°C per 30 years. Additionally, 70% of SNOTEL stations in the Yampa area showed increased ITV, although the highest station (Tower SNOTEL) displayed decreased ITV. In the Rio Grande area, COOP stations showed no clear trend in variability, while all SNOTEL stations exhibited increased ITV. Stations above 3200m exhibited the largest spread of variability increase, although only stations with increases greater than 0.5°C per 30 years were significant above that elevation. No obvious patterns of increased or decreased variability were observed in the winter over the period of record (Figure 3-3e), with the fewest stations (two SNOTEL in the Yampa and one COOP in each study area) showing significant trends.

**Table 3-1.** Summary of the mean and standard deviation (SD) of daily temperatures for the five correction methods, with a comparison to the Morrisey/NOAA9 method with the Nash-Sutcliffe efficiency (NSE) and Kling-Gupta efficiency (KGE) coefficients, plus the Theil-Sen's slopes rate of change and the Mann-Kendall test p-values for the a) Crosho and b) Ripple Creek SNOTEL stations. Bolded values are significant.

| | Temperature | | | | | SD | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Correction method** | **Mean (°C)** | **NSE** | **KGE** | **Theil-Sens *30** | **p-value** | **NSE** | **KGE** | **Theil-Sens *30** | **p-value** |
| a) Crosho SNOTEL | | | | | | | | | |
| Morrisey/ NOAA9 | 3.05 | - | - | **1.49** | 0.001 | - | - | **0.285** | 0.022 |
| Original | 3.33 | 0.993 | 0.899 | **2.73** | $7x10^{-8}$ | 0.226 | 0.703 | -0.021 | 0.783 |
| Morrisey | 3.88 | 0.989 | 0.718 | **1.35** | 0.001 | -0.896 | 0.940 | **0.276** | 0.034 |
| Original/ NOAA9 | 2.96 | 0.993 | 0.971 | **1.71** | $9x10^{-5}$ | 0.999 | 0.994 | **0.276** | 0.029 |
| Oyler | 2.23 | 0.952 | 0.805 | **1.48** | 0.003 | 0.023 | 0.716 | 0.050 | 0.837 |
| b) Ripple Creek SNOTEL | | | | | | | | | |
| Morrisey/ NOAA9 | 0.83 | - | - | 0.25 | 0.272 | - | - | 0.092 | 0.358 |
| Original | 1.20 | 0.992 | 0.553 | **1.89** | $9x10^{-6}$ | 0.458 | 0.811 | **-0.191** | 0.050 |
| Morrisey | 1.82 | 0.983 | -0.180 | 0.286 | 0.272 | -0.653 | 0.946 | 0.076 | 0.374 |
| Original/ NOAA9 | 0.74 | 1.000 | 0.892 | **0.490** | 0.070 | 0.997 | 0.996 | 0.067 | 0.477 |
| Oyler | 4.09 | 0.143 | 0.312 | **4.95** | 0.046 | -1.38 | 0.683 | -0.069 | 0.643 |

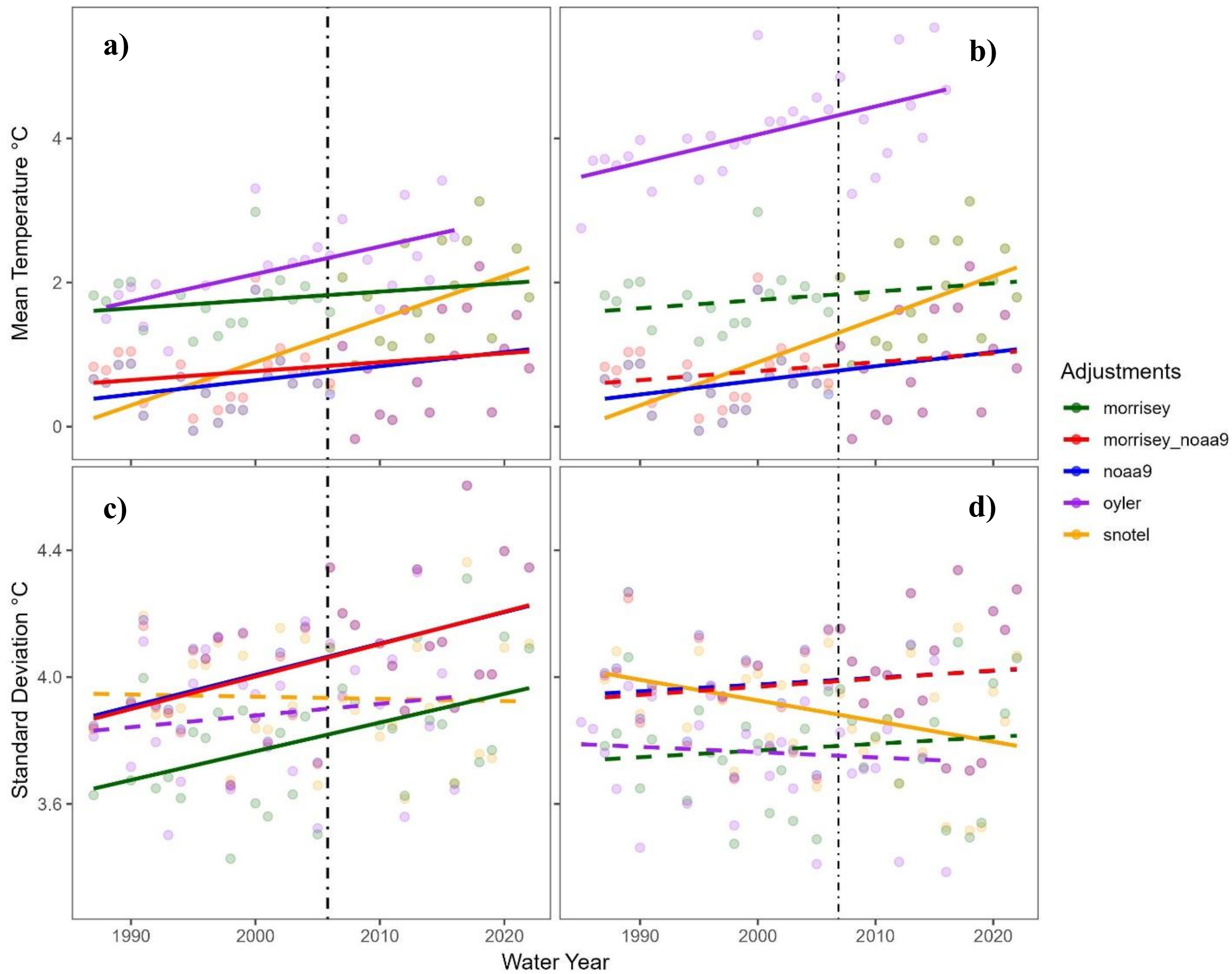


**Figure 3-1.** Bias correction mean annual temperature trends at a) Crosho SNOTEL (station ID 426) and b) Ripple Creek SNOTEL (station ID 717), and the standard deviation of the detrended daily temperature for c) Crosho and d) Ripple Creek SNOTEL stations, for 32 water years from 1987 to 2022. The black vertical line is the date of the YSI sensor change (2007-07-21 at Crosho and 2008-08-07 at Ripple Creek).

**Table 3-2.** COOP and SNOTEL station name and ID, elevation (m), and inter-daily temperature variability (°C/30 years). Bolded values are significant.

| Station | ID | Elevation | Annual | Spring | Summer | Fall | Winter |
|---|---|---|---|---|---|---|---|
| a) Yampa River | | | | | | | |
| Steamboat | CO7936 | 2052 | 0.12 | **0.41** | 0.10 | **0.55** | -0.25 |
| Hayden | CO3867 | 1961 | -0.08 | 0.09 | -0.04 | 0.29 | -0.29 |
| Walden | CO8756 | 2469 | **0.67** | **0.83** | **0.25** | **0.96** | **0.65** |
| Kremmling | CO4664 | 2229 | 0.24 | **0.51** | 0.06 | 0.20 | 0.19 |
| Craig | CO1932 | 1885 | 0.16 | 0.11 | -0.06 | 0.11 | 0.05 |
| Burro Mountain | 378 | 2840 | -0.24 | -0.09 | **-0.39** | -0.04 | -0.29 |
| Columbine | 408 | 2794 | 0.03 | 0.33 | -0.13 | 0.26 | -0.06 |
| Crosho | 426 | 2735 | **0.28** | **0.51** | -0.15 | 0.25 | **0.28** |
| Dry Lake | 457 | 2521 | 0.01 | 0.31 | **-0.41** | 0.35 | 0.06 |
| Elk River | 467 | 2664 | -0.10 | -0.02 | **-0.44** | 0.20 | -0.05 |
| Lynx Pass | 607 | 2719 | -0.06 | 0.19 | **-0.34** | -0.02 | -0.01 |
| Rabbit Ears | 709 | 2868 | 0.38 | 0.40 | 0.89 | 0.36 | -0.21 |
| Ripple Creek | 717 | 3155 | 0.08 | 0.10 | -0.12 | **0.43** | -0.06 |
| Tower | 825 | 3237 | **-0.54** | -0.33 | **-0.60** | -0.21 | **-0.57** |
| Trapper Lake | 827 | 2975 | 0.04 | -0.30 | -0.67 | 0.32 | -0.61 |
| b) Rio Grande | | | | | | | |
| Del Norte | CO2184 | 2403 | 0.01 | 0.16 | **0.17** | 0.25 | 0.01 |
| Hermit 7 ESE | CO3951 | 2743 | -0.07 | 0.17 | -0.07 | 0.15 | 0.01 |
| Pagosa Springs | CO6258 | 2172 | **-0.27** | 0.21 | **-0.45** | -0.08 | **-0.35** |
| Silverton | CO7656 | 2840 | 0.03 | -0.19 | -0.08 | -0.15 | -0.05 |
| Valencito | CO8582 | 2377 | -0.12 | -0.19 | -0.06 | -0.03 | -0.21 |
| Beartown | 327 | 3536 | -0.01 | 0.10 | 0.17 | 0.27 | -0.19 |
| Cascade #2 | 387 | 2747 | 0.21 | 0.28 | 0.14 | 0.40 | 0.18 |
| Idarado | 538 | 2991 | **0.20** | **0.47** | 0.29 | 0.41 | 0.06 |
| Middle Creek | 624 | 3435 | **0.22** | **0.79** | **0.42** | 0.49 | -0.01 |
| Molas Lake | 632 | 3240 | 0.20 | 0.27 | 0.24 | **0.69** | 0.00 |
| Red Mountain Pass | 713 | 3377 | 0.19 | **0.43** | **0.33** | 0.13 | 0.04 |
| Slumgullion | 762 | 3523 | **0.38** | **0.52** | **0.43** | **0.75** | 0.12 |
| Spud Mountain | 780 | 3253 | **0.31** | 0.20 | **0.42** | **0.86** | 0.09 |
| Stump Lakes | 797 | 3428 | -0.10 | 0.02 | -0.11 | 0.35 | -0.19 |
| Upper Rio Grande | 839 | 2859 | **0.25** | 0.41 | 0.05 | **0.49** | 0.08 |
| Upper San Juan | 840 | 3091 | 0.14 | **0.48** | **0.24** | **0.51** | -0.14 |
| Vallecito | 843 | 3286 | **0.25** | 0.38 | **0.27** | **0.64** | 0.07 |
| Wolf Creek Summit | 874 | 3340 | **0.49** | 0.35 | **0.65** | **0.98** | 0.25 |

