Leveraging a time-series event separation method to ~~untangle~~ disentangle time-varying hydrologic controls ~~influence~~ on ~~wildfire disturbed~~ streamflow – Application to wildfire-affected catchments

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Abstract. ~~Watershed disturbances can have broad, long-lasting impacts that result in a range of streamflow response.~~ Increasing watershed disturbance regimes, ~~particularly~~ such as from wildfire, ~~is~~ are a growing concern for ~~watershed~~ natural resource ~~management~~managers. ~~The~~ However, the influence of watershed disturbances on event-scale rainfall-runoff patterns has proved challenging to ~~untangle~~~~isolate~~disentangle from ~~undisturbed~~ other~~streamflow variability, driving the need to increase the understanding of~~ hydrologic controls~~ on event runoff response~~. ~~We~~In order to better isolate watershed disturbance effects, this study evaluates the influence of several time-varying hydrologic controls on event-scale rainfall-runoff patterns, ~~propose that hydrologic controls that vary through time,~~ ~~due to the role of hydrologic controls that vary through time,~~ including water year type, seasonality, and antecedent precipitation. ~~may be used to untangle explain natural streamflow variability and better isolate the effects of wildfire~~. ~~To better assess the influence of hydrologic controlswatershed disturbance on rainfall-runoff event patterns, w~~To accomplish this, we developed the Rainfall-Runoff Event Detection and Identification (RREDI) toolkit, ~~. The RREDI toolkit is~~ an automated ~~novel~~ time-series event separation and attribution algorithm ~~method that automates the pairing and attribution of precipitation and streamflow events, leveragin~~that overcomes several limitations of existing techniques~~g and building on existing~~ ~~rainfall-runoff~~ ~~event separation methods~~. The RREDI toolkit was used to generate~~A~~ a dataset of 5042 rainfall-runoff ~~event dataset of 5042~~ events ~~was generated by the RREDI toolkit~~ from ~~a collection of~~ nine western ~~USA~~ U.S. ~~study~~ watersheds~~spanning a range of streamflow regimes, watershed characteristicsproperties, and burn characteristics~~. Through analyzing ~~the rainfall-runoff event~~this large dataset, ~~we found that w~~water year type and season were identified as significant controls and antecedent moisture as a limited control on rainfall-~~rainfall~~runoff ~~metrics~~~~response~~patterns. ~~The significance of antecedent precipitation was variable between watersheds, indicating a more complex relationship for this control.~~ ~~The identified significant time-varying hydrologic controls were then used to isolate the~~S~~ influence~~pecific effects of wildfire disturbance on runoff response were then demonstrated ~~on event runoff response in~~for two ~~case study~~ burned watersheds by first grouping rainfall-runoff events based on identified hydrologic controls, such as wet versus dry water year types~~years~~. ~~. Post-fire rainfall-runoff events were found to have higher peak runoff than expected when compared to undisturbed trends within the identified watershed-specific significant condition groups.~~ ~~The watershed-specific permutations of significant controls resulted in unique significant condition group trends in the rainfall storm depth and peak runoff relationship in two contrasting watersheds. In general, for each of the significant condition groups post-fire peak runoff was higher than undisturbed peak runoff~~

~~except during winter in snow-dominated watersheds. Consideration of the time-varying hydrologic controls, particularly water year type and season, were identified as important when isolatinguntangling the influence of wildfire on the rainfall-runoff patterns.~~ The role of water year type and season should be considered in future hydrologic analysis to better isolate the increasing and changing effects of wildfire on streamflow~~s~~. The RREDI toolkit ~~can~~ could be readily ~~further~~ applied to investigate the influence of other ~~watershed disturbances and~~hydrologic controls and watershed disturbances ~~to increase understanding of~~on rainfall-runoff patterns~~ across the landscape~~.

1. Introduction

Watershed disturbances can have broad, long lasting, and variable impacts on watershed hydrology (Ebel and~~&~~ Mirus, 2014). A range of disturbances including wildfire, drought, flood, insect infestation, invasive species, agriculture, urbanization, mining, and forest management have been observed to alter streamflow (Adams et al., 2012; Brantley et al., 2013; Ebel ~~&~~and Mirus, 2014; Goeking ~~&~~and Tarboton, 2020; Hopkins et al., 2015; Kelly et al., 2017; Miller ~~&~~and Zégre, 2016). Wildfire is particularly impactful: since 2000 an average of 7.0 million acres has burned annually in the United States~~S~~ (Hoover ~~&~~and Hanson, 2021). Further, with~~in~~ a changing climate the observed occurrence and severity of wildfire has ~~is~~ increased in the western U.S.~~A~~ in recent decades~~ing~~, presenting growing challenges for human and water security (Abatzoglou et al., 2021; Abatzoglou ~~&~~and Williams, 2016; Hallema et al., 2018; Murphy et al., 2018; Robinne et al., 2021). ~~(Hallema et al., 2018; Murphy et al., 2018; Oakley, 2021; Robinne et al., 2021).~~ Distilling the influence of watershed disturbance from the natural variability within streamflow has proved challenging across disturbance regimes (Beyene et al., 2021; Biederman et al., 2022; Hallema et al., 2017; Kinoshita ~~&~~and Hogue, 2015; Long ~~&~~and Chang, 2022; Newcomer et al., 2023; Saxe et al., 2018; Wine et al., 2018; Wine ~~&~~and Cadol, 2016). A better understanding of hydrologic controls that vary in time in disturbed watersheds is critical for watershed management resiliency in the face of increasing disturbance regimes (Mirus et al., 2017).

~~Wildfires can cause abrupt changes to hydrologic processes and properties resulting in altered streamflow patterns that change through time as the watershed recovers (Ebel & Mirus, 2014; Santi & Rengers, 2020; Wagenbrenner et al., 2021). Post-fire changes in soil properties and vegetation may alter runoff generation processes (Ebel, Moody, et al., 2012; Santi & Rengers, 2020). Altered soil properties may include changes in soil-water repellency and infiltration capacity, the presence of ash, and loss of soil organic matter (Balfour et al., 2014; Ebel, Moody, et al., 2012; Santi & Rengers, 2020). Loss of vegetation may alter evapotranspiration and interception within the watershed (Atchley et al., 2018; Poon & Kinoshita, 2018; Santi & Rengers, 2020). The observed influence of these altered hydrologic properties on streamflow is variable in both the direction and magnitude of change. Total annual streamflow has been observed to increase (Bart, 2016; Beyene et al., 2021; Caldwell et al., 2020; Y. Guo et al., 2021; Hallema et al., 2017; Khaledi et al., 2022; Kinoshita & Hogue, 2015; Mahat et al., 2016; Owens et al., 2013; Saxe et al., 2018; Wine et al., 2018; Wine & Cadol, 2016), decrease (Balocchi et al., 2020; Biederman et al., 2022), and stay the same (Bart & Hope, 2010; Vore et al., 2020). Post-fire event flows have similarly been found to increase (Beyene et al., 2021; Hallema et al., 2017; Mahat et al., 2016; Saxe et al., 2018), decrease (Balocchi et al., 2020), and show no significant change (Kinoshita & Hogue, 2015; Long & Chang, 2022; Newcomer et al., 2023; Nunes et al., 2020; Owens et al., 2013). This leaves questions about our ability to distill the influence of the wildfire disturbance from the watershed natural variability.~~

~~In addition to watershed disturbances, t~~Time-varying hydrologic controls including water year type (WYT), seasonality, and antecedent precipitation have been found to influence ~~rainfall-runoff patterns~~event runoff response. ~~Water year type is a commonly used categorization to compare individual years against historical trends (Null & Viers, 2013). Variation between~~Different WYTs ~~wet and dry years~~associated with differences in annual snowpack (Cayan, 1995) or the occurrence and intensity of precipitation from monsoons or atmospheric rivers (Arriaga-Ramierez ~~&~~and Cavazos, 2010; Pascolini-Campbell et al., 2015) may ~~result in differences in~~alter runoff response (Biederman et al., 2022; Null ~~&~~and Viers, 2013). ~~Examples of WYT variation drivers include variation in annual snowpack (Cayan, 1995) or the occurrence and intensity of precipitation from monsoons or atmospheric rivers (Arriaga-Ramierez & Cavazos, 2010; Pascolini-Campbell et al., 2015). Seasonality, specifically seasons defined based on the annual hydrograph, can alter event runoff response across a range of watersheds (Jahanshahi and Booij, 2024; Merz et al., 2006; Merz & Blöschl, 2009; Norbiato et al., 2009; Tarasova, Basso, Zink, et al., 2018b, Zheng et al., 2023). Seasonal~~ Observed seasonal differences in rainfall-runoff patterns~~response~~ have been attributed to precipitation type, rainfall~~storm~~ properties (intensity, depth), water balance, and antecedent wetness conditions (Berghuijs et al., 2014; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Norbiato et al., 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b, Zheng et al., 2023;Jahanshahi and Booij, 2024). ~~Finally, a~~Antecedent ~~precipitation and antecedent~~ moisture - and the more widely available proxy of antecedent precipitation - have also been found to alter event runoff response (Jahanshahi and Booij, 2024; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b, Zheng et al., 2023). ~~Antecedent precipitation is commonly used as a proxy for antecedent moisture (Jahanshahi and Booij, 2024; Merz & Blöschl, 2009; Mishra & Singh, 2003; Tarasova, Basso, Zink, et al., 2018b).~~ Despite their established influence on event runoff response, these time-varying hydrologic controls are inconsistently considered in hydrologic disturbance studies.

~~The event-scale enables a process-based understanding of driving hydrologic processes in catchment hydrology (Gupta et al., 2014; Sivapalan, 2009).~~

~~Selected post-fire streamflow change studies have assessed some of these time-varying hydrologic controls, but to the best of the authors knowledge none to date have considered all three potential controls and very few studies have focused on the event scale. Of these three controls, WYT is most frequently considered when evaluating wildfire influence on streamflow (Beyene et al., 2021; Biederman et al., 2022; Hallema et al., 2017; Long & Chang, 2022; Wine & Cadol, 2016). A common method to account for the role of WYT variability is compare water year expected streamflow and observed streamflow to isolate the influence of the disturbance (Beyene et al., 2021; D. Guo et al., 2023; Hallema et al., 2017; Mahat et al., 2016; Newcomer et al., 2023). Another method for pre- and post-fire comparison is water year typing based on total annual precipitation-streamflow relationships or annual percentiles (Biederman et al., 2022; Long & Chang, 2022). In addition to interannual variability, several studies have evaluated post-fire changes in total streamflow or flow statistics within specific seasons (Balocchi et al., 2020; Biederman et al., 2022; Kinoshita & Hogue, 2015; Saxe et al., 2018; Wine et al., 2018). Antecedent precipitation is less commonly considered in post-fire streamflow response studies. Long & Chang (2022) used three-day antecedent precipitation to normalized runoff event volume, but found no altered streamflow significance. Lack of consistent consideration of~~

~~WYT, seasonal variability, and antecedent precipitation may help explain the inconsistency in observed post-fire effects on streamflow.~~

Large-sample hydrology studies are frequently used to investigate time-varying and static watershed controls on event-scale rainfall-runoff patterns. The rainfall-runoff event-scale enables a process-based understanding of driving hydrologic processes in catchment hydrology (Gupta et al., 2014; Sivapalan, 2009). ~~The event-scale enables a process-based understanding of driving hydrologic processes in catchment hydrology (Gupta et al., 2014; Sivapalan, 2009).~~ Large-sample investigations into event-scale controls in Europe have found that time-varying hydrologic controls influence event runoff ratios (Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Norbiato et al., 2009; Tarasova~~, Basso, Poncelet,~~ et al., 2018a; Tarasova~~, Basso, Zink,~~ et al., 2018b, Zheng et al., 2023). A similar event-scale large-sample study of 432 U.S.~~A~~ watersheds evaluated only static controls on event runoff response, and identified aridity, topographic slope, soil permeability, rock type, and vegetation density as significant factors (Wu et al., 2021). None of these studies considered the separate impact of watershed disturbance. Conversely, the body of wildfire disturbed streamflow change literature has sporadically and inconsistently considered these time-varying hydrologic controls (e.g. Balocchi et al., 2020; Beyene et al., 2021; Biederman et al., 2022; Hallema et al., 2017; Kinoshita ~~&~~and Hogue, 2015; Long ~~&~~and Chang, 2022; Saxe et al., 2018; Wine et al., 2018; Wine ~~&~~and Cadol, 2016). Long ~~&~~and Chang (2022) considered WYT and antecedent precipitation while investigating the influence of wildfire disturbance on event runoff response. However, they analyzed only a small-sample of rainfall-runoff events from two years, one pre- and one post-fire, in a ~~small~~ sample of six watersheds in Oregon, U.S.~~A.~~

~~To i~~Investigat~~e~~ing ~~a~~ large samples of rainfall-runoff events~~,~~ requires ~~the use of an~~ automated, transferable methods for time-series event separation~~ method is critical~~. ~~The most c~~Common rainfall-runoff event separation techniques rely~~ies~~ on established baseflow methods to isolate event flow (e.g. Chapman ~~&~~and Maxwell, 1996; Duncan, 2019; Eckhardt, 2005; Xie et al., 2020). Runoff events are then identified where baseflow diverges from total flow (Long ~~&~~and Chang, 2022; Mei ~~&~~and Anagnostou, 2015; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Tarasova et al., 2018b). Giani et al.~~,~~ (2022b) identified the need for increased method transferability across watersheds as the baseflow separation methods require ~~the use of~~ multiple calibrated parameters in each watershed. To increase transferability, separation methods use fewer modifying watershed parameters (Blume et al., 2007; Nagy et al., 2022) or time-series signal processing to identify rainfall-runoff events (Giani et al., 2022b; Patterson et al., 2020). The commonly used separation methods are not able to identify sub-daily rainfall-runoff events as many are developed or calibrated to use only daily streamflow (Long ~~&~~and Chang, 2022; Mei ~~&~~and Anagnostou, 2015; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Tarasova et al., 2018b). These methods cannot capture the sub-daily rainfall-runoff events that may result from convective rainfall events in mountainous watersheds (Kampf et al., 2016). Further, there are limitations in the existing available separation methods including the lack of identification of rainfall events with no runoff response and the filtering of diurnal cycling influenced runoff events that have limited the application of the available methods in snow-dominated watersheds.

