EXTREMES OF OPPORTUNITY: EXAMINING RECENT TRENDS IN WARM SEASON EXTREME PRECIPITATION FOR NEW MEXICO RIVER BASINS

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ABSTRACT

We explore recent trends in precipitation characteristics within the state of New Mexico and southern Colorado, relevant to the Rio Grande and Pecos basins, where increasing temperatures and decreasing snowpack threaten to reduce the water available for storage and use. To determine how changing precipitation could potentially help to mitigate decreasing water supply, we examine both magnitude and frequency of daily precipitation characteristics for the warm season (June - October) and individual months therein, with a focus on the upper quantiles and extremes within the period 1981 to 2017. We find that the dominant sign of the precipitation trend depends on the season/month examined. Negative trends dominate the warm season, June, and August, while positive trends dominate July and for some September indicators. However, the majority of locations in the study area did not show any significant trends. The increasing trends for the July indicators show the most potential for water supply, with the location of these significantly positive trends mainly concentrated in the southeastern and eastern part of the study region. The frequency of days above the 99th daily precipitation quantile for September also shows increasing trends at some southern and southeastern locations, but this heavy precipitation could be difficult to capture for water supply. However, across most characteristics examined, we find that significant trends are more detectable in the frequency indicators than in the magnitude indicators. As such, for times and locations showing increasing trends, this suggests that water managers looking to exploit changes in precipitation might not need to plan for larger events, but rather for more frequent events. (KEYWORDS: decreasing snowpack, extreme precipitation, warm season, trends, New Mexico)

INTRODUCTION

In many river basins in the Western United States, winter snowmelt provides the primary supply of water, with warm season precipitation as a secondary source (Serreze *et al.*, 1999). However, decreases in snowpack have already been observed (Mote *et al.*, 2005; Chavarria, 2017) and climate models project that these trends will continue (Solomon *et al.*, 2007). This suggests that warm season precipitation may provide a more substantial contribution to water supply. However, it is generally thought that increasing greenhouse gases will increase heavy precipitation. Thus, to investigate if warm season precipitation events might present opportunities to mitigate the impacts of decreasing snowmelt, it is necessary to understand the changing precipitation characteristics, especially the extremes. The goal of this paper is to investigate trends in precipitation, with a focus on the upper quantiles and extremes, to determine how changing precipitation could potentially help to mitigate the impacts of decreasing snowpack on water supply. This is of particular interest in the arid U.S. southwest, where water resources are strained (Pournasiri Poshtiri & Pal, 2016). As such, we provide a case study example relevant to New Mexico river basins, including the Rio Grande and Pecos basins, where some evidence suggests that the strength of the summer monsoon may increase (e.g., Asmerom *et al.*, 2013) and there may be opportunities to exploit changes in precipitation for water management (Gutzler, 2013; Llewellyn & Vaddey, 2013).

DATA AND METHODS

This study focuses on the state of New Mexico and southern Colorado (Longitude: 109 to 103 W & Latitude: 32 to 38 N, and see Figure 3), which includes the Rio Grande and Pecos basins. We use gridded daily precipitation data from PRISM Gridded Climate Data Group (prism.oregonstate.edu), downloadable from http://www.prism.oregonstate.edu/documents/PRISM_downloads_FTP.pdf. The 4 km daily precipitation data is

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processed by averaging 10 x 10 grid cells, resulting in 225 cells total. We examine data from 1981-2017, with a focus on the warm season, here defined as June through October. This is when most of the direct precipitation that falls on New Mexico is associated with summer monsoons and remnant tropical storms.

For precipitation, we examine both magnitude and frequency characteristics. For magnitude, we examine five precipitation magnitude indicators for the upper (higher value) quantiles: q50, q75, q90, q95, and q99 (i.e., the 50th percentile to the 99th percentile), as well as the average (avg) and maximum (max) values. For each magnitude indicator, we construct a time series of the daily value for each year's warm season (or individual month) in each grid cell. For frequency, we consider five thresholds of the upper quantiles (i.e., q50, q75, q90, q95, and q99), which are calculated over the entire precipitation record for the warm season (or individual month) in each grid cell. Consequently, we define the frequency indicators as the time series of the number of days above each of the thresholds in each grid cell.