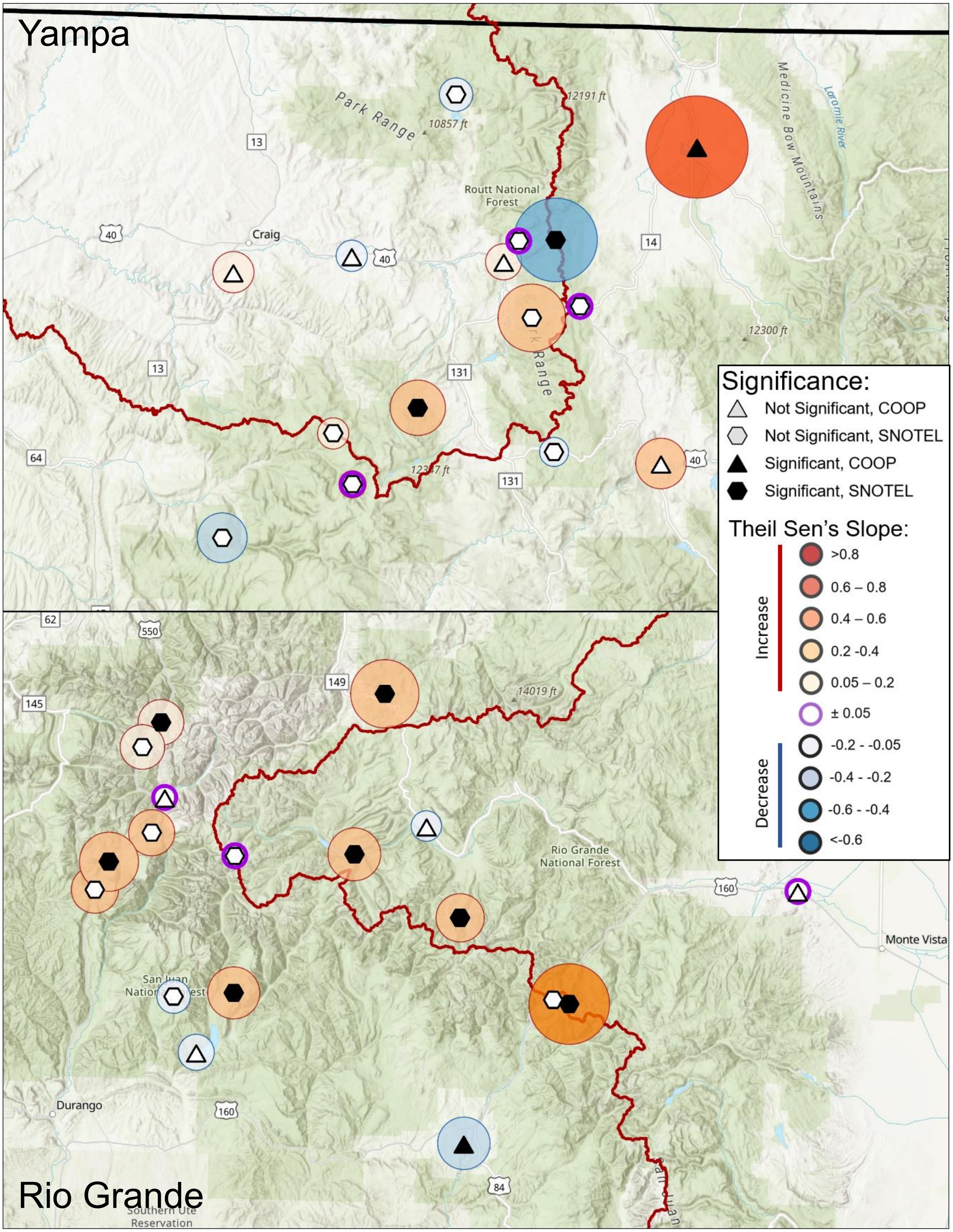


**Figure 3-2a.** Change in the annual ITV (°C) over 30 years. Magnitude is indicated by both color and size.

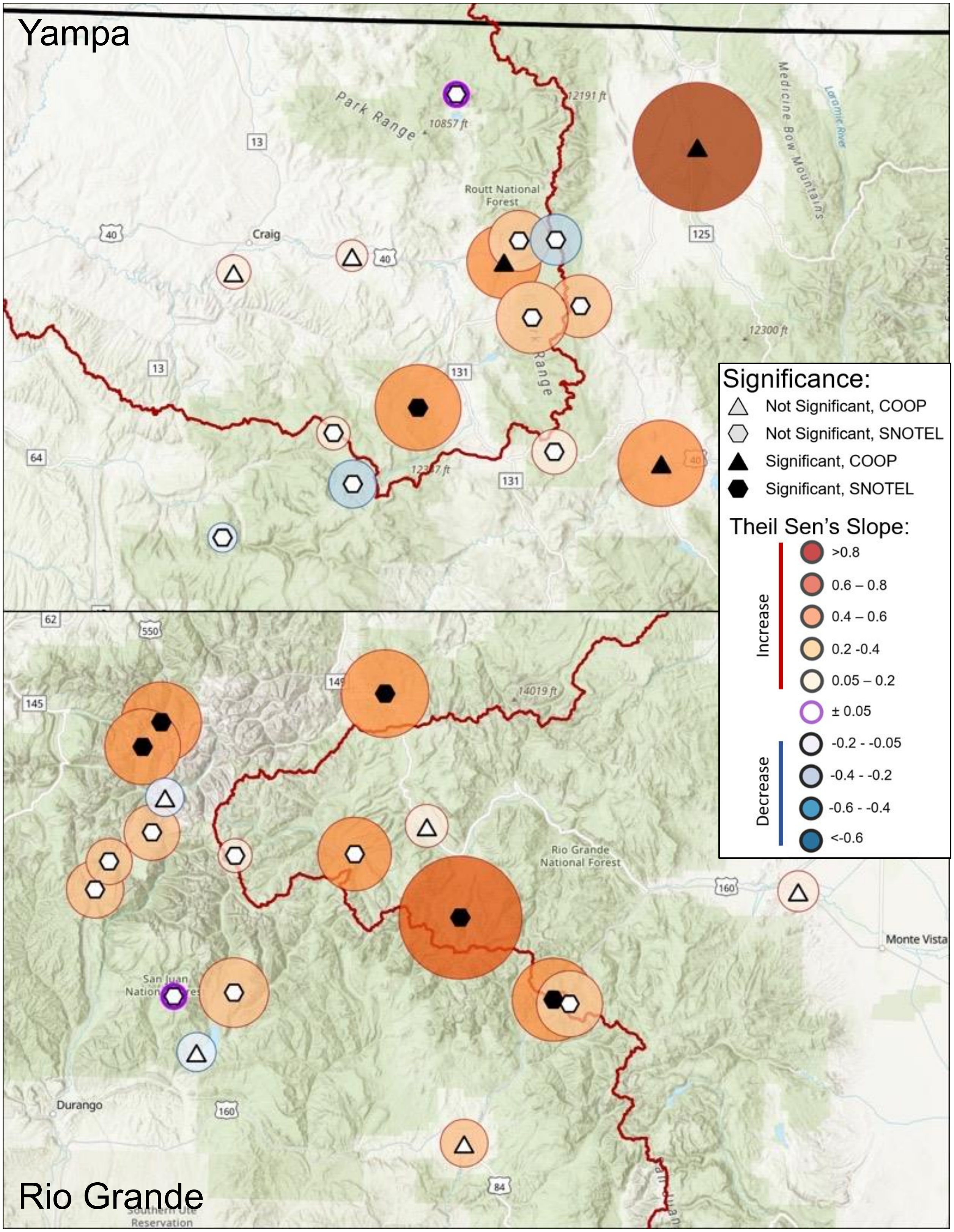


**Figure 3-2b.** Change in the spring ITV (°C) over 30 years. Magnitude is indicated by both color and size.

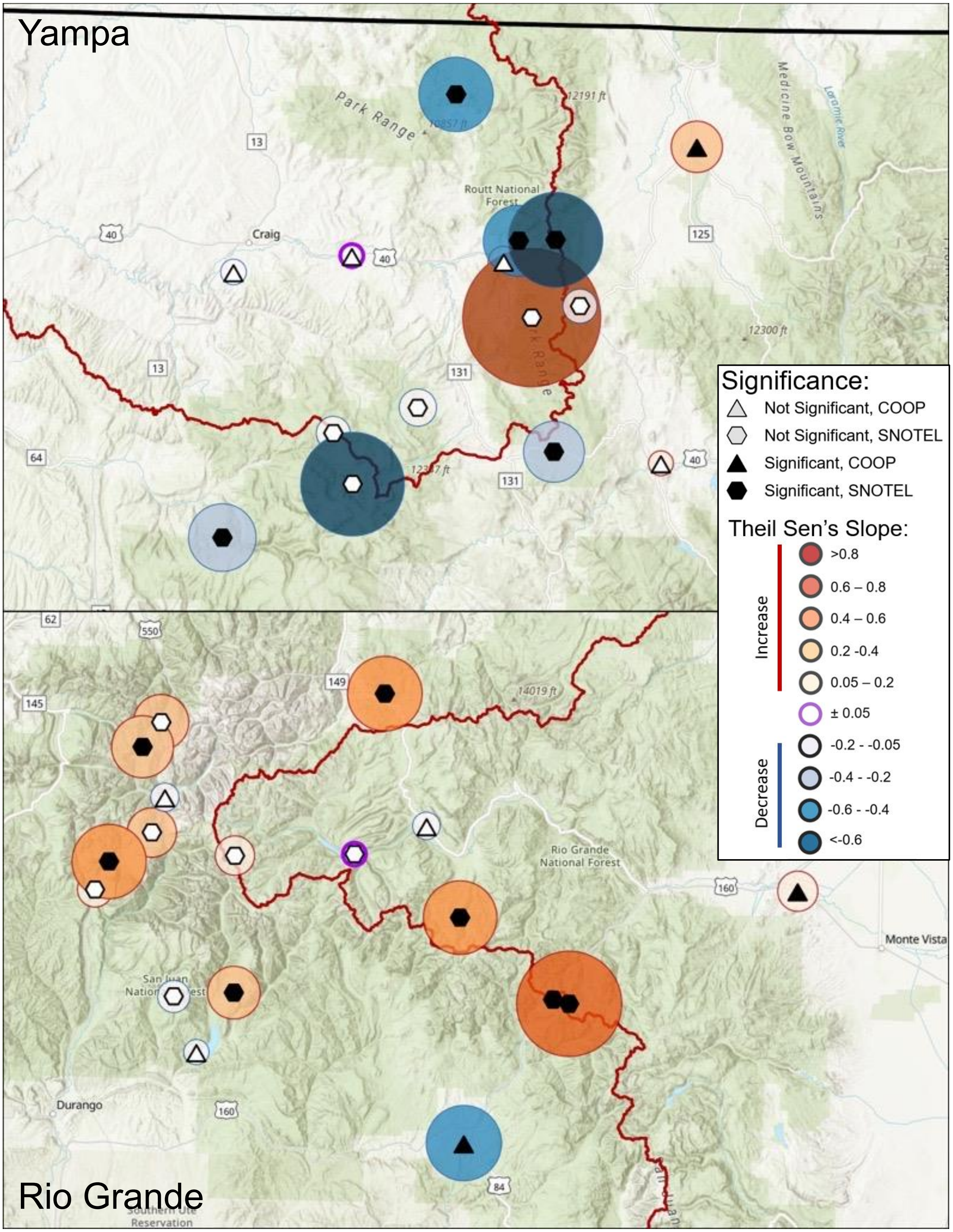


**Figure 3-2c.** Change in the summer ITV (°C) over 30 years. Magnitude is indicated by both color and size.

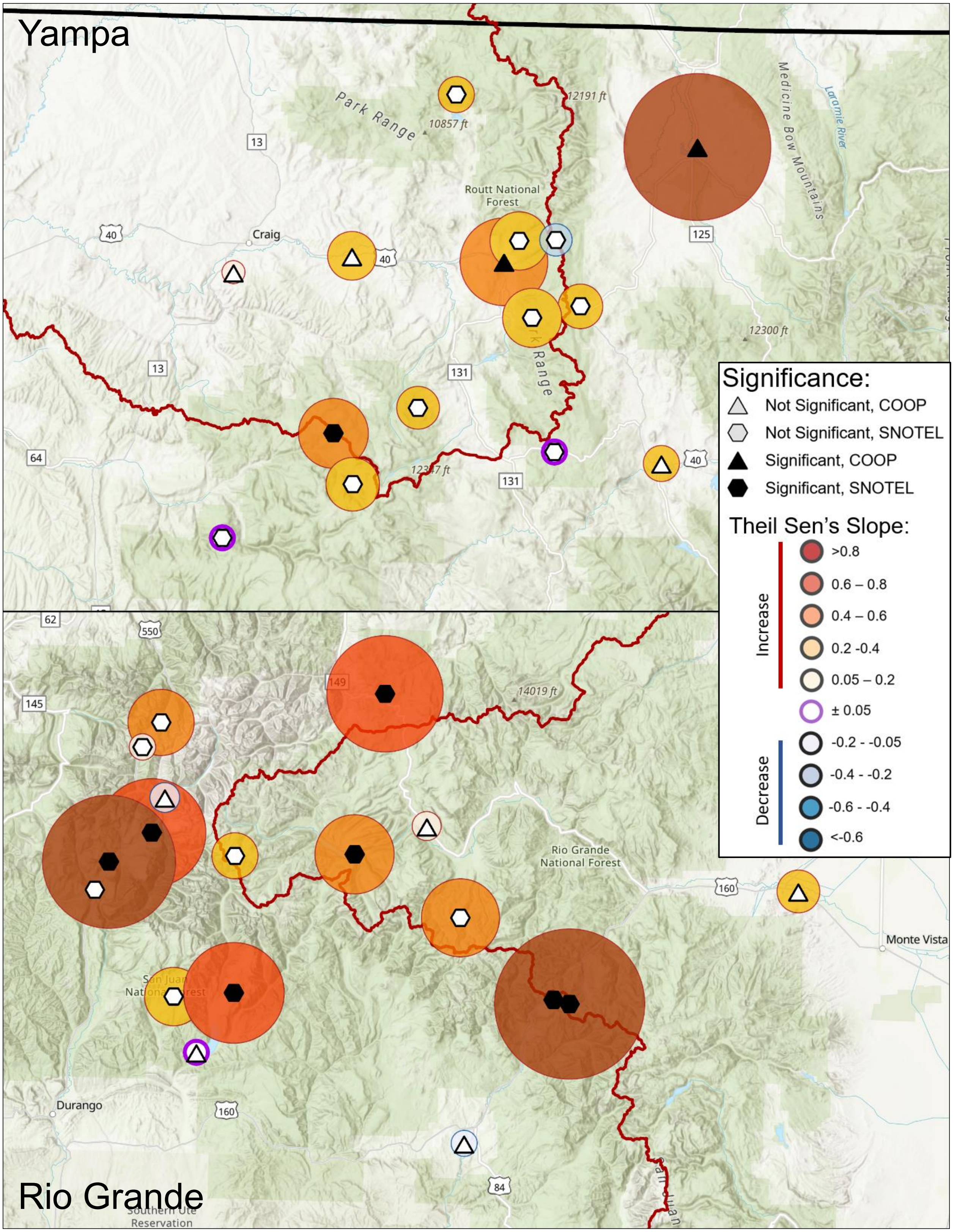


**Figure 3-2d.** Change in the fall ITV (°C) over 30 years. Magnitude is indicated by both color and size.

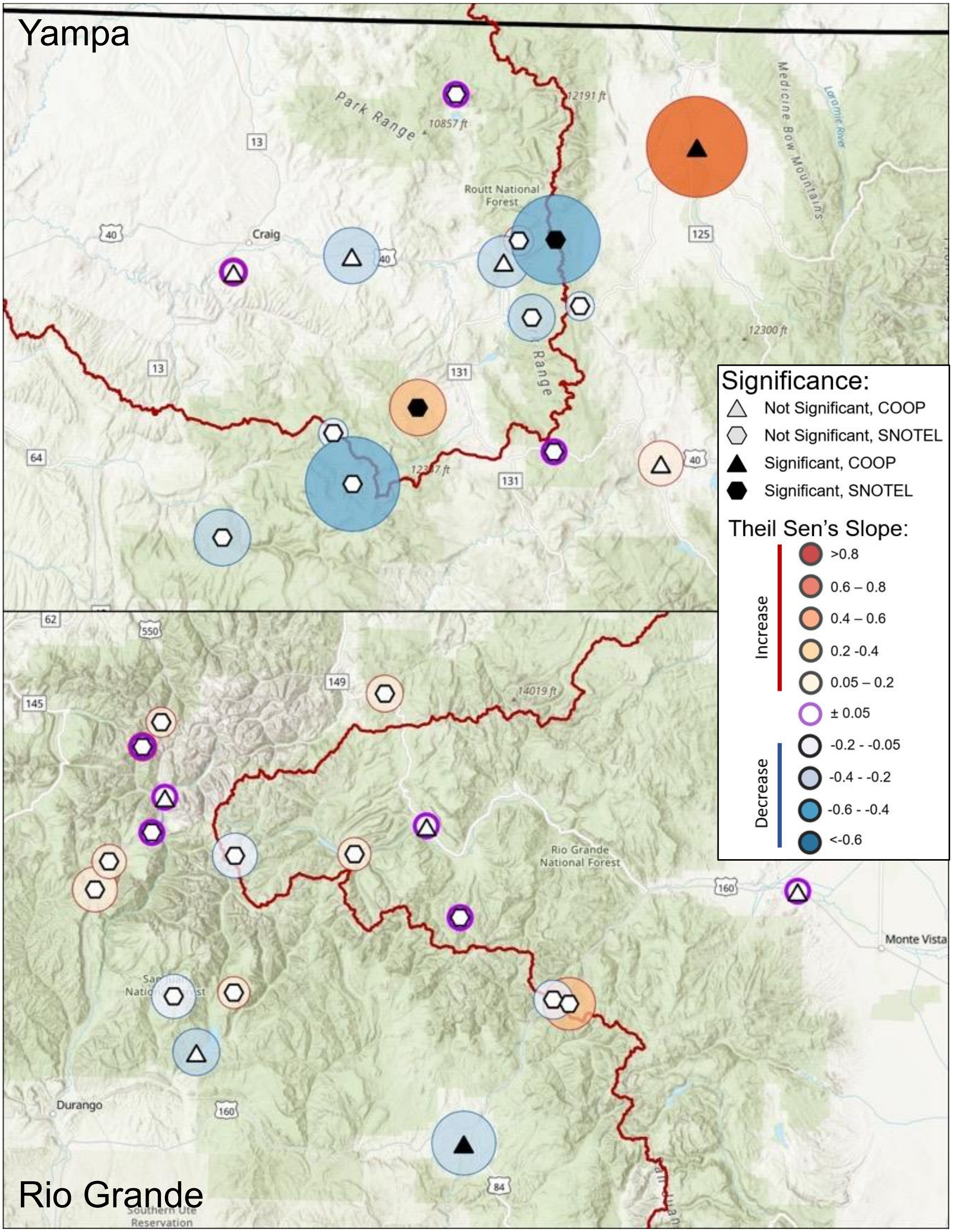


**Figure 3-2e.** Change in the winter ITV (°C) over 30 years. Magnitude is indicated by both color and size.

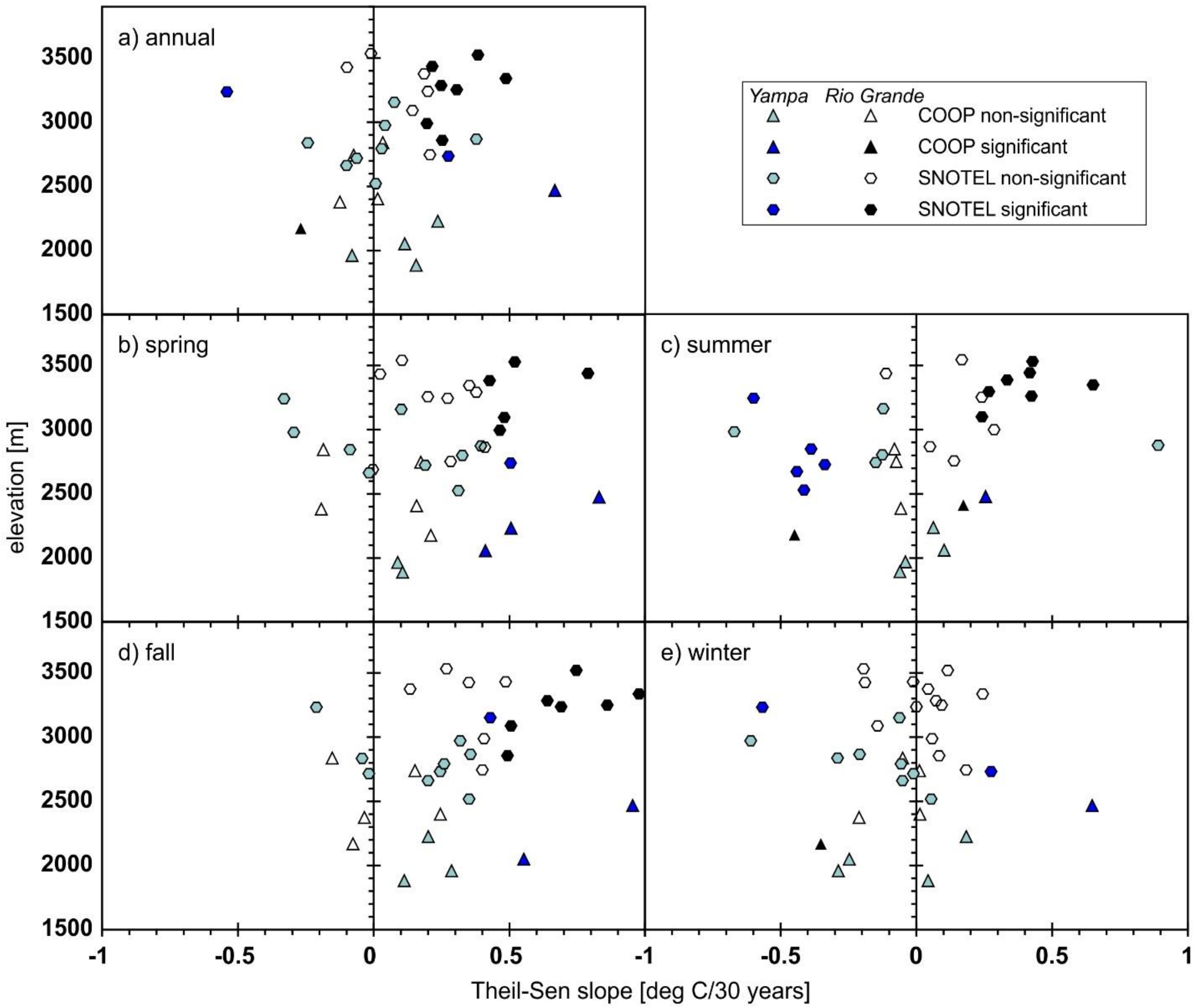


**Figure 3-3.** Elevation (m) vs daily temperature change (°C) per 30 years for a) annual timeseries, b) spring months April through May, c) summer months June through August, d) fall months September through October, and e) winter months November through March for 10 COOP and 23 SNOTEL stations in the Yampa and Rio Grande study sites.

# CHAPTER 4: DISCUSSION

## *4.1 SNOTEL Data Homogeneity*

SNOTEL temperature data has been extensively used to represent high elevation across the western United States and thus have profound implications for quantifying elevation-dependent warming (Diaz and Eischeid, 2007; Clow, 2010; Pederson et al., 2011). Temperature anomalies due to sensor change artifacts (Julander et al., 2007) have exacerbated reported warming trends (Oyler et al., 2015; Ma et al., 2019). SNOTEL data are also used to interpolate regional temperatures which thus affect gridded temperature datasets, such as PRISM (Daly et al., 1994) and Daymet (Thornton et al., 2022).