The objectives of this paper were twofold. The first was to describe and evaluate the performance of the Rainfall-Runoff Event Detection and Identification (RREDI) toolkit, an automated ~~novel~~ time-series event separation method (Canham ~~&~~and Lane, 2022). The second objective was to apply ~~the proposed method~~the RREDI toolkit to investigate the influence of time-varying hydrologic controls including WYT, season, ~~and~~ antecedent precipitation, and wildfire on event runoff response. The specific ~~aims of the investigation into time-varying hydrologic controls were to~~research ~~questions~~aims were to: (1) ~~explore~~ evaluate rainfall-runoff patterns and ~~and,~~ (2) identify significant time-varying hydrologic controls on event runoff response across nine western U.S. watersheds~~.~~, and~~The, ann,d~~ then (3) use these findings to ~~explore~~explore ~~the~~the effects of wildfire ~~findings from research questions 1 and 2~~ in two ~~case study evaluate how time-varying hydrologic controls influence event runoff response in wildfire disturbed~~ burned ~~watersheds~~ ~~watershed~~ case study watersheds~~ies~~. ~~We hypothesize that accounting~~The resulting hydrologic patterns and ~~for these significant~~ time-varying ~~hydrologic~~ controls ~~will~~ are expected to reflect broader trends across western U.S. watersheds and provide foundational methods and understanding related to watershed disturbances~~untangle the natural watershed streamflow variability, ultimately thereby making~~ ~~allow the influence of the wildfire disturbance more apparent~~ ~~to be isolated in the two case study watersheds~~.

2. Study watersheds

Nine ~~study~~ watersheds in the western ~~USA~~ U.S. were ~~hand-selected~~selected for this analysis (Fig. 1 a) ~~-~~to ~~satisfy~~span a wide range of ~~based on~~ watershed properties and streamflow regimes (Table 1). ~~, burn characteristics,from those with and streamflow data availability.The nine selected watersheds spanned a wide range of watershed properties and burn characteristics (Fig.ure 1 a). First, we identified western USA watersheds~~Watersheds were required to have at least 20 years of continuous 15-minute streamflow records including at least 10 years of undisturbed streamflow records including from wildfire (MTBS, 2023; ~~from the GAGES-II dataset (~~Falcone, 2011). ~~with at least 20 years of continuous 15-minute streamflow data including at least 10 years of undisturbed streamflow including from wildfire (Falcone, 2011MTBS, 2023). The selected nine study watersheds spanned a large range of contributing areas, streamflow regimes, and burnwatershed characteristics conditions (Table 1). The~~Study watershed contributing areas ranged ~~over~~ three orders of magnitude, from 14 km^2 (Ash Canyon Creek) to 2,966 km^2 (Cache La Poudre River)~~., with extents defined by the installation locations of the long-term USGS gauges.~~ The mean annual streamflow ranged from 38 mm (Camp Creek) to 1217 mm (Shitike Creek)~~ 12.1 m^{3}s^{-1} in Thompson River to 38 mm0.03 m^{3}s^{-1} (in Camp Creek)~~. The mean annual precipitation ranged from 531 mm (Cache La Poudre River) to 1572 mm ~~in~~ (Shitike Creek) ~~to 531 mm (in Cache La Poudre River)~~ (Falcone, 2011) and the mean annual potential evapotranspiration ranged from 401 mm (Valley Creek) to 780 mm ~~in~~ (Wet Bottom Creek)~~ toand 401 mm in (Valley Creek)~~ (Falcone, 2011). ~~The watersheds included a range of s~~Seven of the ~~streamflow regimes~~ elected watersheds ~~including seven~~had snow-melt dominated ~~systems~~flow regimes with average annual ~~annual hydrograph~~ peak flows ~~dates~~ between April and June and two watersheds had wet season rain dominated ~~systems~~regimes with average annual ~~hydrograph peak dates~~peak flows between January and February.

Two of the nine study watersheds were selected for a more in-depth exploration of ~~watershed disturbance~~wildfire effects ~~on rainfall-runoff events:~~ Arroyo Seco and Clear Creek (Fig. 1 b, c). ~~Figure. 1 b, c.~~ These watersheds ~~were selected first and foremost because they~~ both experienced high severity wildfires ~~during the period of available streamflow record~~ that burned a ~~significant~~substantial portion of the watershed ~~(>25%) and with particularly high severity~~. The Station Fire (2009) burned 100% of Arroyo Seco (78% high and moderate burn severity) and the

Twitchell Canyon Fire (2010) burned 25% of Clear Creek (15% high and moderate severity) (MTBS, 2023)~~.~~. Arroyo Seco and Clear Creek~~Additionally, these two case studies~~~~These two watersheds a~~ also ~~provided~~present an interesting comparison~~ with respect to watershed characteristics~~, as they ~~are an order of magnitude difference in area~~have very different contributing areas, a nearly three~~four~~-fold difference in mean annual streamflow, and are rain and~~vs.~~ snow-melt dominated respectively~~ respectively, and have a four-fold difference in mean annual streamflow~~.

~~All nine study watersheds were impacted with differing size and severity fires. The highest impacted was Arroyo Seco from the Station Fire (2009) with 100% area burned (78% high and moderate burn severity). The least impacted watershed was the Cache La Poudre River from the High Park Fire (2012) with 10% area burned (5% high and moderate severity).~~

~~Of these, we identified watersheds with a greater than 5% area burned within the available record of 1984 to 2020 from the MTBS database (*Monitoring Trends in Burn Severity (MTBS)*, n.d.). This set was further reduced to watersheds with pre-fire and post-fire streamflow records of at least ten and six years respectively and minimal upstream anthropogenic influence, such as reservoirs. The watersheds spanned five magnitudes of contributing area (1.8 to 10,125 km^2) and from 5 to 100% area burned. The final study watershed selection from this set were those with no other fires within the MTBS database exceeding 5% area burned within the watershed. The nine selected watersheds spanned a wide range of watershed properties and burn characteristics (Figure 1).~~

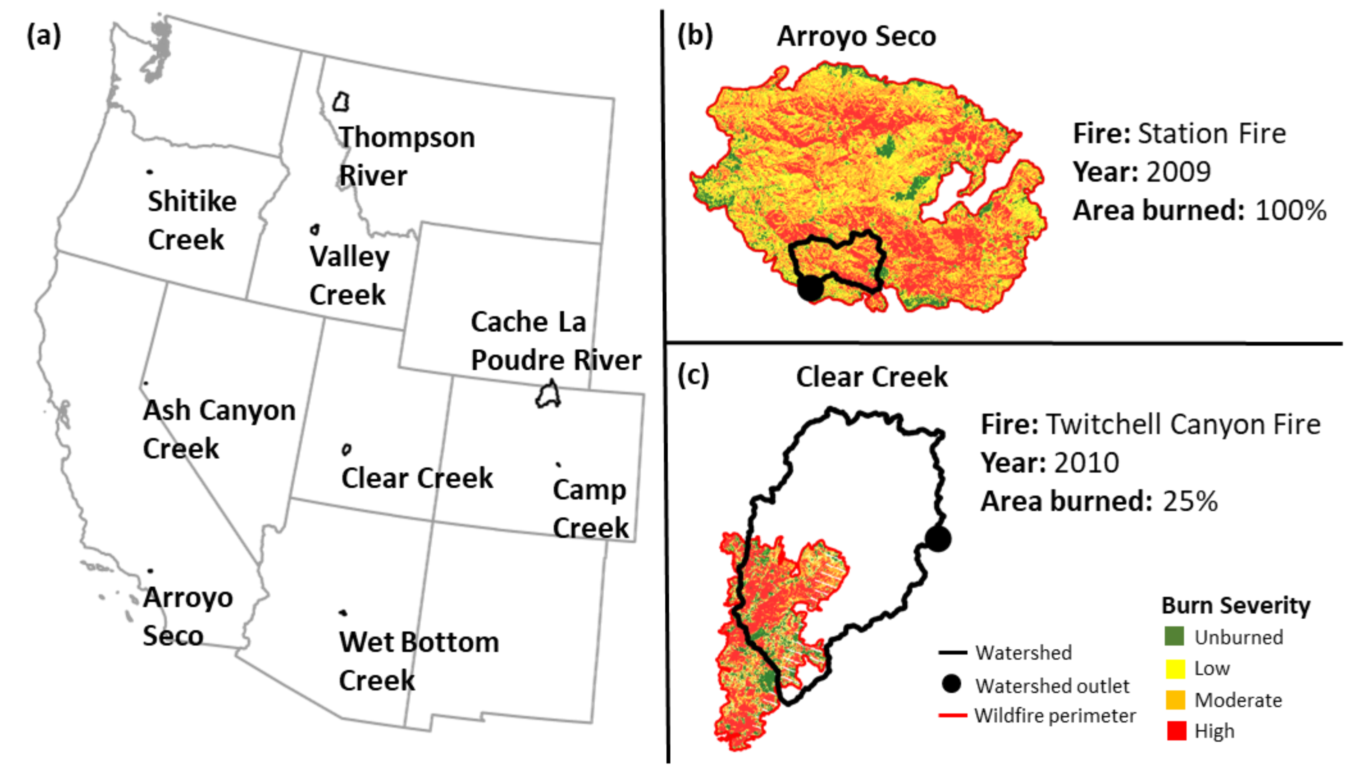


Figure 1: Study watersheds. (a) Nine selected study watersheds (labeled). Case study burned watersheds (b) Arroyo Seco and (c) Clear Creek. Shown are watersheds (black), ~~and~~ fire perimeters (red), and burn severity mosaics (MTBS, 2023).

~~The nine study watersheds spanned a large range of contributing areas, streamflow regimes, and burn conditions (Table 1). The contributing area range was three orders of magnitude, where the largest watershed, the Cache La Poudre River, was 2,966 km^2, and the smallest, Ash Canyon Creek, was 14 km^2. The watersheds included a range of streamflow regimes including seven snow melt dominated systems with average annual hydrograph peak dates between April and June and two wet season rain dominated systems with average annual hydrograph peak dates between January and February. All nine study watersheds were impacted with differing size and severity fires. The highest impacted was Arroyo Seco from the Station Fire (2009) with 100% area burned (78% high and moderate burn severity). The least impacted watershed was the Cache La Poudre River from the High Park Fire (2012) with 10% area burned (5% high and moderate severity).~~

Table 1: Watershed characteristics ~~properties and burn characteristics~~ for the study watersheds. Where P is precipitation and PET is potential evapotranspiration.

Watershed	State	USGS Gage ID	Contributing Aa~~a~~rea (km^2)	Mean Annual Streamflow ~~(mean annual)~~ (mm~~m^2 s^{-1}~~)	Mean Annual Precipitation~~P~~ ~~(mean annual)~~* ((~~c~~mm)	Mean Annual PET ~~(mean annual)~~* (~~c~~mm)	Streamflow regime
Arroyo Seco	CA	11098000	42	203~~0.27~~	788~~9~~	776~~7~~	Rain
Ash Canyon Creek	NV	10311200	14	225~~0.10~~	759~~6~~	479	Snow
Cache La Poudre	CO	06752260	2966	52~~4.9~~	531	449	Snow
Camp Creek	CO	07103703	25	38~~0.03~~	557~~6~~	479	Snow
Clear Creek	UT	10194200	426	74~~1.0~~	537~~4~~	508	Snow
Shitike Creek	OR	14092750	57	1217~~2.2~~	1572	492	Snow
Thompson River	MT	12389500	1652	231~~12.1~~	761	476	Snow
Valley Creek	ID	13295000	376	478~~5.7~~	882	401	Snow

Watershed	State	USGS Gage ID	Contributing A~~a~~rea (km^2)	Mean Annual Streamflow ~~(mean annual)~~ (mm~~m^2 s^{-1}~~)	Mean Annual Precipitation~~P~~ ~~(mean annual)~~* (~~(c~~mm)	Mean Annual PET ~~(mean annual)~~* (~~c~~mm)	Streamflow regime
Wet Bottom Creek	AZ	09508300	94	131~~0.39~~	617~~2~~	780	Rain

*(Falcone, 2011)