To identify if there is a monotonic temporal trend in the magnitude, we use the nonparametric Mann-Kendall test (Kendall, 1975, Mann, 1945); this is done for the magnitudes for each precipitation indicator at each grid cell. To identify if there is any trend in the frequency of days above the threshold, we use Poisson regression. Poisson regression is used because the response variables are in the form of count data and are discrete (e.g., Dobson & Barnett, 2008, Fox, 2015). For both, we consider trends with p-values <0.05 as statistically significant.

RESULTS AND DISCUSSIONS

In this section, we discuss the trend results, compare the trends in magnitude and frequency, and examine the spatial trend patterns.

Trend Results

Trend results for the precipitation indicators over the warm season (June through October) and each individual month are presented in Table 1. The tables summarize the percentage of grid cells where the precipitation trends are statistically significant (p-values <0.05). For June-October, we see that for both magnitude and frequency, for q90 and higher, the significant negative (drying) trend dominates. However, the percentages are not that high: the maximum percent of cells showing drying for the magnitude and frequency indicators are 13% and 50%, respectively. June and August show similar drying trend results. Conversely, July differs by showing more increasing trends, especially for the q50 indicators (45% and 56% for magnitude and frequency indicators, respectively). We point out that many grid cells have a q50 of zero (i.e., more than half the days don't receive any precipitation), so for this, the trend increase indicates an increase in the non-zero precipitation days. For July, we also see that positive (wetter) trends dominate all of the July frequency indicators. Most of September and October indicators don't have many cells with significant trends (many indicators detect trends at less than 5% of the grid cells), with a notable exception: in September, the q99 frequency indicator shows an increasing trend at 22% of the grid cells. However, it is important to note that the majority of locations in the study area did not show any significant trends. Further, this study focuses on trends in the recent period (1981-2017), but it has been shown that trends are dependent on time period analyzed (Pournasiri Poshtiri & Pal, 2016).

Comparing the Trend in Magnitude and Frequency Characteristics

Figure 1 compares the percent of grid cells with statistically significant negative trends between the magnitude and frequency quantile indicators. In June-October (Figure 1A), June (Figure 1B), and August (Figure 1D), we see that across quantiles, there is a higher percentage of grid cells with negative trends in frequency than in magnitude (i.e., the red bars are higher than the orange bars). There is one exception for q99 in June (Figure 1B), where magnitude (orange bar) displays a higher number of grid cells with a negative trend than frequency (red bar). In short, the trend is more detectable in the frequency of extreme precipitation rather than the magnitude, in agreement with the recent study by Mallakpour & Villarini (2017). As previously mentioned, we don't see dominant negative trends in July (Figure 1C), September (Figure 1E), nor October (Figure 1F), and this is reflected in the both frequency and magnitude bars.

We do see some positive trends for July and September (Table 1), so Figure 2 compares the percent of grid cells with statistically significant positive trends for these two months. We clearly see the dominant positive trend in July across all indicators (Figure 2A) and dominant positive trend for q50 and q99 in September (Figure 2B). This shows how in recent years, the sign of the precipitation trend is sensitive to the season or month examined. In the

Table 1. Percentage of grid cells with a statistically significant trend (p-values <0.05) for each precipitation indicator. +Sig indicates a statistically significant increasing (wetter) trend, and -Sig indicates a statistically significant decreasing (drying) trend. Bold values indicate where the percentage of grid cells is greater than 5% and is also higher than that of the opposite sign.