Two methods have previously been presented to adjust the SNOTEL time series: the Oyler dataset, which interpolated temperatures from lower elevation stations (Oyler et al., 2015) and the Morrisey adjustment from concurrent pre- and post-change measurements (Ma et al., 2019), yet neither is systematically better (Ma et al., 2019). The Morrisey and Oyler datasets when applied to the Ma et al. (2019) SWE temperature index model had an average improvement over the original, unadjusted dataset of 69% and 44% respectively. Here, the results were mixed for adjustments to the Crosho SNOTEL; the Morrisey method had a higher NSE but a lower KGE than Oyler when compared to the Morrisey/NOAA9 time series and the SD (Table 3-1; Figures 3-1a and c). The difference between the reference dataset and Oyler equates to 0.2°C increase per 30 years in this analysis (Table 3-1). The Oyler method had the best SWE model performance for Ripple Creek SNOTEL (Ma et al., 2019), but the original method had the best statistics compared to the reference dataset for Ripple Creek SNOTEL (Table 3-1, Figures 3-1b and d). Further, the YSI extended range sensor currently installed does not accurately measure temperature (Atwood et al., 2023) and the NOAA9 homogenization is meant to correct the post-sensor change time series (equation 2-2). Without the NOAA9 bias correction, the ITV in the Yampa and Rio Grande study watersheds used only the original dataset or Morrisey method and produced different results (see Appendix A).

The SNOTEL stations used in this study (Figure 2-1; Table 2-1) have systematic issues related to sensor changes and biases from location and aspirator changes (Julander et al., 2007), as well as changes in nearby vegetation due to fire (Giovando and Niemann, 2022), disease, or insects (Julander et al., 2007). The sensor changes and homogenizations at individual stations necessitate that either stations with known issues are discarded from the analysis, the data are corrected station-by-station, or bias and uncertainty are