2.1. Hydrologic data inputs

Streamflow and precipitation data were obtained for each study watershed as follows. Daily and ~~The~~ 15-minute streamflow records were retrieved from the U.S. Geological Survey's National Water Information System~~,~~ and used to calculate ~~daily, and~~ total annual streamflow data ~~for the full period of record were retrieved from the USGS streamflow gage~~. ~~Additionally, s~~Streamflow was defined as undisturbed before or more than six years post-fire while disturbed streamflow was within six-years post-fire (Ebel et al., 2022; Wagenbrenner et al., 2021). The total annual precipitation at the centroid of each study watershed over the same period ~~for each year with available USGS annual streamflowused to classify WYT~~ was retrieved from the~~gridded~~ Parameter-elevation Regressions on Independent Slopes Model (PRISM) gridded annual precipitation dataset (PRISM Climate Group, Oregon State University, 2022). Hourly precipitation time series were obtained for the watershed centroid from the Analysis of Record Calibration (AORC) 4 km^2 resolution data product for water years 1980 to 2022 (Fall et al., 2023)~~; National Weather Service Office of Water Prediction, 2021)~~. Linear interpolation was used to develop an instantaneous precipitation record ~~spread the hourly rainfall over the timestep~~ at the AORC resolution of 1 mm by identifying uniform sub-timesteps within the hour timestep resolution. For example, hourly precipitation of 2 mm depth was uniformly spread over the hour with two timestamps of 1 mm each. The AORC data product was selected because of the hourly temporal resolution and comparable or higher correlation between the AORC data product and rain gage measurements compared to other gridded precipitation data products in studies in a mountainous area in Colorado~~, USA~~, Louisiana, ~~USA,~~ and the Great Lakes basins (Hong et al., 2022; Kim ~~&~~and Villarini, 2022~~,~~; Partridge et al., 2024)~~)~~. ~~We additionally performed a comparison of storm events in a mountainous region, specifically in Clear Creek watershed, for water year 2011. We compared the AORC-based storm events at the corresponding locations of two rain gages: one temporary rain gage in the mountains installed after a wildfire (Murphy et al., 2019) and a NOAA COOP rain gage in the nearby valley 18 km from Clear Creek watershed (Beaver 4E, UT US COOP:420522). For the storm events in water year 2011, the average storm depth based on the AORC data product was less than that measured at the rain gage by 0.6 mm for the Clear Creek rain gage and by 8.3 mm for the NOAA COOP rain gage. Similarly, the average 60-minute peak storm intensity for the AORC data product was less than the rain gage by 2.3 mm/hr for the Clear Creek rain gage and by 1.5 mm/hr for the NOAA COOP rain gage.Additionally, streamflow was defined as~~

~~undisturbed before or more than six years post-fire while disturbed streamflow was within six-years post-fire (Ebel et al., 2022; Wagenbrenner et al., 2021).~~

3. Methods

We describe the four key steps of the RREDI toolkit in section ~~.~~3.1 (Fig.~~ure~~ 2~~),~~) with additional in-depth details in~~, with additional details and all study specific RREDI toolkit parameters in~~ Supplemental Information~~.~~ ~~(SI)~~ section S1. ~~RREDI toolkit.~~ A rainfall-runoff event dataset~~, available in SI~~ (Table S4), was created by applying the RREDI toolkit to nine western U.S.~~A~~ watersheds ~~(Figure 2)~~. This dataset was then used to explore rainfall-runoff event patterns, identify significant time-varying hydrologic controls, and evaluate the influence of these controls on rainfall-runoff patterns (~~in two case study wildfire disturbed watersheds (~~Fig.~~ure~~ 2). The hydrologic conditions associated with each time-varying hydrologic control were identified and assigned for each rainfall-runoff event as described in section 3.2. The assigned~~sorted~~ rainfall-runoff events were then sorted by hydrologic condition and explored as described in section 3.3. Trends in rainfall-runoff event patterns were identified and ~~using a LOWESS curve. I~~inferential statistics were used to test the significance of the hydrologic conditions to identify ~~the~~ significant time-varying hydrologic controls for generalized runoff metric groups. The influence of ~~the~~ wildfire was then evaluated relative to ~~the~~ undisturbed ~~runoff event~~ significant condition group rainfall-runoff trends in two ~~contrasting~~ burned watersheds.~~,~~ ~~Arroyo Seco and Clear Creek.~~

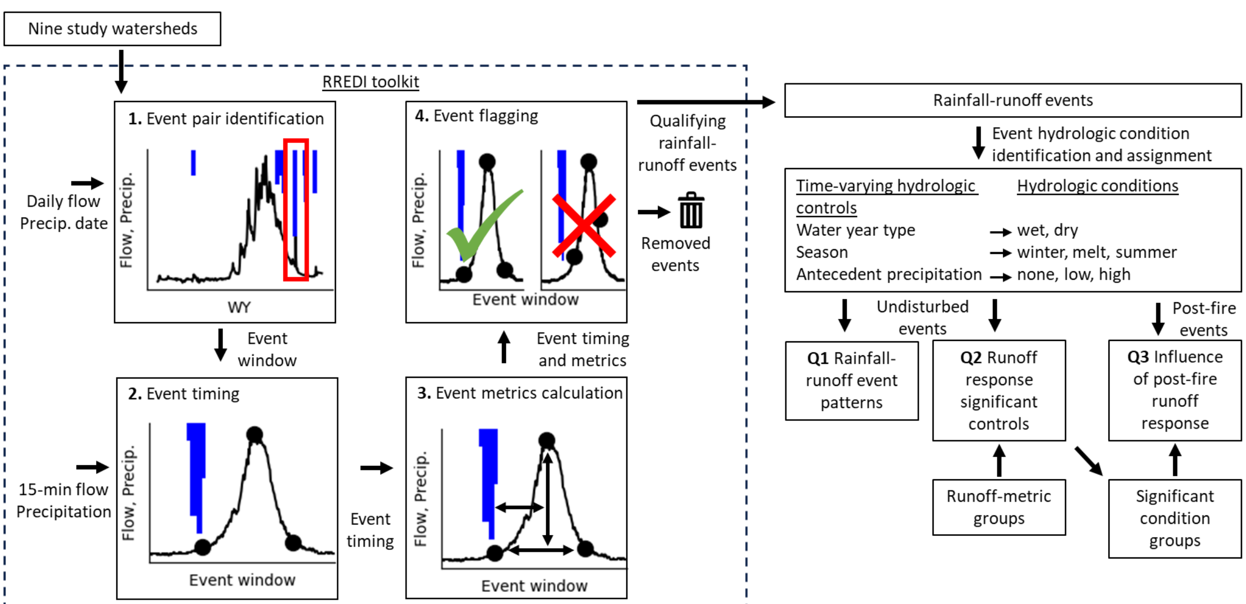


Figure 2: Methods workflow to explore the influence of time-varying hydrologic controls on rainfall-runoff event patterns ~~as described in this paper~~. The four key steps of the RREDI toolkit (black dashed box) are outlined: Step 1. Event pair identification, Step 2. Event timing, Step 3. Event metrics calculation, and Step 4. Event flagging. Major connections between workflow steps and ~~study research questions~~research aims (Q) are shown.

3.1. RREDI toolkit

The RREDI toolkit was developed to automatically separate rainfall-runoff events for any watershed using time-series signal processing in four steps (Fig.~~ure~~ 2~~; SupplementalSupplemental Information~~) (Canham ~~&~~and Lane, 2022). Given the inherent challenges of deterministically identifying rainfall-runoff events from only streamflow and precipitation data, we took a time-series signal processing approach that relies in part on expert understanding to define “accurate” rainfall-runoff events like numerous other large-sample hydrology studies including Patterson et al. (2020), Tarasova et al (2018b), and Giani et al. (2022b). Additional in-depth descriptions of each step are included in ~~SI~~ section S1~~. RREDI toolkit~~ (Fig. S1-S5). All watershed specific and calibrated parameters used are also documented (Table S1, S2). Signal processing theory provided techniques including data smoothing, peak detection, and window processing that were used to automate detection of features from a time series (Patterson et al., 2020). The RREDI toolkit was fully automated using the open-source python language.

In step 1 of the RREDI toolkit, rainfall-runoff event pairs and the associated event window were identified using daily streamflow and precipitation data based on the co-occurrence of separately identified rainfall and runoff events by separating precipitation time-series into storms ~~rainfall storms~~ and runoff into events using signal processing theory from the overlapping period of record (Fig.~~ure~~ 2). Rainfall events were characterized by the duration, depth, and 60-minute intensity. For each rainfall-runoff event pair, the~~ event~~ window from the start of ~~the~~ rainfall to the end of runoff was ~~passed to step 2~~determined. In step 2, t~~T~~he runoff event start, peak, and end timing and magnitude and the runoff event volume were then identified within that time window using ~~then~~ 15-minute streamflow data and ~~the~~ 60-minute rainfall~~storm~~ intensity ~~in step 2~~ (Fig.~~ure~~ 2; Fig.~~ure~~ 3). For each rainfall-runoff event, a set of 17 runoff metrics were calculated using the identified rainfall and runoff~~ event~~ timings in step 3 ~~identified in step 3~~ (Fig.~~ure~~ 2). Metrics fell within four ~~runoff metric~~ groups: runoff volume~~ metrics~~, runoff magnitude~~ metrics~~, runoff duration ~~metrics~~, and rainfall-runoff timing metrics (Fig. S4; Table S3). Selected metrics in each group, respectively,~~,~~ ~~respectively,~~ utilized further in this study ~~included those~~were as follows (Fig.~~ure~~ 3 b):~~.~~ ~~The runoff volume metric group included~~ event volume,~~. The runoff magnitude metric group included~~ runoff peak defined by the runoff peak magnitude, ~~. The runoff duration metric group included~~ event duration calculated as the difference between the runoff event start and end times, and ~~. The rainfall-runoff timing metric group included~~ response time calculated as the difference between the rainfall~~storm~~ start time and the runoff start time. Metric~~s~~s were also normalized by ~~dividing metric values by the~~their respective watershed contributing area to facilitate comparison between study watersheds. Finally, in step 4, event flagging was performed to remove incorrectly identified rainfall-runoff events falling within four ~~rainfall-runoff~~ event identification issues: gaps in 15-minute streamflow data, diurnal cycling identified by regular daily rises and falls of flow commonly due to irrigation or snow melt cycles (Fig. S5), duplicate rainfall-runoff events, and no identified runoff event end time (Fig.~~ure~~ 2; ~~Supplemental Information~~Fig. S3). F~~F~~rom a time-series analysis perspective, t~~T~~hese misidentified rainfall-runoff events were very similar in appearance to true rainfall-runoff events~~,~~ but were functionally driven by different or uncertain processes that were not applicable to the application of the RREDI toolkit and thus removed. ~~The RREDI toolkit was fully automated using the open-source python language.~~

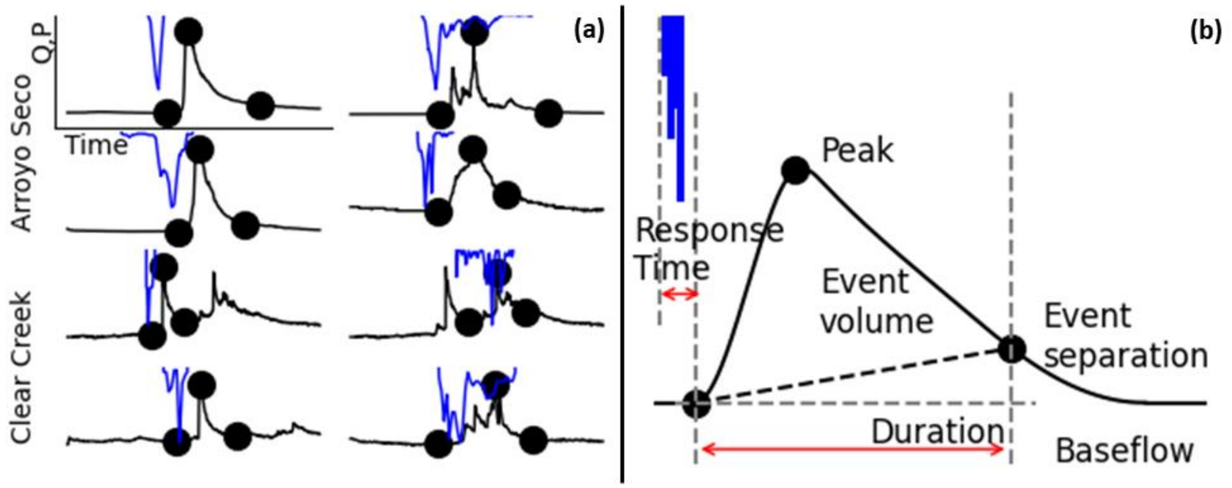


Figure 3. RREDI toolkit rainfall-runoff event examples and metrics. (a) Eight example rainfall-runoff events identified using the RREDI toolkit. Shown are the rainfall event (blue), the paired runoff event hydrograph (black), and the identified runoff start, peak, and end times and magnitudes (black dots). (b) ~~E~~An example rainfall-runoff event showing relevant ~~rainfall-runoff~~ event metrics including runoff event volume, peak, duration, and response time. S~~Event s~~eparation (black dashed) between runoff event ~~flow~~ volume and baseflow is shown.

A visual assessment of the RREDI ~~systematic~~toolkit performance was iteratively completed for all ~~RREDI-~~identified rainfall-runoff events within the wettest, mean, and driest water years for each study watershed~~ to systematically assess the RREDI toolkit performance~~. These years were selected based on the watershed average total precipitation from PRISM (Oregon State University, 2022). ~~assessment of the RREDI toolkit outputs was performed. For each of the study watersheds, all rainfall-runoff events occurring in the wettest, mean, and driest water years based on watershed average annual total precipitation (Oregon State University, 2022) were visually inspected. The~~ For each rainfall-runoff event, the~~The~~ ~~RREDI toolkit identified~~ runoff start, peak, and end timing and magnitude identified by the RREDI toolkit were visually compared with the ~~runoff start, peak, and end timing and magnitudeose~~same metrics independently identified by ~~visual~~ manual inspection ~~for each rainfall-runoff event following~~ similar to the performance assessment ~~methods used for~~in other event separation methods (Giani et al., 2022b; Patterson et al., 2020; Tarasova et al., 2018b)~~ and assessed with respect to the four event identification issues described above~~. A rainfall-runoff event was determined to be accurately identified by the RREDI toolkit if the runoff start, peak, and end magnitude and timing of each rainfall-runoff e~~E~~vent~~s~~ were sufficiently similar to those timings identified through inde~~were consideidentified~~pendent visual assessment such that the rise in runoff from the start to the peak and the runoff duration were considered reasonable. ~~.~~In this manner, we visually assessed 11% of rainfall-runoff events used in this study (774 rainfall-runoff events), that spanned a range of watersheds, watershed wetness conditions, and seasons. ~~-~~RREDI toolkit performance assessment results were summarized for each study watershed and ~~overall~~ across study watersheds (section 4.1). Performance results~~,~~ included the percent of ~~events~~ RREDI-identified rainfall-runoff events within the wettest, mean, and driest water years with accurately identified timing output from the RREDI toolkit, the percent of rainfall-runoff events flagged in step 4, and the percent of rainfall-runoff events retained after removal of flagged rainfall-runoff events.