Characteristic	Indicator	June-October		June		July		August		September		October	
		+Sig	-Sig	+Sig	-Sig	+Sig	-Sig	+Sig	Sig	+Sig	-Sig	+Sig	-Sig
Magnitude	avg	0.89	**5.8**	0	**24**	4.0	0	0	**17**	0	0	0	0
	q50	**19**	5.3	4.4	4.9	**45**	0	4.0	**14**	**8.4**	2.7	0	0.44
	q75	2.7	4.0	0.44	**17**	**11**	0	0	**19**	0	0.44	0	0
	q90	0	**11**	0	**27**	2.7	0	0	**20**	0	3.1	0	0
	q95	0.44	**13**	0	**28**	4.0	0	0.44	**17**	0	0.44	0	0
	q99	5.3	**8.9**	0.44	**19**	2.7	0	1.3	**10**	0.44	0.89	0.44	**6.2**
	max	3.6	**6.7**	0.44	**18**	3.6	0.44	1.8	**8.0**	1.3	1.3	0.89	**7.6**
Frequency	q50	**28**	26	8.4	**31**	**56**	0	7.6	**21**	**7.6**	**7.6**	**5.8**	0.89
	q75	3.1	**39**	3.6	**37**	**28**	3.6	0	**26**	0.44	2.7	2.7	0.89
	q90	0.89	**50**	0	**43**	**13**	5.8	0	**32**	0	4.9	0	**5.3**
	q95	0.44	**39**	0	**40**	**15**	3.1	1.3	**27**	4.9	1.3	0	**10**
	q99	5.8	**13**	0	**16**	**12**	3.6	0.89	**10**	**22**	1.8	0.89	**13**