quantified (Pielke et al., 2007). Ideally, the original standard YSI sensors at each SNOTEL station would be reinstalled at their initial mounting locations and run alongside the YSI extended range sensors to determine temperature range differences in the sensors. However, this is likely logistically prohibitive, and the existing sensors and shields may no longer be available. Instead, the NOAA9 bias-corrected SNOTEL data (Atwood et al., 2023) could be analyzed again to determine the most appropriate homogenization method, as per the Ma et al. (2019) SWE model. While this should reduce uncertainty, it is beyond the scope of this research.

*4.2 ITV Calculation Method*

Previous studies have focused on variability through either variance (Michaels et al., 1998; Fischer and Schar, 2008), temperature anomalies (Collins et al., 2003), absolute value differences in the mean temperature from one day to the next (Karl et al., 1995; Robeson 2002), SD (Rebetez 2001; Holder et al., 2006, Huntington et al., 2013), or a combination of these methods (Gough 2008; Babina and Semenov, 2019). Attempts at removing the autocorrelation seen in daily temperature data include computing the average absolute temperature differences or standard deviation of observed temperatures within a discrete period (e.g., a week, 15 days, intra-monthly, etc.) compared to the mean temperature (e.g., Karl et al., 1995). Efforts at removing seasonal influences during the spring and fall when diurnal variability increases involve smoothing done with a longer discrete period of time, occasionally with a binomial filter or Fourier method (e.g. Moberg et al., 2000). Some studies have detrended their data due to climate change influences (e.g., Moberg et al., 2000), but not all. The method presented here (Figure 2-3) filters the data, after removing the trend, specifically the annual mean, and then computes the trend in variability.