3.2. Hydrologic condition identification and assignment

Hydrologic conditions were identified and assigned for each rainfall-runoff event with respect to ~~the~~ three time-varying hydrologic controls~~ considered in this study~~: WYT, season, and antecedent precipitation. ~~Instead of developing entirely new methods to define WYT or season across many watersheds with different hydrologic settings, we chose to provide sufficient details on methods and results of our expert-informed selections to support a robust, transparent assessment of these time varying hydrologic variables on event runoff response.~~ Water year type was assigned as wet or dry following Biederman et al. (2022) ~~based on total annual streamflow and watershed average total annual precipitation following Biederman et al. (2022) for all study watersheds~~ (Fig.~~ure~~ 4 a; ~~Figure~~Fig.~~ure.~~ S6). ~~Total annual streamflow~~Plots of annual cumulative runoff ~~and~~ versus precipitation ~~were plotted for~~over the undisturbed period of record were used to visually identify pronounced ~~the~~ annual precipitation ~~threshold~~ breakpoints above which streamflow increased linearly with precipitation. Years (both undisturbed and disturbed) with annual precipitation above or below the threshold were then classified as wet or dry, respectively. For watersheds where no ~~precipitation threshold~~breakpoint was identified, the driest third of years (both undisturbed and disturbed) by annual precipitation were considered dry. Alternative methods such as change point detection may be able to more objectively identify that breakpoint, but automating water year or season identification was beyond the study scope~~ of our study~~. Winter, melt, and summer hydrologic seasons were identified for each watershed based on inspection of the average annual hydrograph and the earliest and latest mean (2001–2018) snow-off dates within the watershed (O'Leary III et al., 2020) (Fig.~~ure~~ 4 b; ~~Figure~~Fig.~~ure.~~ S7). The start of winter season was uniformly set as November 1 to capture the change in precipitation pattern and type between summer and winter. Melt season started the month after the earliest snow-off date in the watershed and summer season started the month after the latest snow-off date to account for the lagged streamflow response to snowmelt. Watersheds with less than 10% ~~of the watershed~~ area with an identified snow~~-~~melt date were considered to have no melt season (i.e., only winter and summer). In watersheds with no melt season, summer season started the month ~~where~~ that baseflow dominated over winter rainfall ~~storm~~ peaks in the mean annual hydrograph. ~~Rainfall-runoff e~~E~~E~~vent-scale antecedent precipitation was assigned as none (<1mm), low (1-25mm), ~~and~~ or high (>25mm) based on ~~the~~ cumulative precipitation ~~depth~~ over the six days prior to the rainfall~~precipitation~~ event start time (Long ~~&~~and Chang, 2022; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b) (Fig~~ure~~. 4 c). When evaluating antecedent moisture to isolate the influence of soil moisture on runoff rather than snowmelt and rain-on-snow influences, o~~O~~nly snow-off rainfall-runoff events were considered ~~in this assessment,~~ including only summer ~~rainfall-runoff~~ events in watersheds with a melt season and all ~~rainfall-runoff~~ events in watersheds without a melt season~~, to isolate the influence of soil moisture on runoff rather than snowmelt and rain-on-snow influences~~. ~~We do not expect that u~~We do not expect that using alternative available methods ~~other than those described here~~ to ~~adjust the thresholds~~assign rainfall-runoff events to ~~re-assign rainfall-runoff events~~ hydrologic conditions would substantially alter ~~our~~the proposed approach or findings in this study.

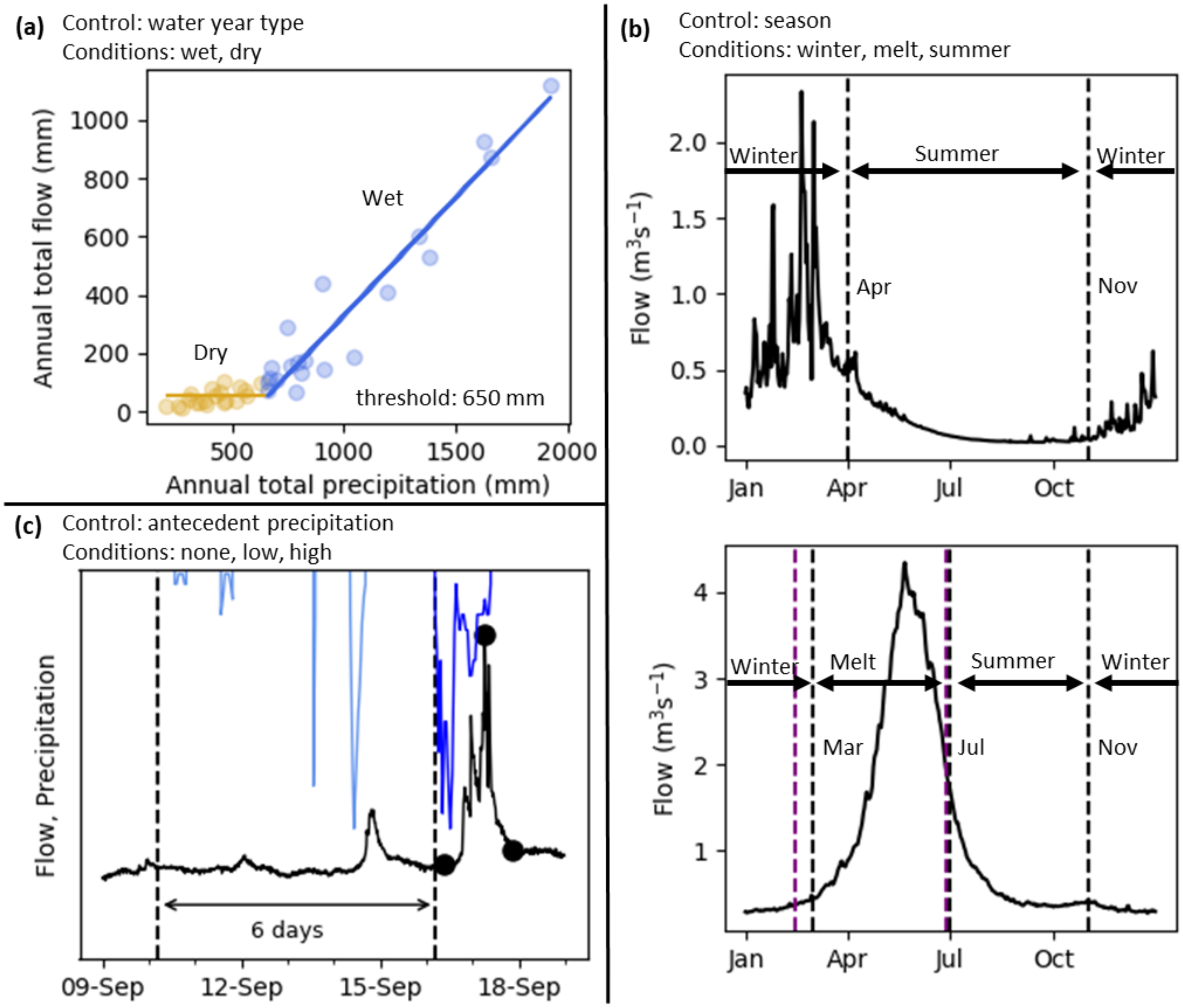


Figure 4: Example hydrologic condition identification for time-varying hydrologic controls. (a) Water year type wet (blue) and dry (orange) years for Arroyo Seco. The ordinary least squares linear regression lines for above and below the threshold are shown. (b) Seasons (vertical dashed) delineated from the undisturbed average annual hydrograph for a no-snow watershed (top) with winter and summer (Arroyo Seco) and a snow dominated watershed (bottom) with winter, melt, and summer (Clear Creek). The minimum and maximum snow melt dates are shown consecutively (purple dashed). (c) The six-day prior to rainfall~~storm~~ start antecedent precipitation period (between dashed) for an example rainfall-runoff event (rainfall is dark blue, runoff is black). Shown are all rainfall events~~storms~~ that~~which~~ were~~are~~ summed within the antecedent precipitation period (light blue).

3.3. Statistical assessment of ~~event-scale hydrologic variability~~rainfall-runoff patterns

Several~~A number of~~ statistical methods were used to investigate the influence of the time-varying controls and wildfire disturbance on event runoff response. ~~To address the first research question (Q1; Fig.ure 2) Figure 2), t~~Trends in undisturbed rainfall-runoff event patterns were first evaluated using a LOWESS curve (Q1; Fig. 2). Inferential statistics and the kernel density estimation (KDE) distributions were ~~then~~ used to assess the effects of time-varying hydrologic conditions on undisturbed rainfall-runoff event metrics (Q2; Fig.~~ure~~ 2). The non-parametric Mann Whitney U Test was used to evaluate the effect of WYT ~~between the two hydrologic conditions~~, and the non-parametric Kruskal Wallis ~~Test~~ and Dunn Tests were ~~was~~ used to evaluate the effect of season and antecedent precipitation ~~between three hydrologic conditions each~~, all at a 95% confidence level. ~~If significant differences were found based on the Kruskal Wallis Test, the Dunn Test was used to identify specific significant hydrologic conditions.~~ The null hypothesis for all tests was that hydrologic conditions did not impact rainfall-runoff event metrics (Table S3). The effect size ~~for each significant test result~~ was calculated using the Glass biserial rank correlation coefficient for ~~the~~ Mann Whitney U ~~T~~test results and the Eta squared test for ~~the~~ Kruskal Wallis ~~T~~test results (Tables S7, S8, S9).

The statistical test results for all area-normalized metrics were summarized into relative significance~~t~~ rates for~~by~~ each of four runoff metric groups across and within study watersheds to facilitate comparisons ~~to identify highlight significant important hydrologic controls on event runoff response~~. The use of ~~the~~ relative significance~~t~~ rates reduced the issue of multiple comparisons and reduced the emphasis on specific metric calculation methods. ~~SSummarizing by area-normalized runoff metrics facilitated comparison between different sized watersheds while . Ssummarizing by runoff metric groups facilitated comparison between time-varying hydrologic controls and reduced the emphasis on specific metric calculation methods. The relative importance of each time-varying hydrologic control was assessed for each watershed and runoff metric group.~~ For each runoff metric group and hydrologic condition, the relative significance rate was calculated, either across all ~~for the~~ study watersheds or for an individual watershed, ~~together and individually~~ by dividing the number of statistically significant rainfall-runoff event metrics in the category ~~(based on the Mann Whitney U or Kruskal Wallis test)~~ by the number of metrics in the runoff metric group. ~~When a single hydrologic condition (e.g. melt season) was identified as significant by the Dunn Test, the significancet rate for thise condition was similarly calculated by dividing the number of significant rainfall-runoff event metrics for the condition by the number of metrics in the runoff metric group.~~ The relative importance of each time-varying hydrologic control was assessed by comparing the significance~~t~~ rates for each watershed and runoff metric group.

3.4. ~~Statistical a~~Wildfire effects on rainfall-runoff patterns~~response~~ ~~ssessment in wildfire disturbed watersheds~~

Additional ~~statistical methods were~~analysis was performed ~~on~~for two contrasting burned study watersheds, Arroyo Seco and Clear Creek (Table 1; Fig. 1 b, c), to ~~further~~ explore the influence of wildfire ~~disturbance~~ relative to other time-varying hydrologic controls (Q3; Fig~~ure~~. 2). ~~Arroyo Seco and Clear Creek were contrasting watersheds, with differing watershed characteristics, notably contributing area and streamflow regimes (Table 1) and burn characteristics (Fig.ure 1 b, c). For this analysis, rainfall-runoff events were defined as undisturbed or disturbed, where disturbed rainfall-runoff events were those occurring within six years post-fire (Ebel et al., 2022; Wagenbrenner et al., 2021). For the two w~~Watersheds, ~~specific s~~Significant hydrologic condition groups were identified for the rainfall

~~storm~~ depth ~~and~~ versus runoff peak relationship. ~~in two contrasting watersheds: Arroyo Seco and Clear Creek.~~ To do this, the undisturbed rainfall-runoff events in each watershed were sorted into hydrologic condition permutations of the significant hydrologic controls for peak runoff. A power trend was fit to each permutation using ordinary least squares regression. The significant condition groups were identified by combining the permutations with similar power trends. An updated power trend was fit to each significant condition group.

~~T~~Considering the runoff peak metric, the influence of ~~the~~ wildfire ~~disturbance~~ on event runoff response was then evaluated relative to each significant condition group undisturbed trend and standard deviation. The percentage of ~~wildfire disturbed~~post-fire rainfall-runoff events falling above and over one standard deviation above the significant condition group trend ~~and one standard deviation~~ was calculated for all post-fire years combined and individually. The calculated ~~post-fire rainfall-runoff event percents~~ percentages were compared to the expected 50% above the trend line and 16% above ~~the~~one standard deviation.