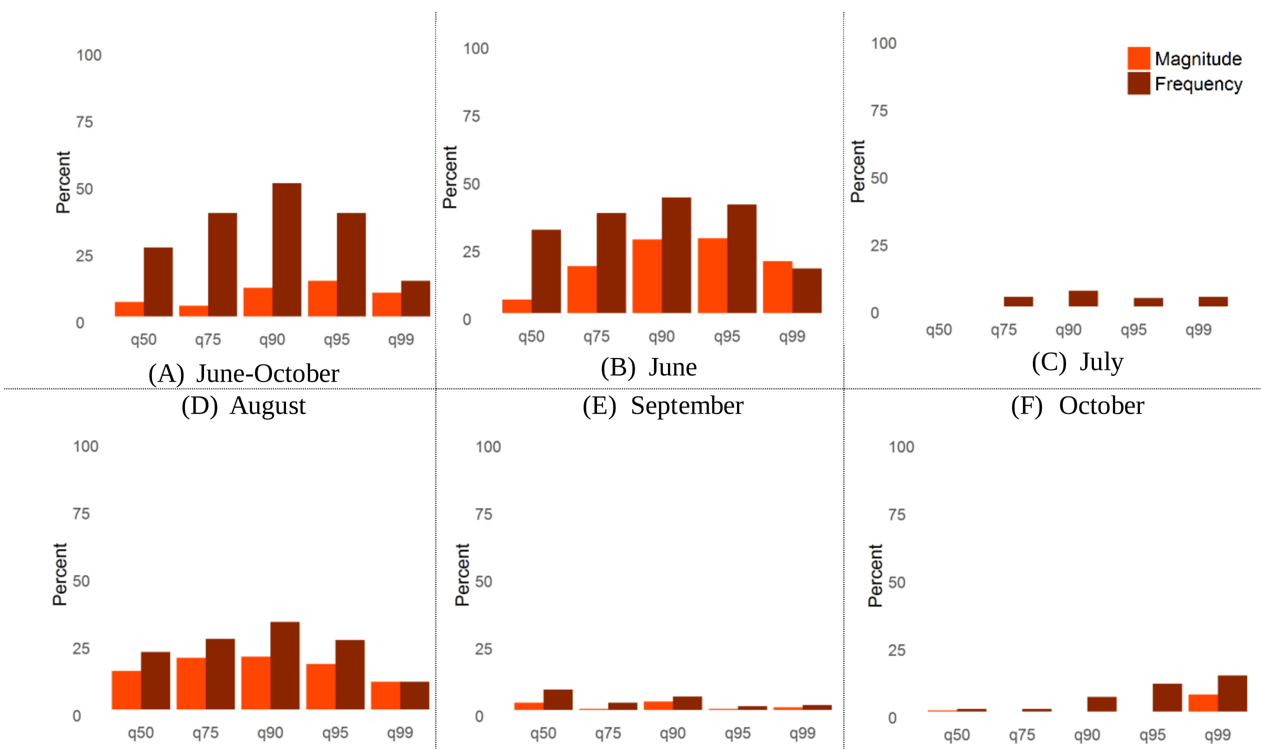

Figure 1. Percent of grid boxes with statistically significant negative (drying) trends (p-values <0.05, Table 1) for different quantiles of the magnitude and frequency precipitation indicators.

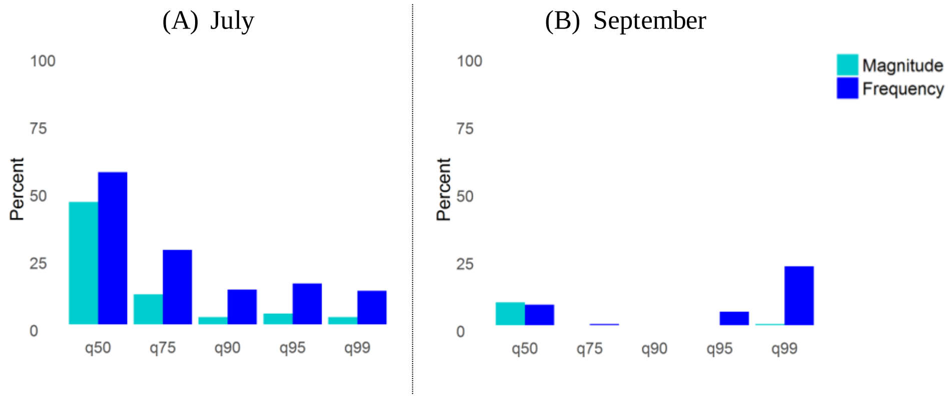

Figure 2. Percent of grid boxes with statistically significant positive (wetter) trends (p-values <0.05 , Table 1) for different quantiles of the magnitude and frequency precipitation indicators for July and September.

next section, we explore the spatial patterns of the precipitation trends during June-October as well as July and September.

Examining the Spatial Trend Patterns

In this section, we illustrate the spatial patterns in the magnitude and frequency of the indicators for June-October (Figure 3), July (Figure 4), and September (Figure 5) within the study region. These figures show that the spatial pattern of both increasing and decreasing trends vary across the different quantiles and seasons/months. Over the warm season (Figure 3), the regions in the northwest and southwest exhibit the strongest decreasing trends, which is more notable in frequency for q75, q90, and q95 (Figure 3 B-D). On the other hand, positive trends are observed from the southern regions to the central parts for q50 (Figure 3A), while it is concentrated in a few areas over the east for q75 (Figure 3B) and q99 (Figure 3E). In July, q50 (Figure 4A) shows positive trends over much of the domain except in the west and northwestern parts. As we move from lower quantile (i.e., q50, Figure 4A) to higher quantiles (i.e., q99, Figure 4E), the spatial coverage decreases and positive trends are more concentrated in the southern part with some speckling to the north. The locations of the positive trends in September for q99 (Figure 5E) and q50 (Figure 5A) tend to be concentrated in the southern regions. Results indicate that increasing trends in precipitation are more widespread over the southeast and northeast, likely due to moisture coming in from the Gulf of Mexico. Further, the increasing trends seen in the warm season are probably coming mainly from July and September contributions.