ITV studies often present results in percent changes from the mean, temperature differences (e.g., Karl et al., 1995), or SD (e.g., Huntingford et al., 2013). There is no one correct method to determine changes in temperature variability, although differences in methods and results complicate direct comparisons between studies. Similar to Moberg et al. (2000), we also used a trend analysis to determine change over time, however we used different statistical tests and measures to determine trend significance. In the current study, due to non-stationarity (Milly et al., 2008) that amplifies variability trends, we removed the long-term climate change induced signal. Removing the seasonal sinusoidal oscillation (Figure 2-3b), including at a daily time step, unlike other (e.g., Moberg et al., 2000 used monthly means while James and Arguez, 2015 used half-month periods) ensures results are not influenced by season temperature variation, even though spring and fall exhibit increased diurnal temperatures fluxes (Figures 3-2b, 3-2d, 3-3b, and 3-3d). Performing discrete period ITV analyses over multiple spatial scales (Moberg et al., 2000) is less preferable than inter-seasonal or inter-annual analyses as seasonal shifts require the time period is fixed within the calendar year, which again assumes stationarity. Other hydroclimatic factors, such as decadal oscillations (e.g., Oceanic Niño Index, Pacific Decadal

Oscillation), further argue against stationarity, and must be evaluated separately to comprehend their influence.

It is possible that removing seasonal averages (Table 2-3) could yield different results (Figures 3-2 and 3-3) than removing the annual average (Figure 2-3). However, this is beyond the scope of the current work and could be evaluated separately (see Moberg et al., 2000 and James and Arguez, 2015). Climatology often uses three-month periods to represent a season, but this is not based on actual seasons. Here the seasons were chosen for fixed monthly periods (Table 2-3); future work could consider snowpack phases, i.e. accumulation, melt, and no snow. These are available for SNOTEL but not easily available for COOP stations. The method presented herein (Figure 2-3) could be a different approach to evaluate extremes (see Fischer and Schär, 2009 and citations therein). It may also be possible to use the general method for other variables, specifically changes in the amount and timing of precipitation (e.g., Figure 3 in Tumenjargal et al., 2020 who presented cumulative precipitation).

Using the standard deviation (SD) on the translated (by the annual mean) and detrended (with the daily normal temperature) time series does not indicate any temporal structure in the day-to-day variability. Specifically, the SD does not account for the timing of warmer or colder than daily-average days. For example, SD would be the same if the temperature was warmer than average for half the year and cooler than average for the other half compared to one warmer than average day followed by one cooler than average, followed by one warmer than average day, etc. (Figure 2-3c). It may be possible to use statistics that compute spatial structure (e.g., autocorrelation, variogram analysis) for temporal structure (Fassnacht et al., 2009 summarizes a variety of these metrics).

*4.3 ITV Between the Watersheds*

Seasonal variability fluctuations (Figures 3-2b to 3-2e and 3-3b to 3-3e) muted annual ITV for both the Yampa and Rio Grande watersheds (Figures 3-2a and 3-3a), with increased variability and significance in the southern watershed compared to the oscillating northern watershed. Spring and fall, each of which only comprised two months, were the largest contributors to increased variability in both watersheds; increased spring and fall variability were in 46% and 40% of the Yampa stations, respectively, and 38% and 61% of the Rio Grande stations, respectively. Fall also saw the highest variability of either watershed, at nearly 1° per 30 years for the southern Wolf Creek Summit SNOTEL and for the northern Walden COOP station. However, the outsized effects of spring and fall increases in the Yampa were offset by the three-month long summer, with most (73%) of stations decreasing in ITV. Nearly opposite, only one SNOTEL station and a majority of COOP stations decreased in ITV in the southern Rio Grande area. Variability in the five-month long winter is also unequal, with two-thirds of stations decreasing in ITV in the Yampa area, whereas variability in the Rio Grande fluctuated with most stations either increasing or decreasing less than ±0.2°C per 30 years. Using different time periods for each season (Table 2-3) could change the seasonal trends (Fassnacht et al., 2018; Fassnacht et al., 2020).

Located outside of the Yampa watershed, Walden COOP station had increased significant annual variability at 0.7°C per 30 years, with increases for all seasons. Walden COOP's increased variability compared to the remaining stations in the Yampa study watershed could be cold air drainage (Collados Lara et al., 2021) within North Park basin due to its enclosure by four mountain ranges, whereby cold air is entrapped, stagnates, and stratifies (Hansen et al., 1978). Pagosa Springs COOP saw similar isolated effects in the Rio Grande, with significant decreases for summer and winter that are unlike nearby SNOTEL or COOP stations (Figures 3-2 and 3-3). Whereas Walden is cool year-round, Pagosa Springs in the San Juan basin has an unusually mild climate (Fassnacht et al., 2013).

The results suggest annual ITV was not dependent upon elevation in the Yampa watershed basin (Figure 3-3). Other than Walden increasing in ITV, the difference in variability was most drastic in summer for the Yampa area, where SNOTEL stations largely decreased in ITV while COOP stations increased. Contrary to the Yampa area, ITV increased in the Rio Grande when comparing SNOTEL to COOP (Figure 3-3). Spring, summer and fall all showed increases in variability, some significantly, at elevation in the Rio Grande area. Elevation appears to have little effect in both basins during winter. Elevation-based warming has been observed (Diaz and Eischeid, 2007; Clow, 2010; Pederson et al., 2011), but since the method presented herein is novel, no elevation-based trends in variability have been observed elsewhere.

# CHAPTER 5: CONCLUSION

This study asked the question "has the ITV changed at high elevation across two study watersheds in Colorado?" Our objectives were as follows: 1) determine and apply the temperature bias correction for individual SNOTEL stations within the study sites, 2) compute ITV after removing seasonal and long-term climate change-induced trends, and 3) examine the elevational, seasonal, and spatial distribution of ITV across the two study watersheds. We evaluated 10 SNOTEL and five COOP stations in the Yampa watershed, and 13 SNOTEL and 5 COOP stations in the Rio Grande watershed from the mid 1980's through 2022. Due to temperature sensor changes at the SNOTEL stations in the mid 2000's, we evaluated five bias correction methods and combinations to identify the most appropriate reference dataset for each SNOTEL station based off the work of Ma et al. (2019). Data from each station was detrended to remove long term climate and seasonal signals, and the standard deviation of detrended average daily temperatures was calculated for annual and seasonal time periods. Trend analyses for the 30-year dataset length were performed using Mann-Kendall and Theil-Sen's slope tests.

The results of this study are uncertain due to the heterogeneity in early SNOTEL temperature sensor placement; accurate bias correction is not possible due to each station's own different sensor data, and due to site-specific issues related SNOTEL station location, such as fire or changes in surrounding vegetation. The Oyler et al. (2015) dataset was not assessed since it extended only to 2016, nor is the station interpolation they used reliable for this application, as per Pielke et al. (2002) and Fassnacht et al. (2016). Depending on the station, either the Morrisey correction (Ma et al., 2019) for the pre-sensor change period, or no change (the original time series) with the NOAA9 adjustment for the data after the sensor change yielded the correct reference dataset for each SNOTEL station. Since the change occurred 20 or more years ago, it is recommended that only the post-sensor change data be used with the NOAA9 adjustment.

This study found increased ITV in the Southern Rocky Mountains of Colorado seasonally, but that variability is watershed dependent. The day-to-day variability in temperature changed over time and depends on the time period. Annual trends were mixed with increases and decreases in ITV throughout the Yampa and Rio Grande watersheds. Seasonal trends are more definitive, with spring and fall stations across both watersheds experiencing significant increases in variability upwards of 0.8°C and 1.0°C per 30 years, respectively. Summer variability was mixed with increases in the Rio Grande area and decreases in the Yampa area. Minimal winter changes in variability were observed in the Rio Grande area, while the Yampa area experienced decreased ITV. In comparing elevation at SNOTEL and COOP stations, spring, summer and fall all showed increases in variability, some significantly, in the Rio Grande watershed. There was less distinction between the variability at elevation in the Yampa area, or in winter in either watershed.

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# APPENDIX A: PREVIOUS NON-HOMOGENIZED RESULTS

The resulting change in methods due to either lack of available SNOTEL data or the lack Oyler data extending throughout the entire period of record can have profound effects on the resulting magnitude and potentially significance of variability in this study. Before the NOAA9 bias correction was released, our first explorations of ITV in the Yampa and Rio Grande study watersheds used only the original dataset or Morrisey method, which produced different results compared to the current study (Figures A-1a-d). 100% of Rio Grande SNOTEL stations in the current study show increasing spring ITV (Figure 3-2b), whereas only 30% of the previous study demonstrated any increase (Figure A-1b). In the previous study, 83% of summer Rio Grande stations showed ITV decreases of up to 0.4°C/30 years (Figure A-1c); 72% in the current study show increases upwards of 0.8°C/30 years (Figure 3-2c). Fall largely showed increases in variability but not to the same amount or significance (Figure A-1d), Overall, the exclusion of the NOAA9 bias correction shows an annual decrease in variability, while only 13% of SNOTEL show a mild increase (Figure A-1a).