4. Results

4.1. RREDI toolkit performance

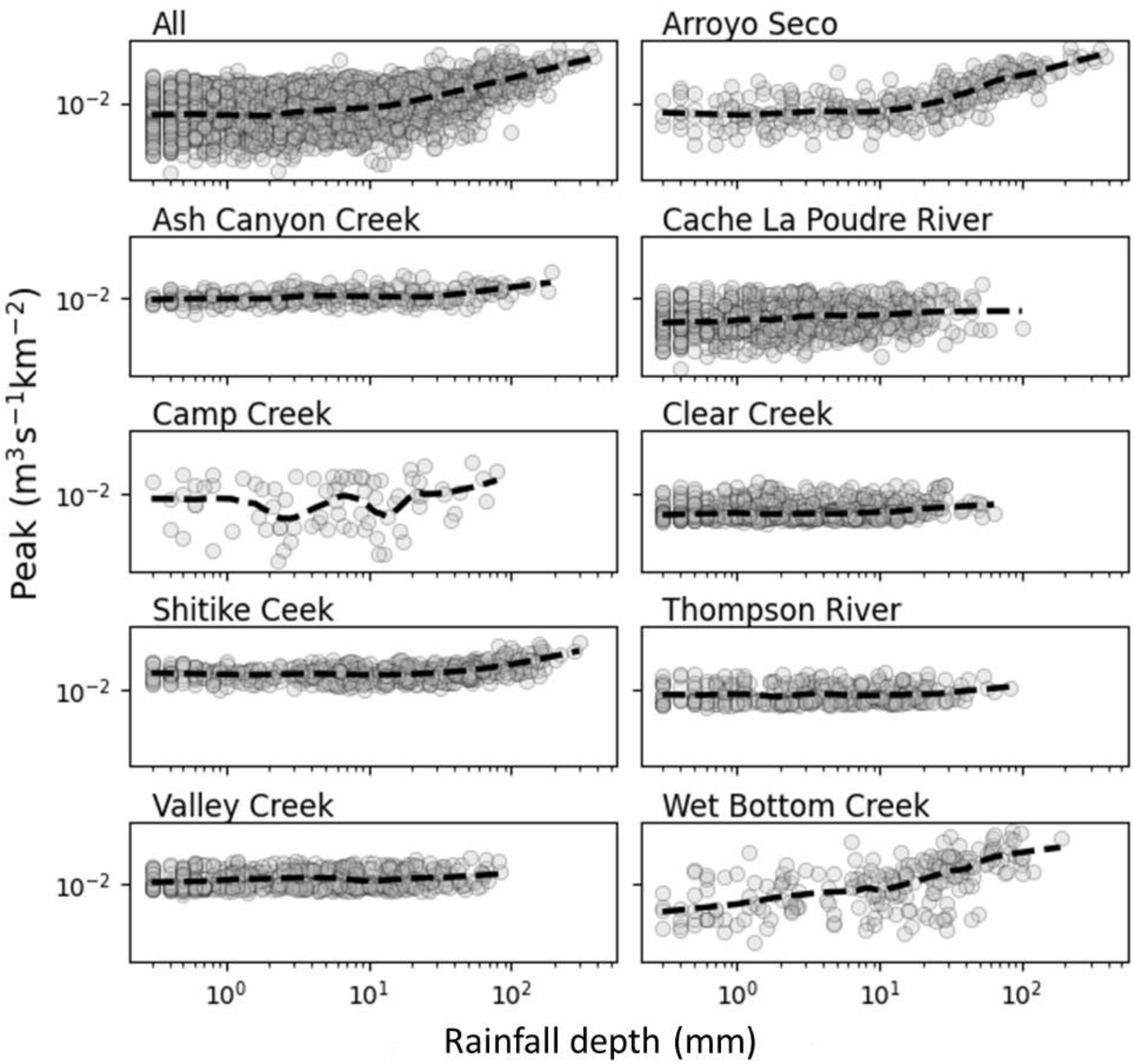
The RREDI toolkit ~~performed well across the nine study watersheds and~~ resulted in a ~~rainfall-runoff event~~ dataset of 5042 rainfall-runoff events across the nine study watersheds (Table S4). 7026 rainfall-runoff events were initially identified after step 2 ~~by the RREDI toolkit in step 2~~. Of these, 774 rainfall-runoff events (11% of total events, 5 to 34% ~~range~~ of events ~~across study watersheds~~by watershed) were ~~systematically~~ inspected for runoff event timing and flagging accuracy (Table 2). ~~Accuracy rates were calculated based on the comparison of the RREDI toolkit identified and independently visually identified runoff event start, peak, and end timing.~~ Rainfall-runoff ~~E~~events were identified at a 69% accuracy rate pre-flagging (step 2) and a 90% ~~the~~ accuracy rate ~~rose to 90%~~ after flagging (step 4). The ~~identified~~ occurrence rates for each of the four known issues across ~~all~~ watersheds ~~was~~ were 2% for 15-minute streamflow data gaps, 13% for diurnal cycling, 4% for duplicate rainfall-runoff events, and 15% for no identified end time rainfall-runoff events (Table S5). The total rainfall-runoff event retention rate after flagging was 72%, with the highest retention rate of 83% in Arroyo Seco and the lowest of 45% in Camp Creek. The rainfall-runoff event dataset generated by the RREDI toolkit was sufficiently large to allow for the use of the described inferential statistical methods (Table S6).

Table 2: RREDI toolkit ~~rainfall-runoff~~ performance results including pre- and post-flagging rainfall-runoff event accuracy rates and pre- and post-flagging retention numbers (#) and rates~~, flagging, and retention rates~~ across the study watersheds.

Watershed	Rainfall-runoff ~~E~~event accuracy pre-flagging (%)	Rainfall-runoff e~~E~~vent accuracy post-flagging (%)	Rainfall-runoff e~~E~~vents retained post-flagging (#)	Rainfall-runoff e~~E~~vents retained post-flagging (%)
Arroyo Seco	88	91	394	83
Ash Canyon Creek	75	78	374	75
Cache La Poudre	80	93	1208	72
Camp Creek	42	88	162	45
Clear Creek	77	89	886	73
Thompson River	67	91	449	75
Shitike Creek	62	93	663	75
Valley Creek	74	91	624	73
Wet Bottom Creek	70	100	282	63
Overall	69	90	5042	72

4.2. ~~Hydrologic variability~~Undisturbed rainfall-runoff patterns

~~The resulting rainfall-runoff event dataset consisting of 5042 rainfall-runoff events across the study watersheds allowed for a data-driven analysis of event runoff patterns and controls. The rainfall-runoff event dataset was sufficiently large such that the proportion of rainfall-runoff events in the hydrologic conditions for each watershed should allow for the use of the described inferential statistical methodsrainfall-runoff events were assigned to all hydrologic conditions in each watershed (Table S6). For undisturbed rainfall-runoff events a~~Across ~~all the study~~ watersheds, ~~there was an increasing trend in~~event runoff peak generally ~~with~~ increas~~ing~~ed with rainfall~~storm~~ depth (Fig.~~ure~~ 5). ~~A slope break~~A breakpoint~~s~~ in these relationships ~~was~~ was visually identified at approximately 10 mm rainfall ~~storm~~ depth, above which the runoff peak increases more rapidly with increasing rainfall~~storm~~ depth. ~~Variation between runoff peak and rainfallstorm depth existed across the watersheds.~~ The ~~identified slope break~~breakpoint was most apparent in ~~three watersheds:~~ Arroyo Seco, Shitike Creek, and Wet Bottom Creek~~. Rainfall-runoff eEvents above the threshold in the other six watersheds were limited~~. ~~Four watersheds,~~ Arroyo Seco, Cache La Poudre River, Camp Creek, and Wet Bottom Creek had larger spreads in the LOWESS curve residuals compared to the other five watersheds. ~~Detailed undisturbed rainfall-runoff event results are presented here for the two case study watersheds, The remainder of the study results focus on two contrasting watersheds, Arroyo Seco and Clear Creek and Arroyo Seco (Fig.ure 1 a; Table 1).~~


All
Arroyo Seco
Ash Canyon Creek
Cache La Poudre River
Camp Creek
Clear Creek
Shitike Ceek
Thompson River
Valley Creek
Wet Bottom Creek
Peak ($m^3s^{-1}km^{-2}$)
10^{-2}
10^0
10^1
10^2
Rainfall depth (mm)

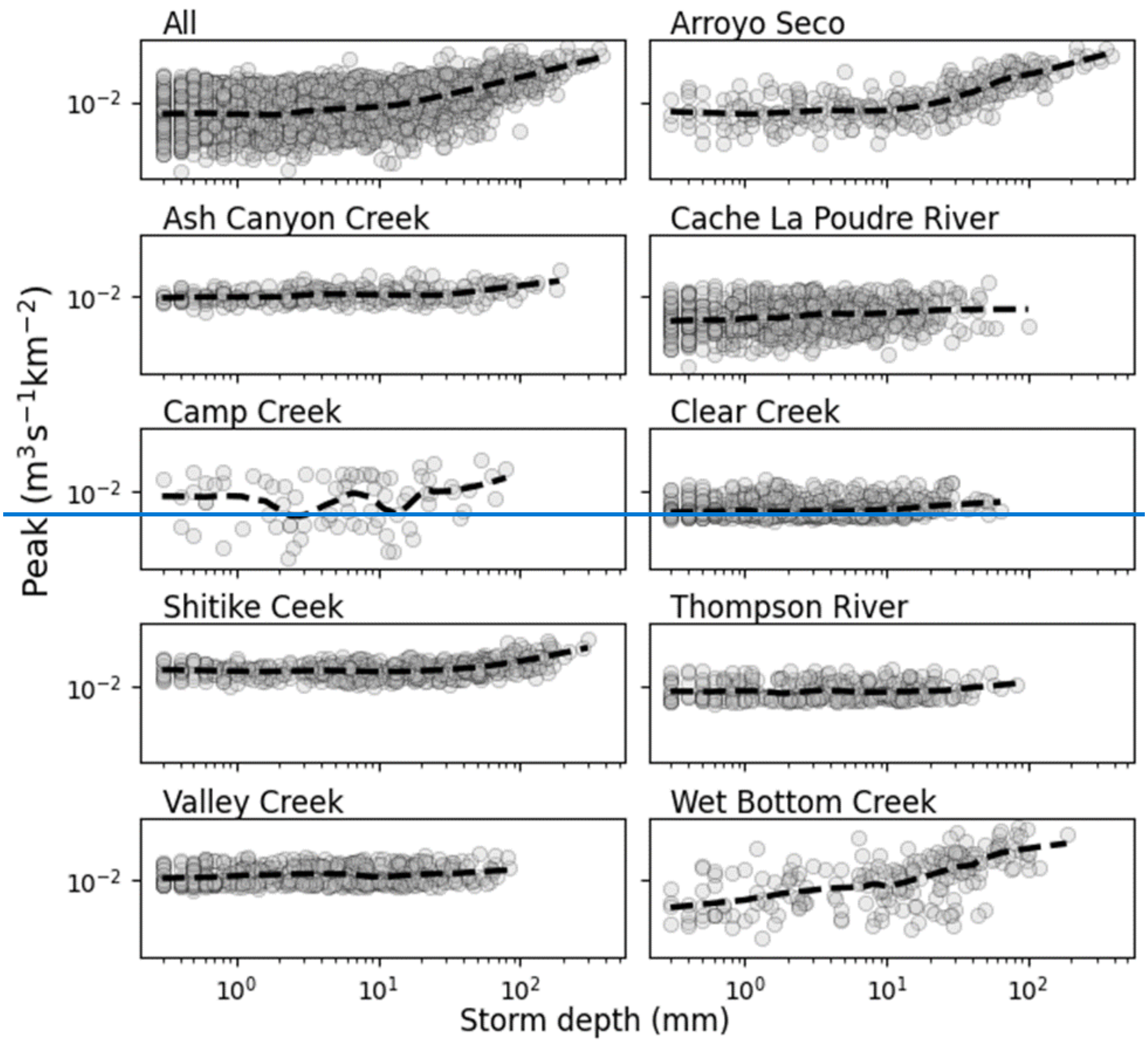


Figure 5: **The relationship between rainfall depth (mm) and runoff peak ($m^3 s^{-1} km^{-2}$) for u~~U~~ndisturbed rainfall-runoff events in all study watersheds and each individual watershed~~for rainfallstorm depth (mm) and runoff peak ($m^3 s^{-1} km^{-2}$)~~. ~~A~~ Dashed black lines are LOWESS curves~~ (dashed black line) for the undisturbed rainfall-runoff events for all study watersheds and each individual watershed is shown~~.**

~~Clear d~~~~Directional shifts~~Differences ~~that varied by runoff metric and watershed~~ were apparent in four selected undisturbed runoff event metric ~~undisturbed rainfall-runoff event~~ distributions ~~for~~ based on WYT, season, and antecedent precipitation. In both Arroyo Seco and Clear Creek watersheds, wet years ~~had a~~ exhibited higher median values than dry years for runoff volume, peak, duration, and response time ~~runoff~~ metrics (Fig.~~ure~~ 6). Winter had higher median values than summer for runoff volume, peak, and response time ~~runoff~~ metrics in Arroyo Seco, but directional shifts were ~~not as~~less consistent~~ in direction~~ in Clear Creek. ~~For With respect to antecedent precipitation,~~

~~in both Arroyo Seco and Clear Creek, t~~The ~~largest~~ highest median peak runoff and shortest median response time ~~was for~~occurred during high antecedent precipitation conditions in both ~~Arroyo Seco and Clear Creek~~watersheds.