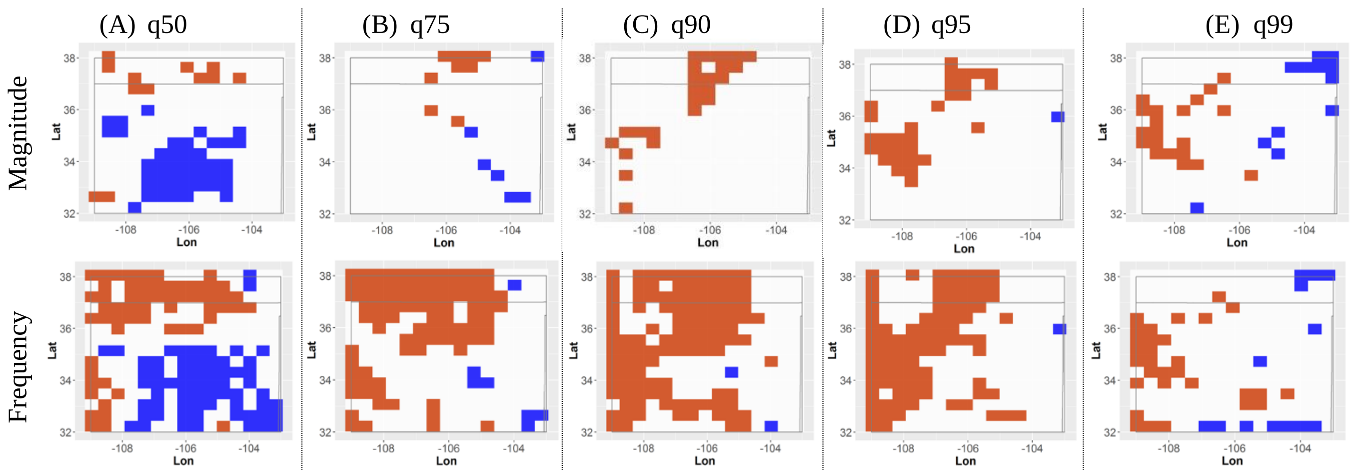

Figure 3. Spatial trend pattern in magnitude (top row) and frequency (bottom row) precipitation indicators for the warm season (June – October). The blue (red) areas indicate the location of the stations with increasing (decreasing) trends (p-values <0.05).

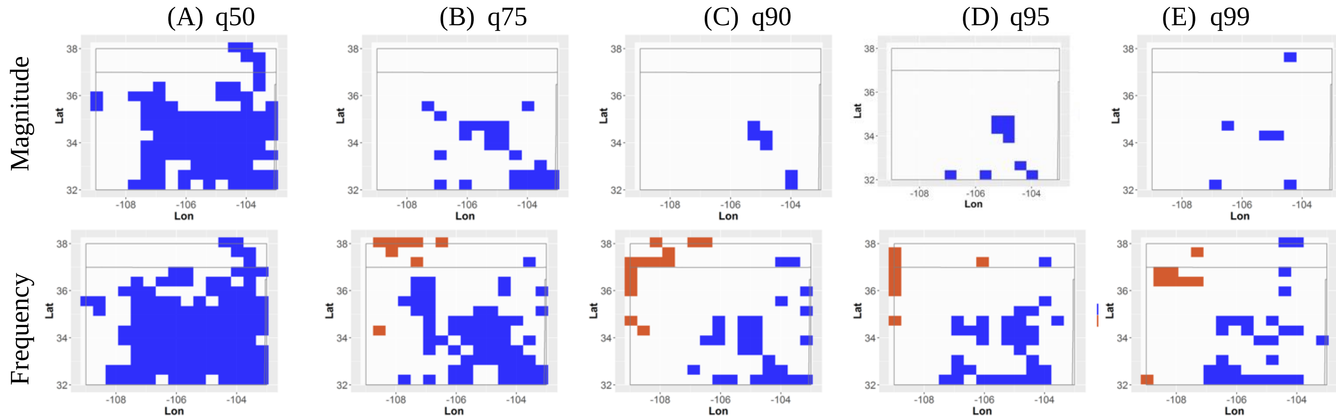

Figure 4. Spatial trend pattern in magnitude (top row) and frequency (bottom row) precipitation indicators for July. The blue (red) areas indicate the location of the stations with increasing (decreasing) trends (p-values <0.05).