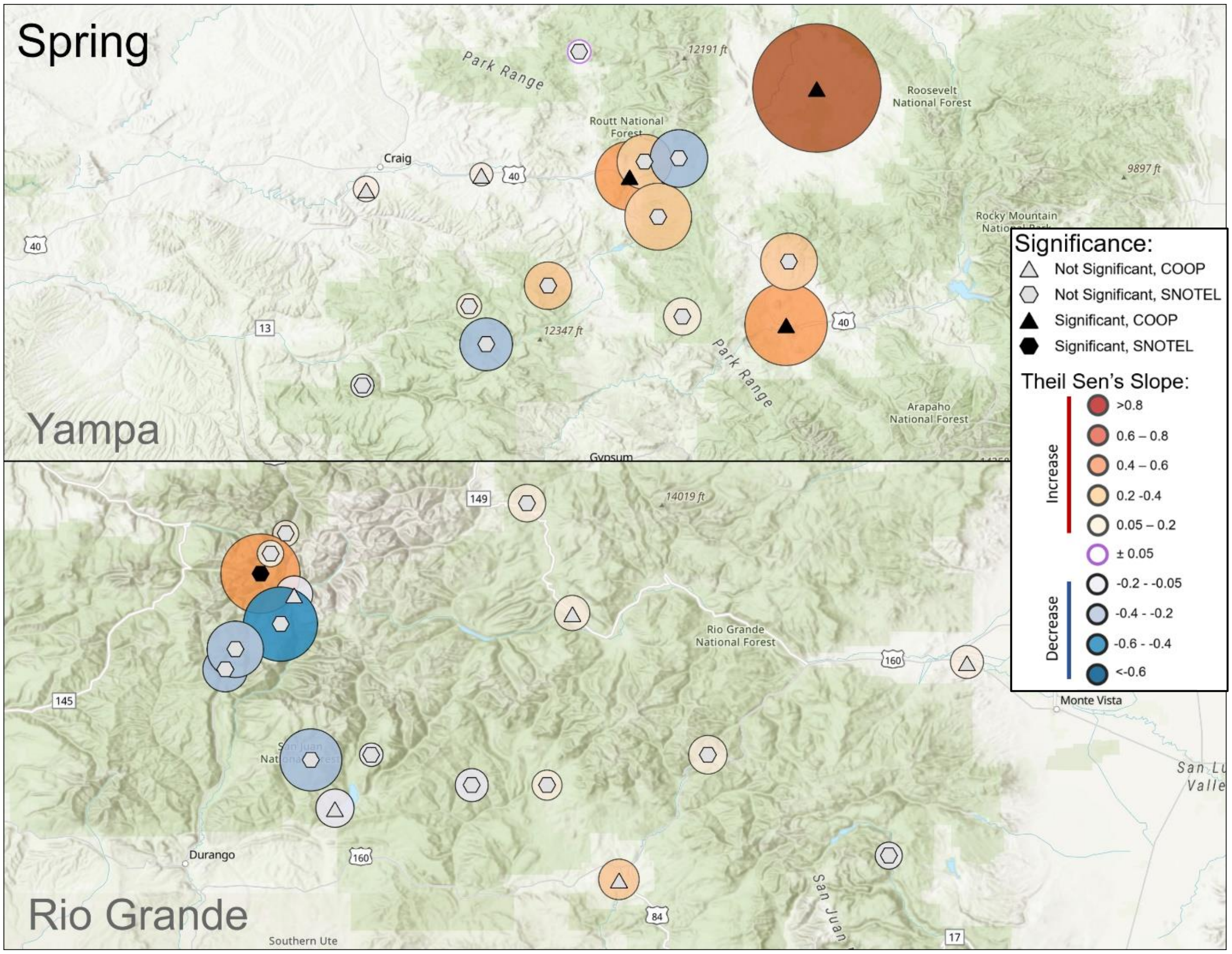


**Figure A-1a.** Spring inter-daily temperature (°C) change per 30 years. Magnitude is indicated by both color and size.

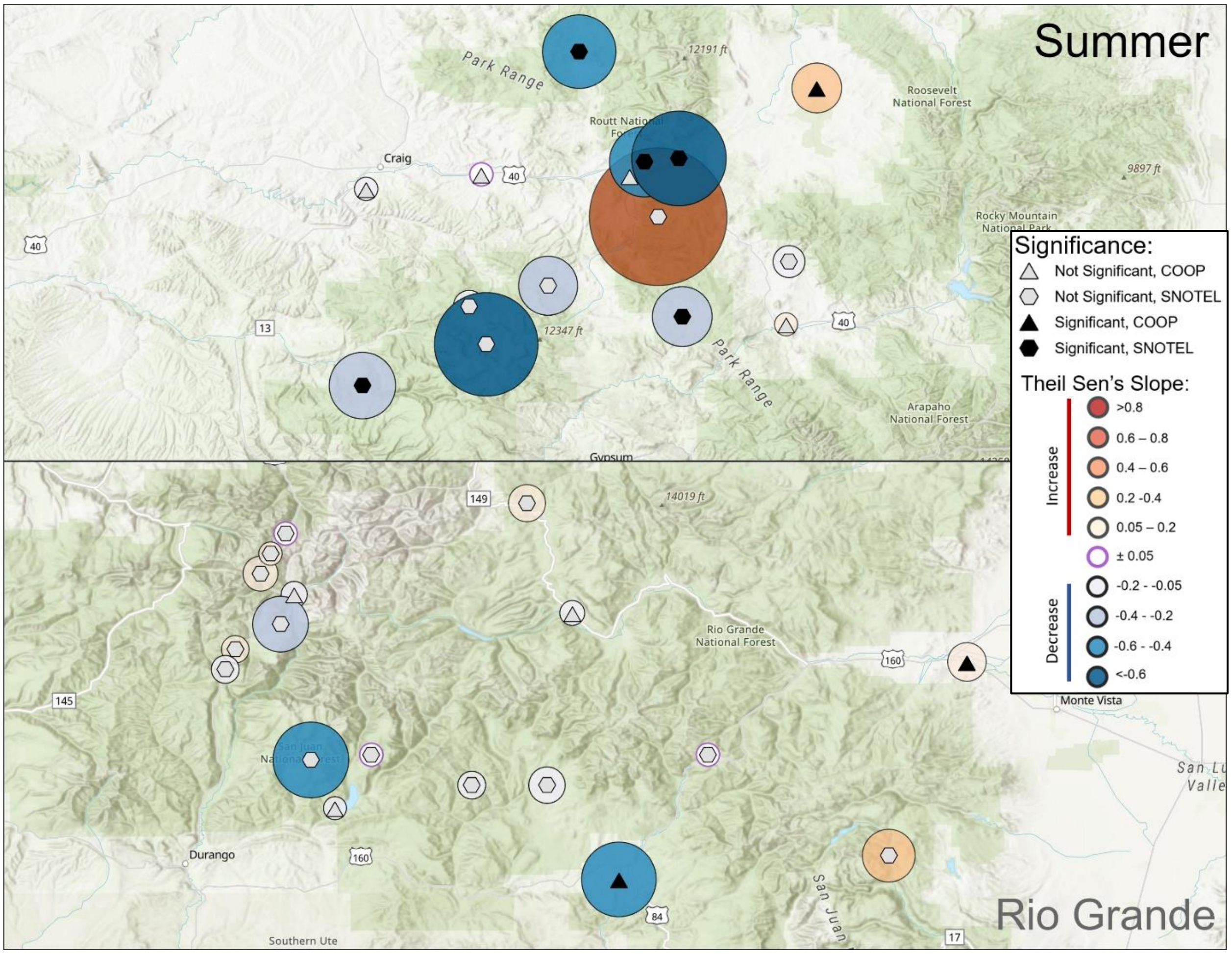


**Figure A-1b.** Summer inter-daily temperature (°C) change per 30 years. Magnitude is indicated by both color and size.

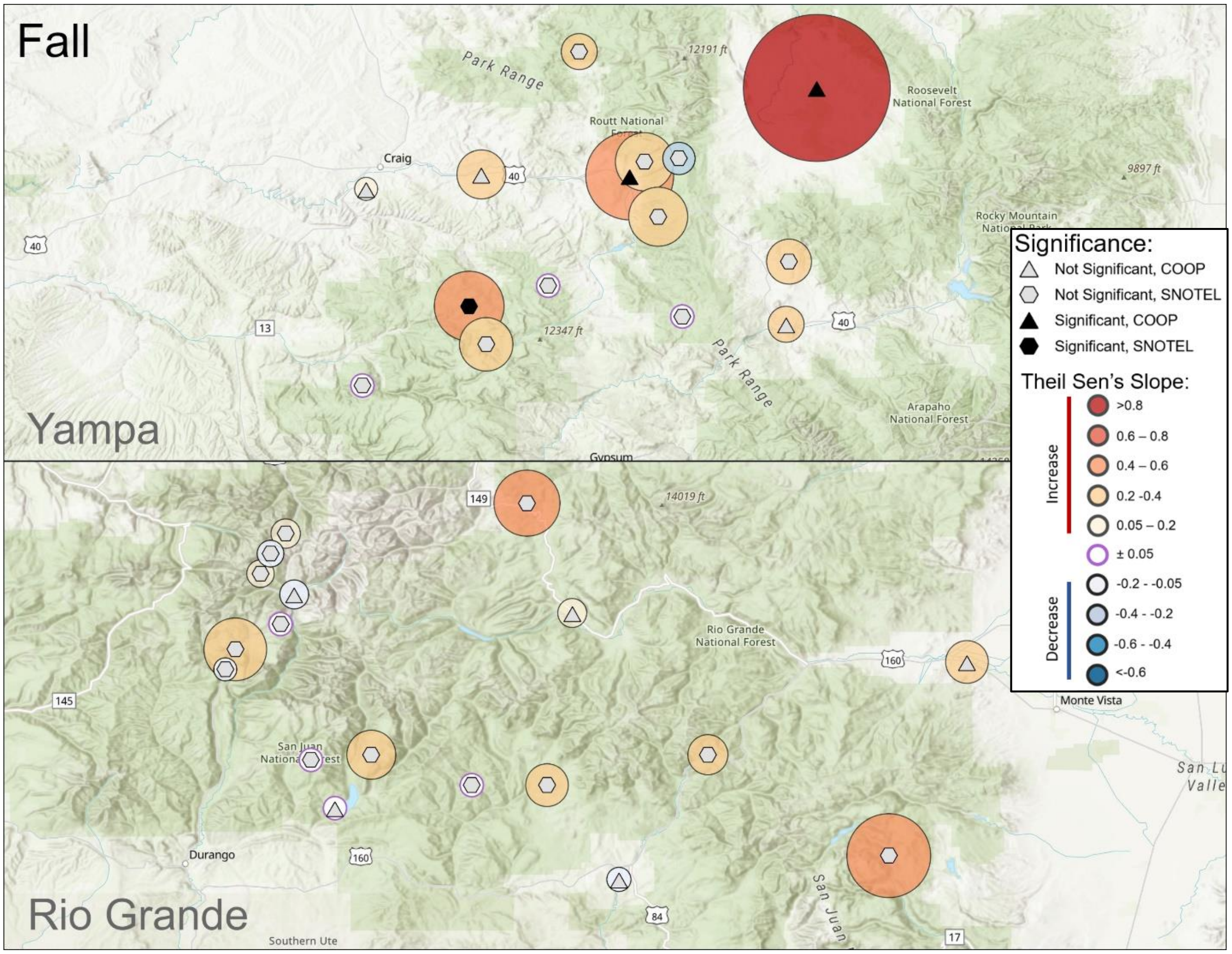


**Figure A-1c.** Fall inter-daily temperature (°C) change per 30 years. Magnitude is indicated by both color and size.

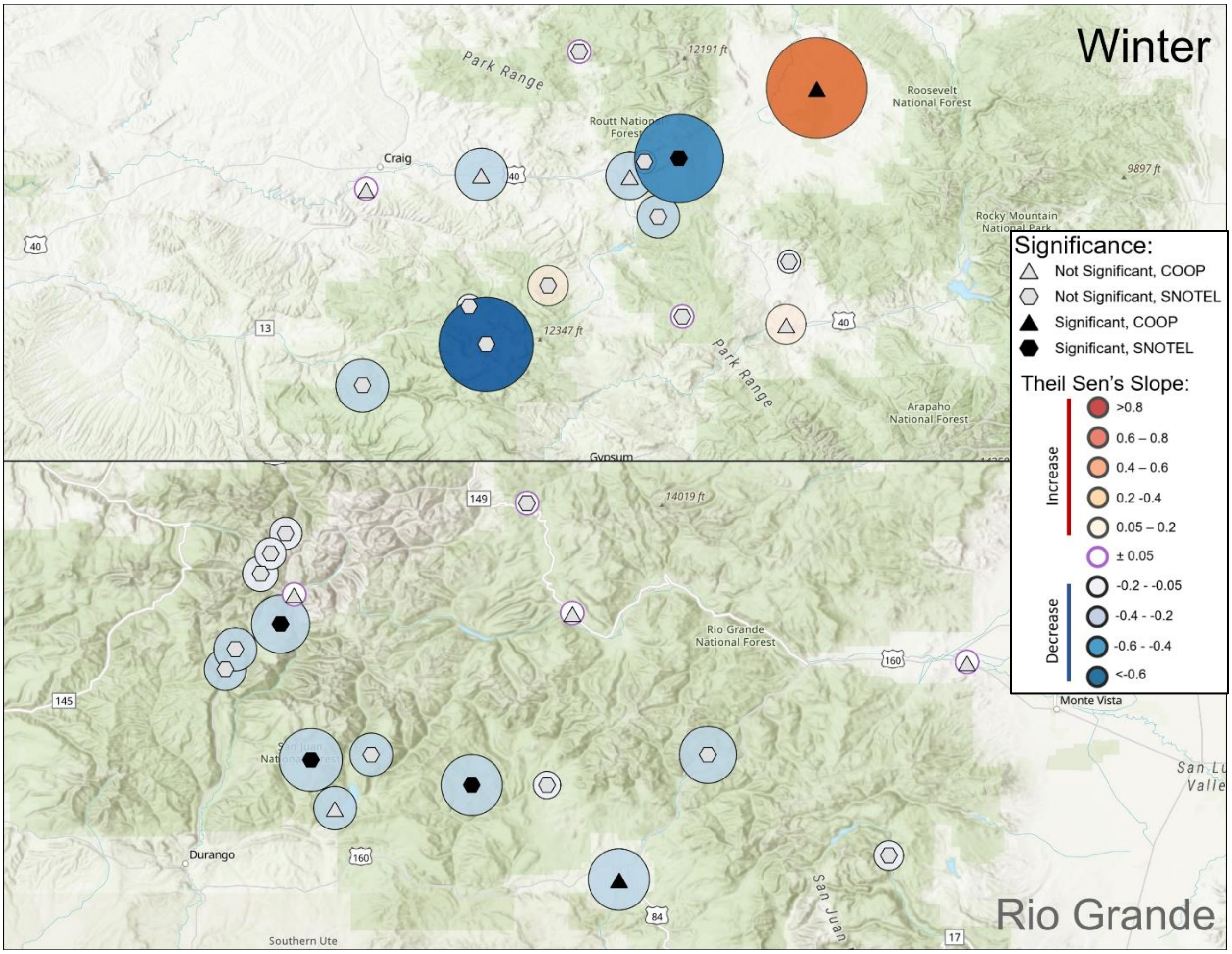


**Figure A-1d.** Winter inter-daily temperature (°C) change per 30 years. Magnitude is indicated by both color and size.

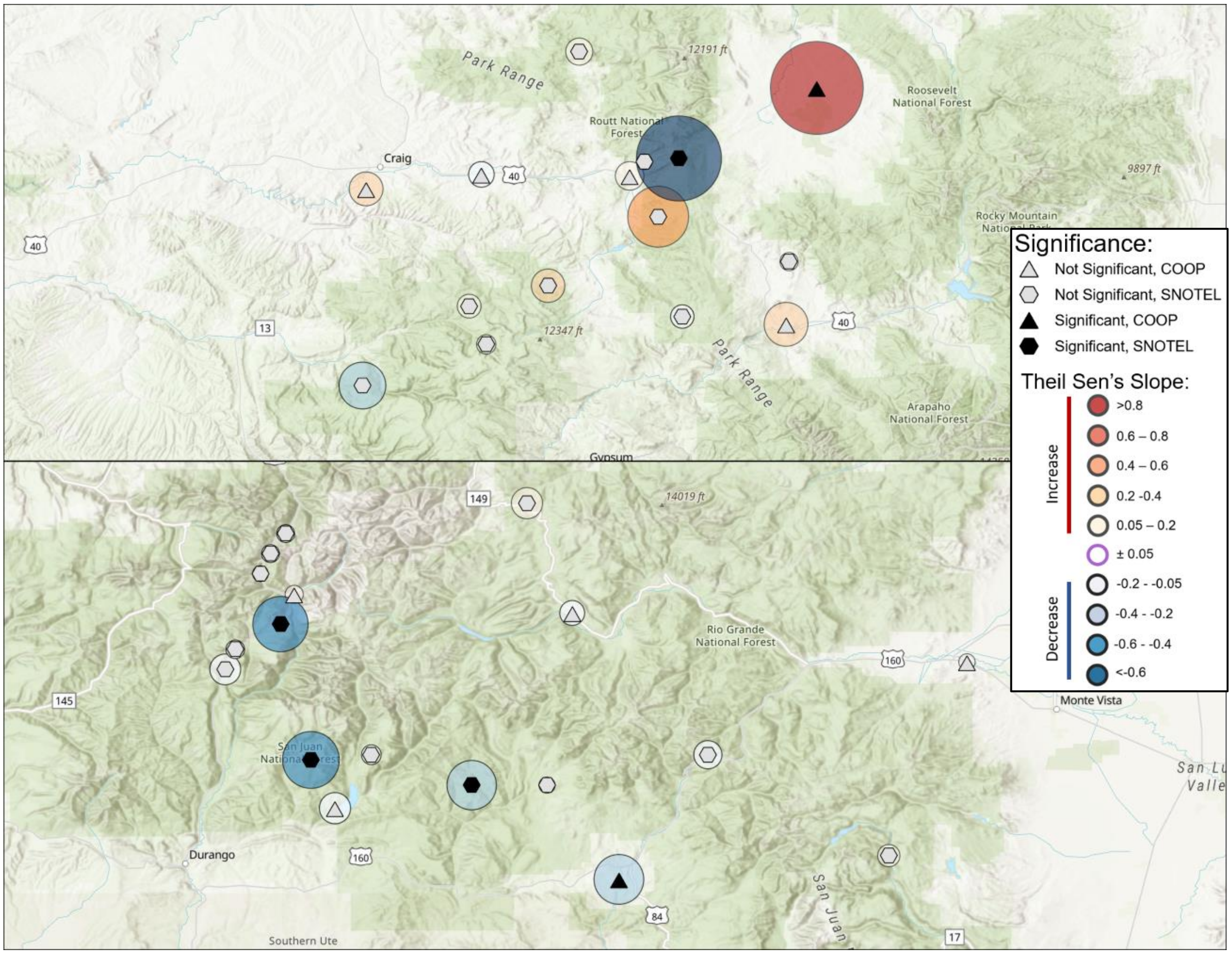