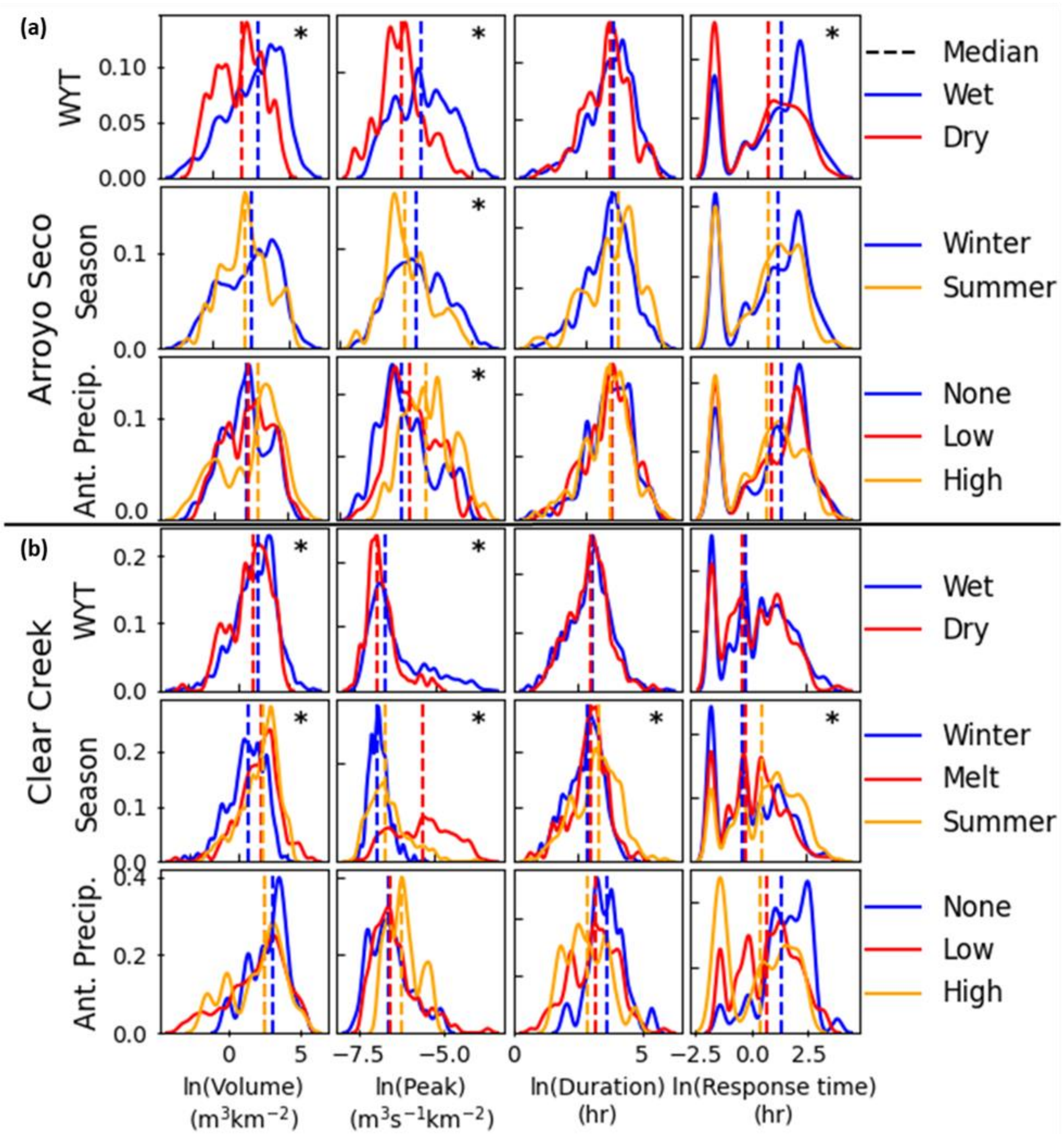


Figure 6: Undisturbed rainfall-runoff event KDE distributions for hydrologic conditions for natural log transformed WYT, season, and antecedent precipitation in (a) Arroyo Seco and (b) Clear Creek for four selected runoff metrics: volume, peak, duration, and response time. Distributions are colored by hydrologic

condition. The median value of each distribution is shown (dashed line). Significant differences between distributions ~~is~~ are indicated (*). Note there is no melt season in Arroyo Seco.

In Arroyo Seco and Clear Creek, a~~A~~ll three time-varying hydrologic controls were ~~found to be~~ significant ~~for~~with respect to the ~~in~~ undisturbed rainfall-runoff events~~ in Arroyo Seco and Clear Creek,~~ but relative significance rates varied by ~~event~~ runoff metric and watershed (Fig.~~ure~~ 6; Table 3). Water year type was the most often significant hydrologic control across the four selected runoff metrics in Arroyo Seco while season was the most often significant control in Clear Creek (Fig.~~ure~~ 6; Table 3). Antecedent precipitation ~~was the least significant control~~ had the lowest relative significance rates in both watersheds and exhibited the most variation ~~in significance between~~by runoff metric~~s across the two watersheds~~. ~~Of the four selected runoff metrics, p~~Peak runoff ~~was most commonly significant~~was the most often significant runoff metric across ~~all the~~ study watersheds ~~for all~~and ~~three time-varying~~ hydrologic controls (Tables S7, S8, S9), and was ~~. Peak runoff was also~~ significant across ~~the three~~all ~~time-varying~~ hydrologic controls ~~for~~ in both Arroyo Seco and Clear Creek except antecedent precipitation in Clear Creek (Fig.~~ure~~ 6; Table 3). Conversely, the least frequently significant ~~least common significant~~ runoff metric ~~least frequently identified as significant~~ varied across ~~all the study watersheds~~hydrologic controls~~ varied by runoff metric~~, including runoff duration and response time for WYT, runoff duration for season, and runoff volume for antecedent precipitation (Tables S7, S8, S9). ~~Despite being least commonly frequently significant overall~~Even so, WYTs ~~corresponded with~~exhibited significant differences in runoff response time ~~for WTY~~ in Arroyo Seco and seasons ~~corresponded with~~exhibited significant differences in runoff duration ~~for season~~ in Clear Creek~~ were significant~~ (Fig.~~ure~~ 6; Table 3).

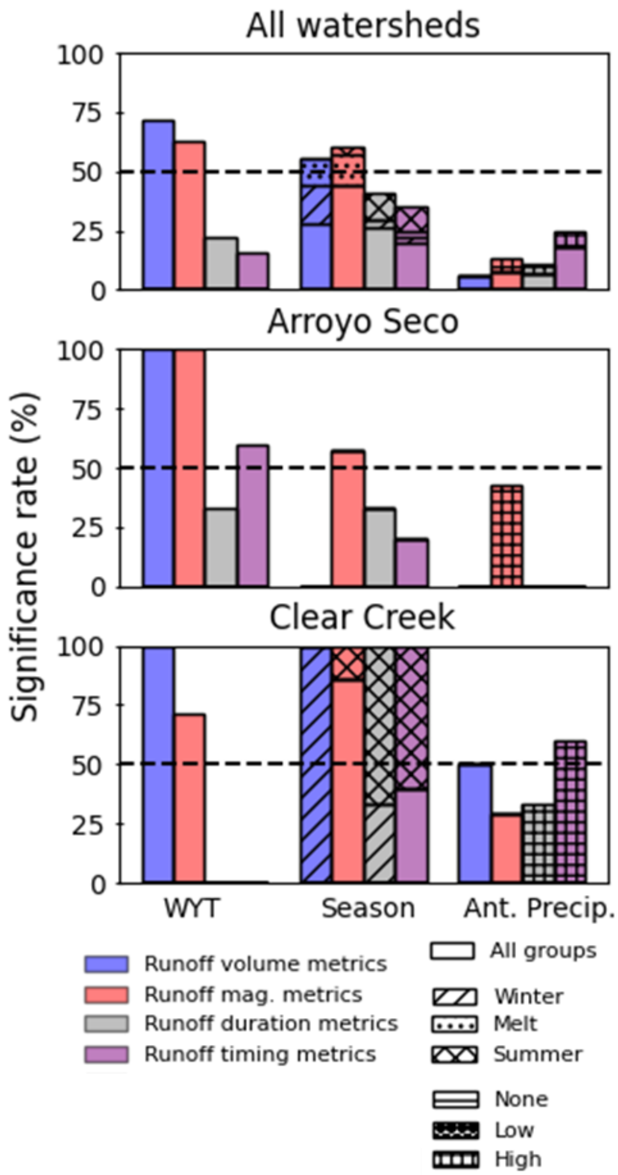
Table 3: Undisturbed rainfall-runoff event hydrologic condition statistical test p-value results for the Mann Whitney U Test (WYT) and Kruskal Wallis and Dunn Tests (season, antecedent precipitation) for Arroyo Seco and Clear Creek for four selected area-normalized runoff event metrics. Shading indicates rejection of the null hypothesis at a significance level of 0.05. In shaded cells, an indicator marks the significantly different condition from the Dunn Test and no indicator means all conditions were significantly different.

Watershed	Time-varying hydrologic control	~~Rainfall r~~Runoff e~~E~~vent metric statistical test p-value~~s~~			
		Volume	Peak	Duration	Response time
Arroyo Seco	Water year type	<0.001	<0.001	0.05	0.005
	Season	0.48	0.013	0.15	0.47
	Antecedent precipitation	0.55~~32~~	<0.001 +	0.29~~57~~	0.33~~12~~
Clear Creek	Water year type	0.009	<0.001	0.56	0.60
	Season	<0.001 *	<0.001	<0.001 #	<0.001 #
	Antecedent precipitation	0.34~~07~~	0.05~~11~~	0.15~~003 &~~	0.32~~0.008 &~~

Seasons: *Winter, ^Melt, #Summer
Antecedent precipitation: ~~&~~andNone, ~Low, +High

Water year type and season ~~were generally more important differentiating~~ differentiate runoff event metrics ~~(greater than~~>~~—~~50% ~~average~~relative significance rate) ~~while antecedent precipitation was generally less~~

~~important~~differentiating of runoff event metric values across all study watersheds~~, evaluated by the relative significance rates, across all study watersheds~~ (Fig.~~ure~~ 7)~~. However~~, but ~~time-varying hydrologic control importance~~results varied ~~for individual~~across watersheds and ~~area-normalized~~ runoff metric groups. For example, in Arroyo Seco, the relative significant rate was 100% for the WYT runoff volume metric group ~~was 100%~~(~~, as two out of the two metrics within this group,~~both runoff volume and runoff ratio ~~(Table S3),~~ were ~~found to be significant by the Mann Whitney U Test~~significant (Table S3, Table S7)) ~~while the significance rate for the~~but only 33% for the WYT runoff duration metric group ~~with respect to WYT was 33% because only one out of three metrics was significant~~. ~~The~~ When averaging across watersheds, the runoff duration and magnitude metric groups were differentiated with respect to both WYT and season ~~relative significance rate for the runoff duration with respect to WYT averaged across all nine study watersheds was 72%. The watershed-average With respect to WYT, across all study watersheds, WYT the average significance rates of runoff volume and runoff magnitude metric groups exceeded 50% exceeded 50% for runoff volume and runoff magnitude metric groups~~ (Fig.~~ure~~ 7 a). ~~In Arroyo Seco, Water year type was more important than the watershed-average ft~~The ~~average~~relative significance rates of ~~all~~most metric groups in Arroyo Seco~~exceeded those calculated across watersheds or all metric groups in Arroyo Seco~~ (Fig.~~gure~~ 7 b) and ~~for runoff magnitude and runoff volume metrics groups in~~ Clear Creek (Fig. 7 c) ~~the average significance rates of runoff magnitude and volume metric groups~~ exceeded ~~exceeded those calculated across watersheds~~the watershed-average rates ~~(Fig.ure 7 c)~~. Compared to the watershed-average, ~~W~~WYT~~ater year type~~ was generally more ~~important~~ differentiating of runoff response ~~than the watershed-average~~ in Arroyo Seco, Ash Canyon Creek, Camp Creek, and Shitike Creek ~~than across all watersheds~~; less ~~important~~ differentiating in Clear Creek, Valley Creek, and Wet Bottom Creek ~~than across all watersheds~~; and similarly ~~important significant~~important in Cache La Poudre River and Thompson River ~~to the average significance across watersheds~~ (Fig. S8). By contrast, compared to the watershed-average, season was generally more differentiating of runoff response in Cache La Poudre River, Clear Creek, Thompson River, and Valley Creek, less differentiating in Ash Canyon Creek and Camp Creek; and similarly differentiating in Arroyo Seco, Shitike Creek, and Wet Bottom Creek (Fig. 7 b; Fig. S8).