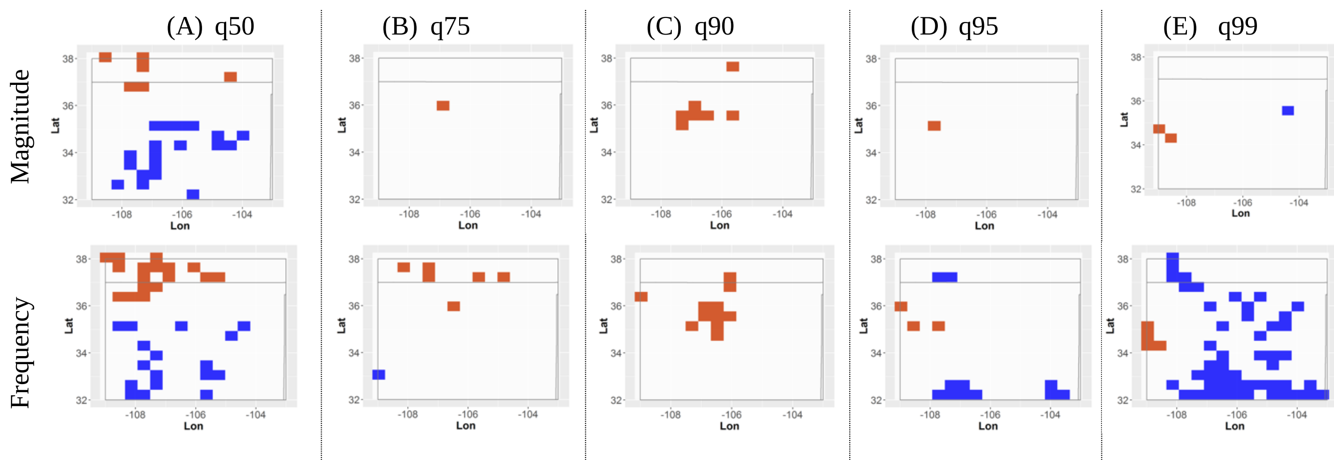

Figure 5. Spatial trend pattern in magnitude (top row) and frequency (bottom row) precipitation indicators for September. The blue (red) areas indicate the location of the stations with increasing (decreasing) trends (p-values <0.05).

CONCLUSION

In this study, we explore the trends in precipitation magnitude and frequency characteristics within the state of New Mexico and southern Colorado, relevant to the Rio Grande and Pecos basins. We examine both magnitude and frequency characteristics for the warm season (June - October) and individual months therein, with a focus on the upper quantiles and extremes. The purpose of this study is to determine how changing precipitation could potentially help mitigate decreases in water supply due to increasing temperatures and decreasing snowpack. For the period analyzed (1981-2017), we found that the dominant sign of the precipitation trend depends on the season/month examined. Negative trends dominate warm season, June, and August, while positive trends dominate July and for some September indicators, although the majority of locations in the study area did not show any significant trends. This suggests that the increasing trends across many of the July indicators show the most potential for water supply, with the location of these positive trends mainly concentrated in the southeastern and eastern part of the state. The frequency of days above q99 for September also showed increasing trends at some southern and southeastern locations, but this very heavy precipitation could be difficult to capture for water supply. However, across most characteristics examined, we find that significant trends are more detectable in the frequency indicators than the magnitude. For times and locations showing increasing trends, this suggests that water managers looking to exploit changes in precipitation might not need to plan for larger events, but rather more frequent events. Finally, we note that trend analysis provides important insight for water managers, especially in terms of where to focus further analysis. To this point, it is also critical to understand the drivers of the trends. In future work, the authors plan to investigate some of the factors that may be contributing to these trends, such as large-scale climate phenomena (e.g., the El Nino Southern Oscillation) or changes in the frequency of weather conditions (e.g., Prein *et al.*, 2016).

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