**Figure A-1e.** Annual inter-daily temperature (°C) change per 30 years. Magnitude is indicated by both color and size.

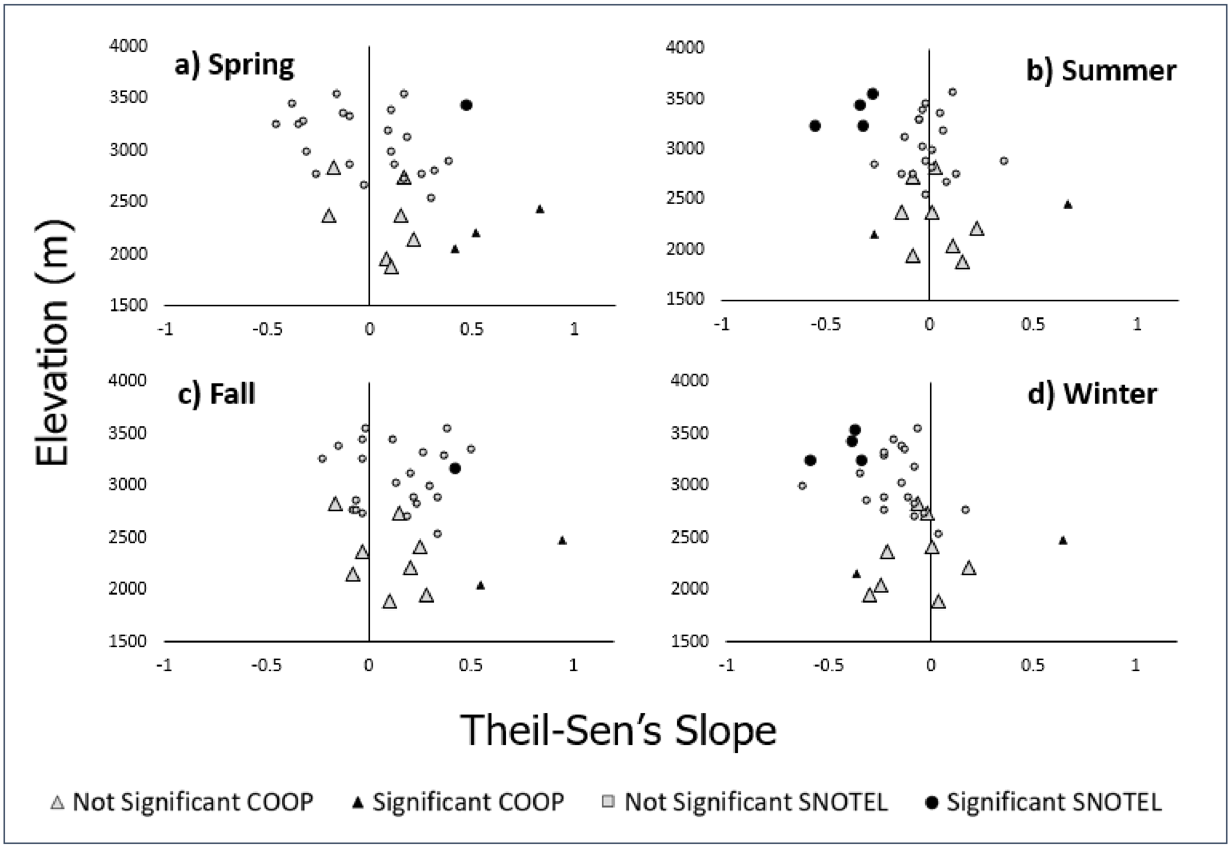


**Figure A-2.** Elevation (m) vs daily temperature change (°C) per 30 years for a) spring months April through May, b) summer months June through August, c) fall months September through October, and d) winter months November through March for 10 COOP and 23 SNOTEL stations in the Yampa and Rio Grande study sites.

APPENDIX B: Residual histograms for Crosho and Ripple Creek SNOTEL