All watersheds
Arroyo Seco
Clear Creek
Significance rate (%)
100
75
50
25
0
WYT
Season
Ant. Precip.
Runoff volume metrics
Runoff mag. metrics
Runoff duration metrics
Runoff timing metrics
All groups
Winter
Melt
Summer
None
Low
High

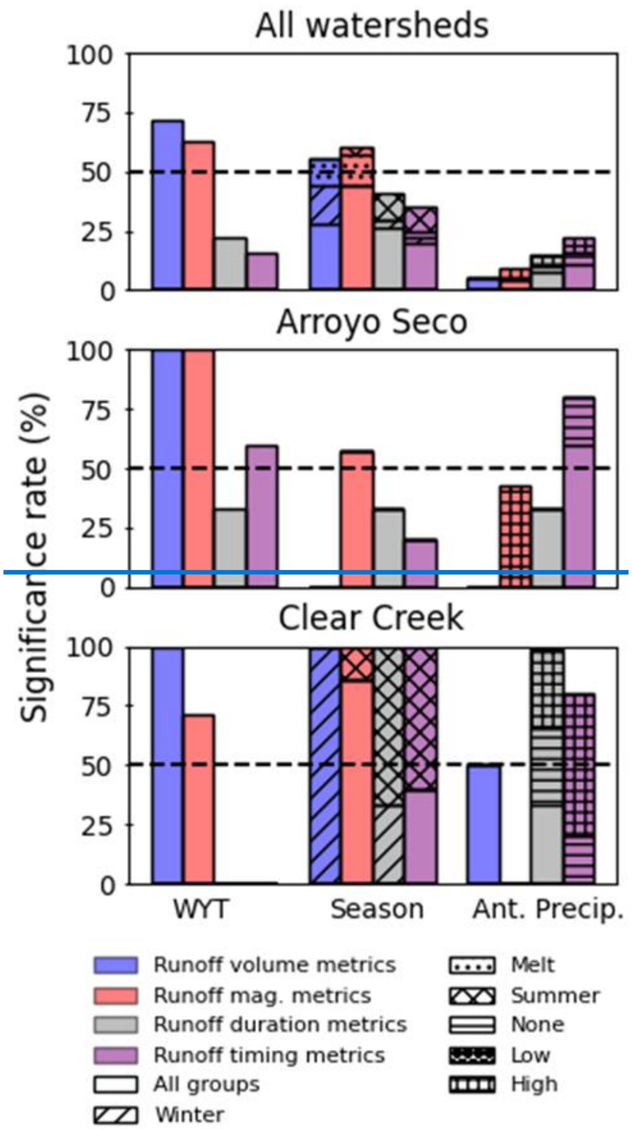


Figure 7: Summary plots of the ~~statistical~~relative significance rates of four a~~Area-normalized event~~ runoff event metric~~s averaged by runoff metric~~ groups (colored bars) with respect to three time-varying hydrologic controls (x-axis)~~ significance summary rates for statistical test results~~ ~~. Individual plots for~~ ~~show results for~~~~the~~ ~~watershed-average~~ a~~A~~ll ~~W~~watersheds (~~a~~top panel), Arroyo Seco~~ (b)~~, and Clear Creek (~~c~~bottom panel) under undisturbed conditions. The 50% relative significance rate is indicated (black dashed). ~~Shown are the average significance rates within t~~The ~~four rainfall-runoff metric groups~~ include ~~including runoff volume metrics (blue), runoff magnitude metrics (red), runoff duration metrics (grey), and rainfall-runoff timing metrics (purple)~~ ~~metrics~~. ~~Bars are grouped by time-varying hydrologic control (WYT, season, antecedent precipitation). The~~ Water Year Type (WYT) ~~group~~ significance rates are based on ~~shows results of the Mann Whitney U Test. The season and antecedent precipitation groups~~ significance rates ~~show results from~~are based

~~on the Kruskal Wallis Test.~~ The hatching within the season and antecedent precipitation bars represents statistically different ~~individual~~ hydrologic conditions from the Dunn Test, where no hatching indicates all ~~hydrologic~~ conditions were ~~statistically~~ different. ~~The 50% relative significance rate is highlighted indicated (black dashed).~~

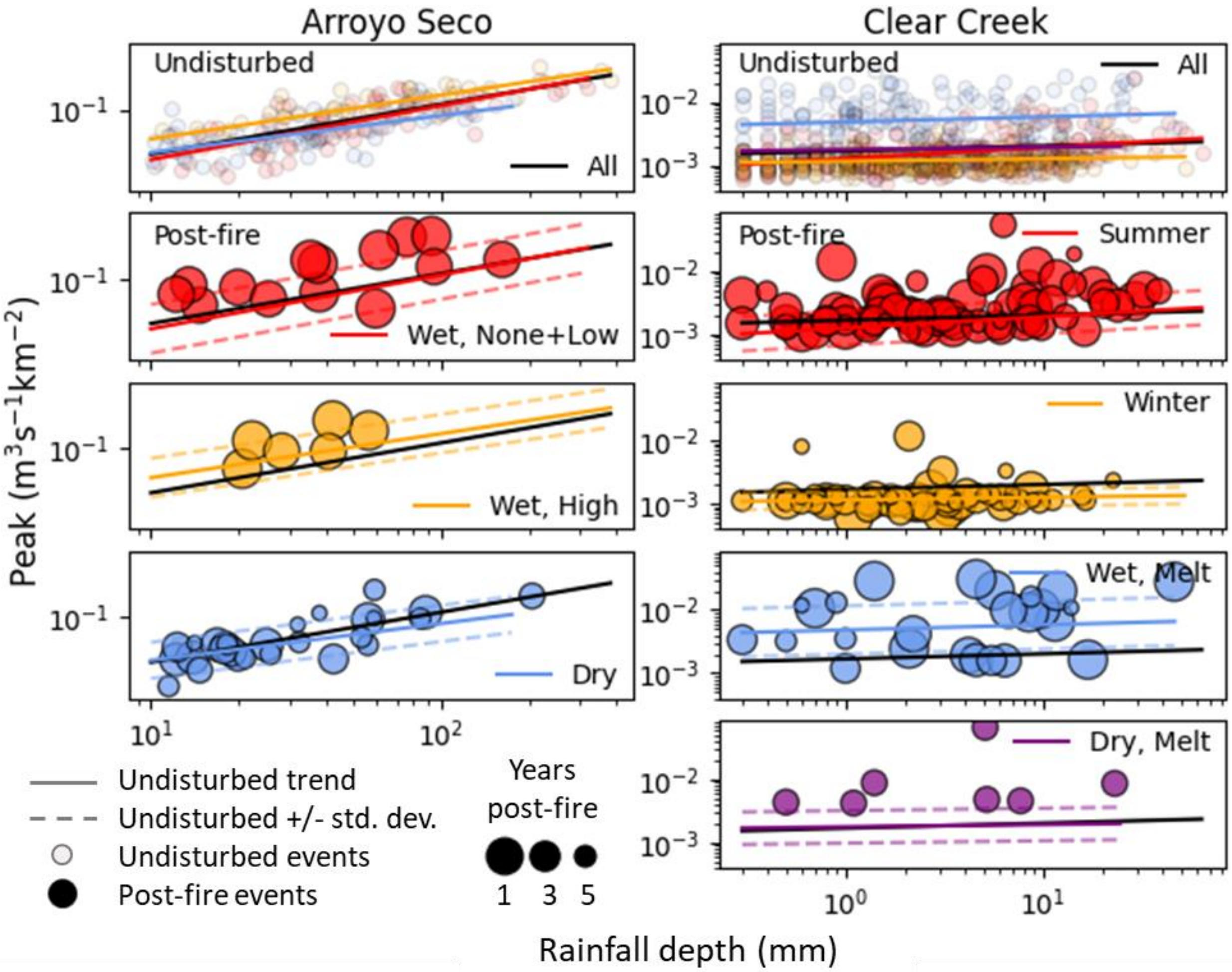
~~The Across watersheds, the average significance rate of the runoff volume and magnitude metric groups with respect to season exceeded 50%, suggesting that season generally acted as a hydrologic control season watershed-average significance rate exceeded 50% for runoff volume and runoff magnitude metric groups (Fig.ure 7 a). In Arroyo Seco, no runoff metric groups were better differentiated with respect to season than the average significance across all watersheds (Fig. 7 b). Conversely, all runoff metric groups in Clear Creek were better differentiated with respect to season than across all watersheds (Fig. 7 c). Season was more important than the watershed-average for in no metric groups in Arroyo Seco (Fig.ure 7 b) and for all metric groups in Clear Creek (Fig.ure 7 c). Season was generally more important differentiating than the watershed-average in Cache La Poudre River, Clear Creek, Thompson River, and Valley Creek than when considering all watersheds; less important differentiating in Ash Canyon Creek and Camp Creek; and similarly important differentiating in Arroyo Seco, Shitike Creek, and Wet Bottom Creek (Fig. S8).~~

~~Across watersheds, the~~Compared with WYT and season, antecedent precipitation did a poor job of differentiating event runoff response across watersheds ~~average runoff metric significance rates never exceeded 50% with respect to antecedent precipitation The antecedent precipitation watershed-average significance rate exceeded 50% for no metric groups~~ (Fig.~~ure~~ 7~~a~~). ~~In~~Compared to the watershed-average, antecedent precipitation better differentiated ~~Arroyo Seco, the~~ runoff magnitude~~, duration, and timing~~ metrics ~~groups~~ in Arroyo Seco w~~as~~ere ~~better differentiated with respect to antecedent precipitation than when considering all watersheds (Fig. 7 b) Antecedent precipitation was more important than the watershed-average for the runoff magnitude , runoff duration, and rainfall-runoff timing metric groups in Arroyo Seco (Fig.ure 7 b)~~ and ~~in~~all runoff metric groups in Clear Creek ~~for all four runoff volume, runoff duration, and rainfall-runoff timing metric groups in Clear Creekwere better differentiated~~ (Fig.~~ure~~ 7 c), and ~~. Antecedent precipitation~~ was generally ~~more important than the watershed-average in Arroyo Seco and Clear Creek;~~ less ~~important~~ differentiating of runoff response in ~~Ash Canyon Creek,~~ Camp Creek, Shitike Creek, ~~Thompson River,~~and Valley Creek~~, and Wet Bottom Creek;~~ and similarly ~~important~~ differentiating in ~~Arroyo Seco,~~ Cache La Poudre River, Thompson River, and Wet Bottom Creek ~~(Fig. S8) than when considering all watersheds~~ (Fig. S8).

4.3. ~~Hydrologic variability in wildfire disturbed~~Rainfall-runoff ~~trends~~patterns in burned watersheds

~~Three and four unique~~ Several significant condition groups and trends emerged for the~~m~~ undisturbed rainfall~~storm~~ depth ~~and~~ versus peak runoff relationship in Arroyo Seco and Clear Creek~~, respectively~~ (Fig.~~ure~~ 8). The watershed specific significant condition groups were identified from eight and six hydrologic condition permutations of the watershed specific significant hydrologic controls~~ in Arroyo Seco and Clear Creek~~, respectively (Fig. S9). The three significant condition groups in Arroyo Seco were (1) wet none+low, (2) wet high, and (3) dry. The four significant condition groups in Clear Creek were (1) summer, (2) winter, (3) wet melt, and (4) wet dry. Significant condition group trends were only assessed above 10 mm rainfall~~storm~~ depth in Arroyo Seco, consistent with the rainfall~~storm~~

depth threshold observed in this watershed (Fig.~~ure~~ 5). Each significant condition group's power trend ~~was distinct,~~ ~~falling~~fell within a different portion of the ~~un-grouped~~full rainfall-runoff ~~all~~ event~~s~~ distribution (Fig.~~ure~~ 8; Table S10).


Arroyo Seco
Clear Creek
Undisturbed
All
Post-fire
Wet, None+Low
Summer
Wet, High
Winter
Dry
Wet, Melt
Dry, Melt
Peak (m^{3}s^{-1}km^{-2})
Rainfall depth (mm)
Undisturbed trend
Undisturbed +/- std. dev.
Undisturbed events
Post-fire events
Years post-fire
1 3 5