Residual values were the result of the detrending process and represent temperature values based off the mean temperature for a specific year for the whole time series after removing the long term climate change induced trend, as well as the seasonal trend.

The absolute value of the daily temperature residual is then subtracted from the subsequent day, the resulting value is then used to find the annual or seasonal standard deviation.

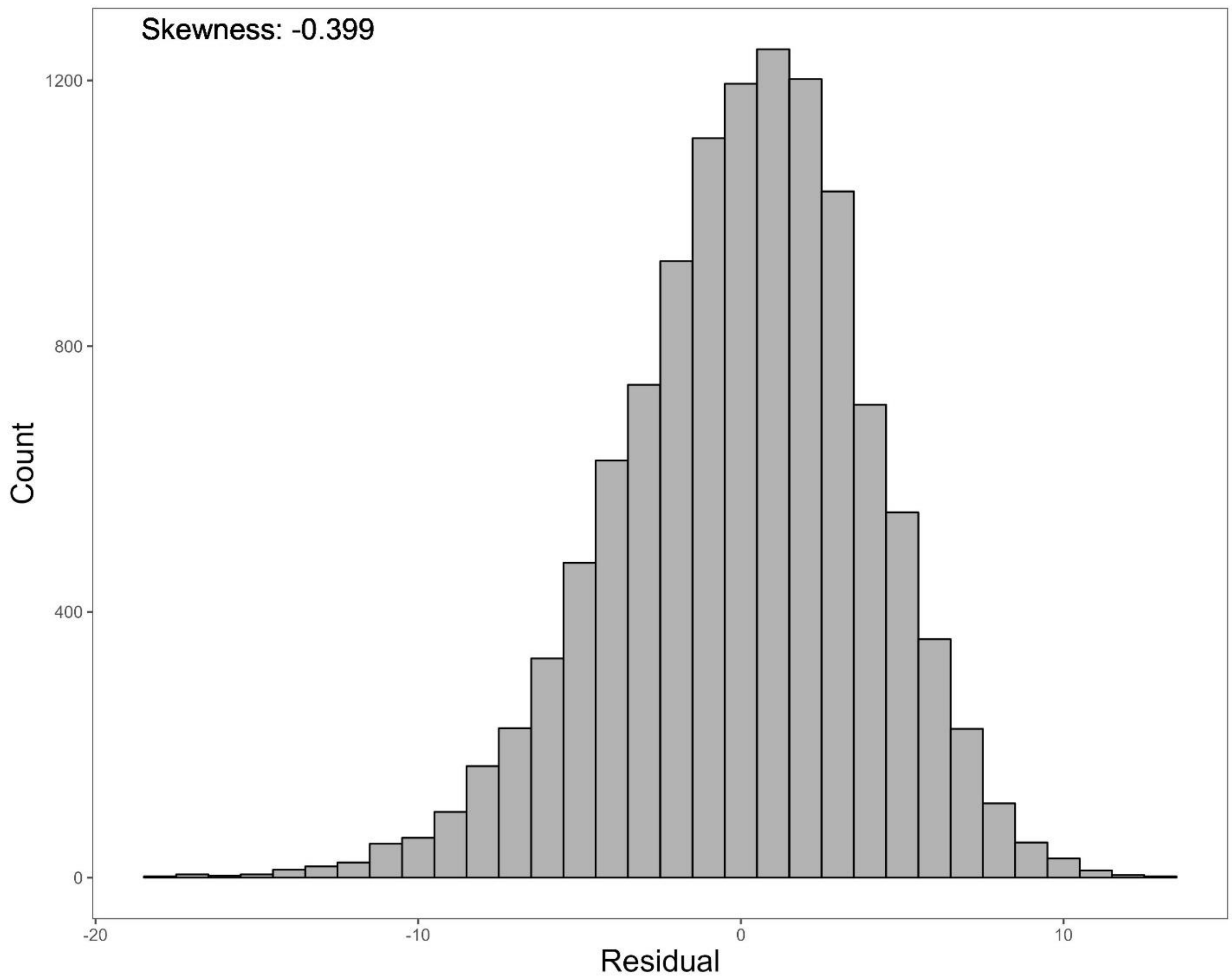


**Figure B-1.** Histogram of residual temperatures °C for Crosho SNOTEL, station 426.

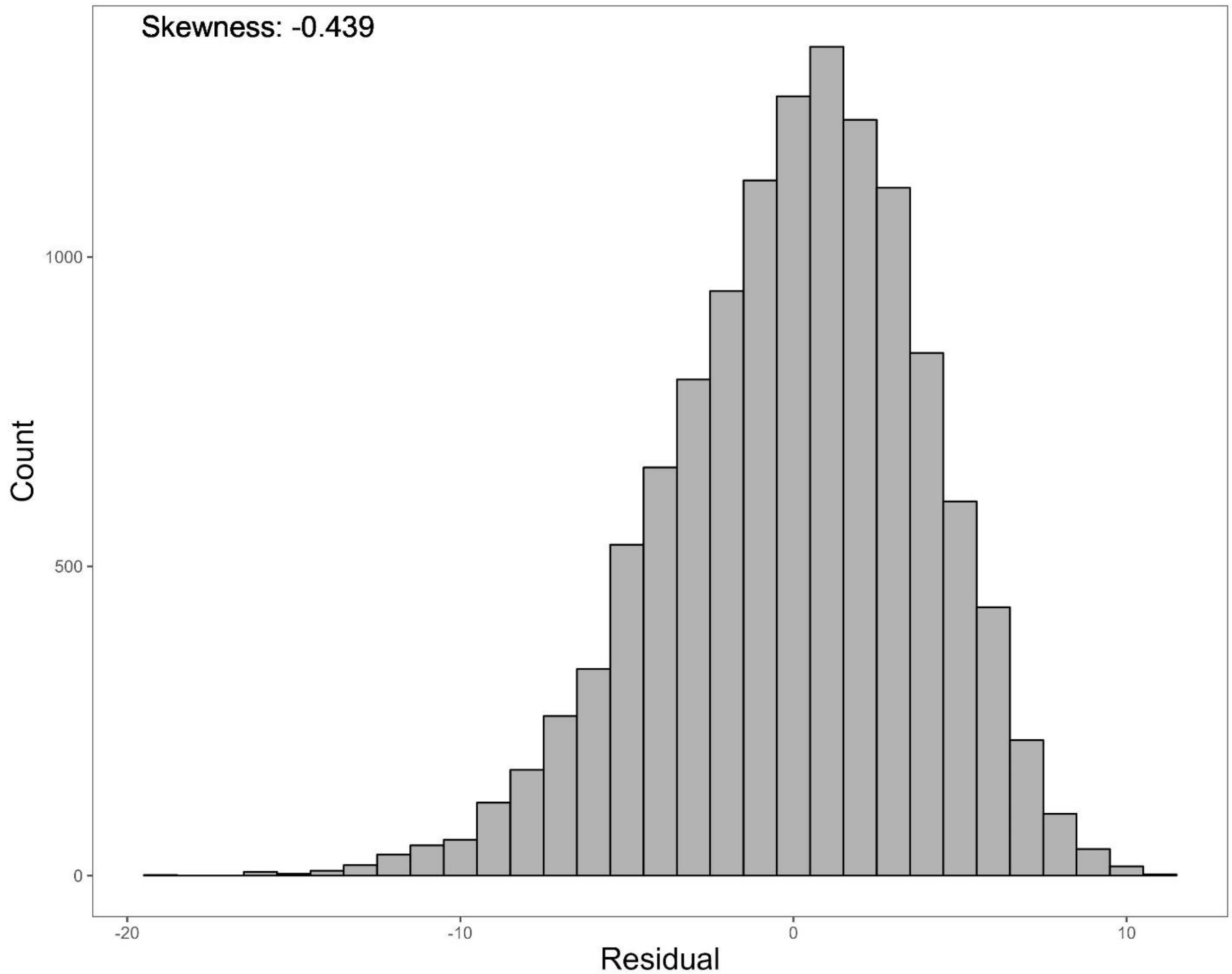


**Figure B-2.** Histogram of residual temperatures °C for Ripple Creek SNOTEL, station 717.