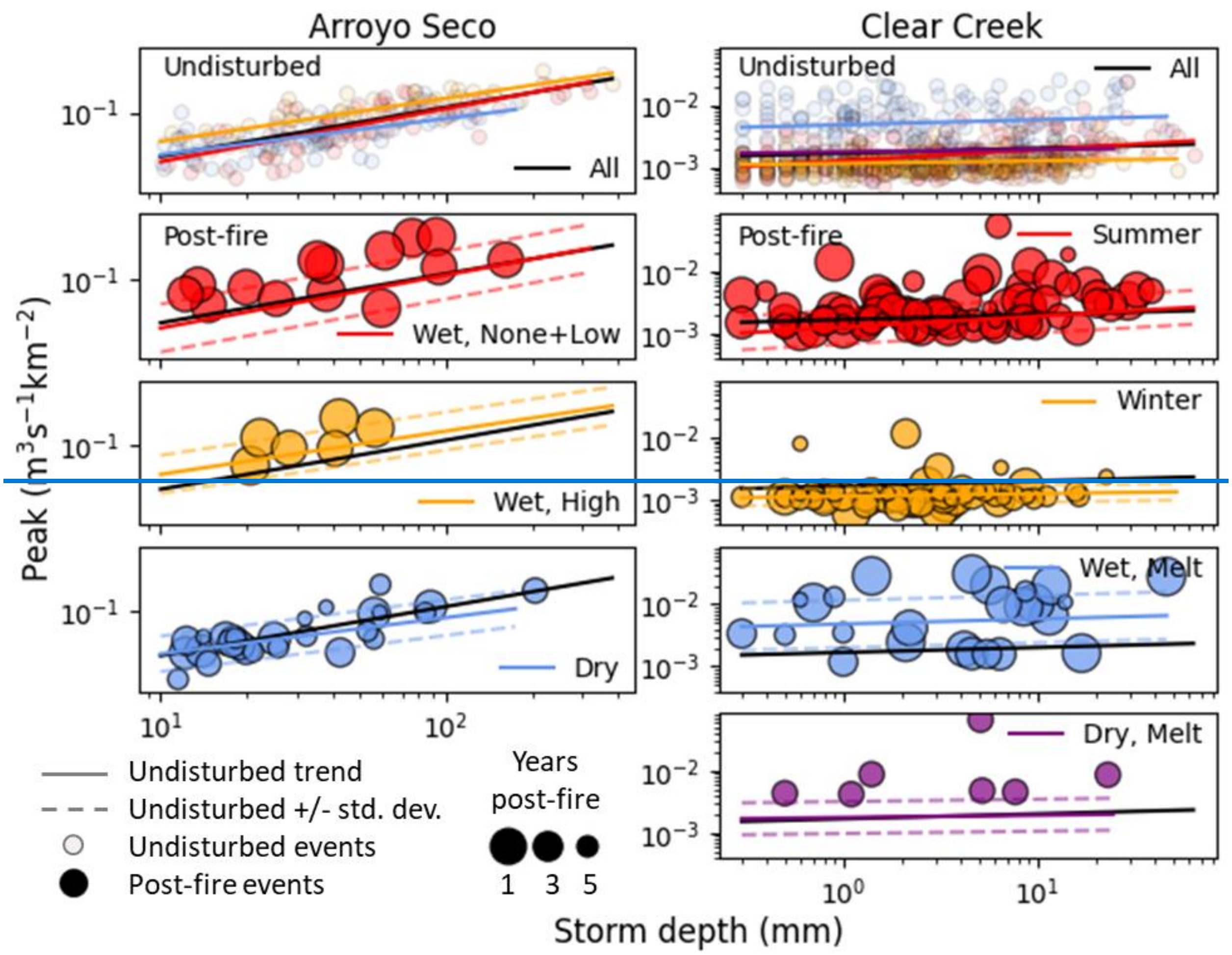


Figure 8: Significant condition groups for event runoff peak ($m^3 s^{-1} km^{-2}$) in Arroyo Seco and Clear Creek. Shown for the rainfall~~storm~~ depth ~~(mm)~~ versus~~and~~ runoff peak relationship are the undisturbed trends (black) and ~~($m^3 s^{-1} km^{-2}$). Shown are the~~ significant condition group trends (colored) and thei~~r~~ ~~and one~~ standard deviation bounds (dashed).~~for each of the significant condition group (colored) and the un-grouped the trend when considering all undisturbed rainfall-runoffall events trend (black).~~ The undisturbed ~~rainfall-runoff events~~ (top) and post-fire rainfall-runoff events within each significant condition group are plotted~~shown.~~.

For the rainfall depth versus runoff peak relationship, the ~~The~~ portion of post-fire rainfall-runoff events that plotted both above and one standard deviation above the significant condition group undisturbed trends was generally greater than undisturbed expectations~~that fell above the significant condition group trend for the undisturbed rainfall depth versus peak runoff relationship was generally greater than expected for peak runoff in Arroyo Seco and Clear Creek, however this varied by significant condition group~~ (Fig.~~ure~~ 8;~~). The percent of post-fire rainfall-runoff events above the significant condition group trend was at least 50% for all significant condition groups in Arroyo Seco and all groups groups except winter in Clear Creek (~~ Table S11). In Arroyo Seco, post-fire events plotted above the significant condition group trend more than 50% of the time for all groups and above one standard deviation more than 16% of the time for all groups except dry. In Clear Creek, post-fire events plotted above one standard deviation from the undisturbed trend more than expected for all groups except winter. ~~The percent of rainfall-runoff events more than one standard deviation above the significant condition group trend was at least 16% for all significant condition groups except dry in Arroyo Seco and all except winter in Clear Creek.~~ In general, the percent of post-fire rainfall-runoff events above the significant condition group trend and one standard deviation decreased with increasing time since fire as illustrated in Figure 8 by decreasing point size ~~(Figure 8; Table S11)~~.

5. Discussion

5.1. RREDI toolkit

The RREDI toolkit ~~was developed to~~ automatically separated ~~-~~co-varying streamflow and precipitation time-series into rainfall-runoff events ~~in a method~~ using an approach that ~~could be applied in any watershed~~ is~~is~~ transferable across watersheds. ~~The rainfall-runoff event dataset generated by the RREDI toolkit allowed for a large-sample analysis of hydrologic trends and controls across the study watersheds.~~ The RREDI toolkit had an overall accuracy rate of 90%, ~~rainfall-runoff event accuracy rate,~~ ranging from 78 to 100% across study watersheds. There were no clear watershed characteristics influencing ~~physio-climatic patterns to the~~ performance. Lower rainfall-runoff event accuracy rates in Ash Canyon Creek, Camp Creek, and Clear Creek may be associated ~~with a range of~~ with factors including poor quantification of rainfall ~~storm~~ timing, water withdrawals, temporally aggregated streamflow, and extended periods of diurnal cycling. ~~The rainfall-runoff event a~~Accuracy increased after the removal of flagged rainfall-runoff events for all study watersheds. Rainfall-runoff e~~E~~vent retention rates were below average in Camp Creek and Wet Bottom Creek, but post-flagging ~~rainfall-runoff event~~ accuracy rates were near average and 100%, respectively. Both watersheds have flashy hydrology and substantial periods of low flow diurnal cycling that ~~. This~~ resulted in several identified rainfall-runoff event pairs where no ~~the~~ event runoff response was identified~~outside of the allowable response window~~.

~~Quantification of rainfallstorm events influenced t~~The RREDI toolkit performance~~,~~ was effected by precipitation data processing challenges, particularly the accurate ~~where rainfallstorm timing was a common reason for poor rainfall-runoff event~~ identification of rainfall timing. A gridded precipitation data product was used to overcome sparse rain gage density and limited or sporadic periods of record in the mountainous western U.S~~A.~~. The rainfall measured in valleys, where long term rain gages are more common (such as the NOAA COOP network), often diverges from mountain rainfall characteristics due to orographic gradients (Roe, 2005). Differences in rain gage distance to the watershed and watershed outlet also complicated inter-watershed comparison. Using gridded precipitation allowed for a spatially consistent precipitation time series to be created for all study watersheds. The centroid of the watershed was used to extract precipitation ~~here~~ as the best available method given the large computational requirement for additional watershed ~~summary~~analysis, but future work could incorporate watershed average~~d~~ precipitation or other methods to better ~~-~~capture ~~precipitation~~ spatial variability (Giani et al., 2022a; Kampf et al., 2016; Wang et al., 2023). The high spatial and temporal resolution of the AORC data product performed well compared to rain gage measurements (Hong et al., 2022; Kim ~~&~~and Villarini, 2022; Partridge et al., 2024). However, the hourly temporal resolution did result in some loss of information related to short duration, high intensity rainfall events~~storms~~ as precipitation was linearly interpolated across the timestep.

The RREDI toolkit time-series event separation method improves on existing methods by being readily ~~is~~ is~~was~~ transferable across diverse watersheds ~~using only two watershed specific parameters,~~ and implementing an event flagging ~~with the implementation of the flagging~~ algorithm ~~addressed issues that have been limiting in other methods. addressesd several common issues identified by past studies.~~ Watershed transferability, a need identified by Giani et al., (2022b), was accomplished here using time-series signal processing and only two watershed parameters ~~in the RREDI toolkit~~. ~~Good agreement in rainfall-runoff event identification rates and metrics was found between a timeseries signal processing method and a baseflow separation method with the bonus of transferability in the former method (Giani et al., 2022b). The most common rainfall-runoff event separation technique relies on established baseflow methods to isolate event flow (e.g. Chapman & Maxwell, 1996; Duncan, 2019; Eckhardt, 2005; Xie et al., 2020). Runoff events are then identified where baseflow diverges from total flow (Long & Chang, 2022; Mei & Anagnostou, 2015; Merz et al., 2006; Merz & Blöschl, 2009; Tarasova, Basso, Zink, et al., 2018b). However, Giania et al., (2022b) identified the need for increased method transferability across watersheds. To increase transferability, methods use fewer modifying watershed parameters (Blume et al., 2007; Nagy et al., 2022) or time-series signal processing, as used in the RREDI toolkit, to identify rainfall-runoff events (Giania et al., 2022b; Patterson et al., 2020). A comparison of a baseflow separation method against a time-series signal processing method found good agreement in rainfall-runoff event identification rates and metrics with the added bonus of transferability in the latter method (Gianai et al., 2022b). The RREDI toolkit performed best when separating discrete rainfall-runoff events, however with the implementation of the flagging algorithm was able to address issues that have been limiting in other methods. The baseflow separation methods use daily streamflow (Long & Chang, 2022; Mei & Anagnostou, 2015; Merz et al., 2006; Merz & Blöschl, 2009; Tarasova, Basso, Zink, et al., 2018b), however~~ ~~B~~by using 15-minute streamflow time-series, the RREDI toolkit could identify and characterize sub-daily rainfall-runoff events, a critical limitation in many other time-series separation methods (Long ~~&~~and Chang, 2022; Mei ~~&~~and Anagnostou, 2015; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Tarasova et al., 2018b). The use of time-series signal processing also allowed for the identification of rainfall events with no runoff response, providing more information about precipitation ~~the rainfall~~ thresholds and antecedent wetness conditions required for runoff generation. An algorithm to remove diurnal cycling events was also implemented, something not previously addressed.

The time-series event separation method introduced in this study allowed for large-sample hydrologic analysis to investigate event-scale rainfall-runoff patterns and controls. Future work could expand this analysis to a larger set of watersheds and potential controls (Gupta et al., 2014). The RREDI toolkit could also be applied to address other pressing event-scale hydrologic challenges, including the influence of other watershed disturbances (e.g. urbanization, forest treatments, insect infestation) (Ebel ~~&~~and Mirus, 2014; Goeking ~~&~~and Tarboton, 2020), evaluation of design rainfall events, flood prediction, or event recurrence interval analysis. Beyond rainfall-runoff event analysis, the RREDI toolkit could be used to identify paired rainfall-runoff events in other rainfall-peaking time-series data relationships such as water quality events (e.g., turbidity) or soil moisture events.

5.2. Undisturbed rainfall-runoff event patterns~~Hydrologic variability~~

~~In general, across the study watersheds, WYT and season were significant time-varying hydrologic controls on event runoff response while antecedent precipitation played a lesser role, but significance varied by watershed and~~

~~runoff metric.~~ Differences in the significance of time-varying hydrologic controls between study watersheds correspond~~s~~ with the findings of other large-sample rainfall-runoff analysis (Jahanshahi and Booij, 2024; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Norbiato et al., 2009; Tarasova~~, Basso, Poncelet,~~ et al., 2018a; Tarasova~~, Basso, Zink,~~ et al., 2018b; Wu et al., 2021, Zheng et al., 2023). Variability in the significance of runoff metrics within a watershed ~~within a watershed~~ underline~~d~~ the importance of comparing similar metrics between watersheds and studies to assess event runoff response. Differences between event runoff response in wet and dry years were significant across the runoff metrics in six of the seven watersheds where a WYT precipitation threshold was identified (Fig.~~ure~~ 7; Fig. S8). This aligns with Biederman et al.'s (2022) finding that the threshold between wet and dry years ~~were~~ was important in event runoff response in semi-arid watersheds. Differences in rainfall-runoff processes ~~in~~ between wet and dry years, such as the interaction between soil drainage and vegetation rooting depth ~~as the watershed recovers,~~ may drive these observed differences in runoff response (Bart, 2016; Biederman et al., 2022). High interannual variation in snowpack (Cayan, 1995) may be a driver in~~-~~ WYT significance identified ~~-~~in six of the seven snow-dominated watersheds. Water year type was significant for one of the two rain dominated watersheds, Arroyo Seco, which may be explained by the~~. In Arroyo Seco,~~ extreme interannual variability in the ~~interannual~~ frequency and intensity of atmospheric rivers that ~~bring~~ generate ~~a majority of~~most of the precipitation~~ may explain the WYT significance~~ (Lamjiri et al., 2018). Surprisingly, WYT was not significant in Wet Bottom Creek despite interannual variation in the summer North American Monsoon in this watershed (Arriaga-Ramierez ~~&~~and Cavazos, 2010; Pascolini-Campbell et al., 2015). This may be because, despite the monsoon influence, ~~the majority of~~most of the watershed precipitation ~~in this watershed instead~~ instead comes from winter rainfall events~~storms~~ (Arriaga-Ramierez ~~&~~and Cavazos, 2010).

Seasonal differences in event runoff response were significant across the runoff metrics in seven watersheds including both snow- and rain-dominated systems (Fig.~~ure~~ 7; Fig. S8). Similar patterns have been observed across other ~~a variety of~~ watersheds spanning ~~with~~ a range of precipitation and streamflow regimes and ~~watershed~~ catchment properties (Jahanshahi and Booij, 2024; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Norbiato et al., 2009; Tarasova~~, Basso, Poncelet,~~ et al., 2018a, Zheng et al., 2023). In snow-dominated watersheds, observed seasonality has been attributed to differences in precipitation type (Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b), seasonal water balance (Berghuijs et al., 2014; Merz et al., 2006; Tarasova~~, Basso, Poncelet,~~ et al., 2018a), and the influence of snow on antecedent moisture conditions (Hammond ~~&~~and Kampf, 2020; Jahanshahi and Booij, 2024; Merz et al., 2006; Merz ~~&~~and Blöschl, 2009; Norbiato et al., 2009). Seasonality in rain-dominated watersheds has been attributed to differences in rainfall ~~storm~~ properties (intensity, depth) and antecedent moisture driven by seasonal water balance (Berghuijs et al., 2014; Jahanshahi and Booij, 2024; Merz ~~&~~and Blöschl, 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b). In fact, seasonal water balance has been identified as more important than topography in event runoff response differences between watersheds (Merz et al., 2006). As rainfall~~storm~~ properties were separately accounted for in this analysis by evaluating event runoff response with respect to specific rainfall~~storm~~ metrics (e.g. rainfall~~storm~~ depth), the significance of seasonality is likely associated with seasonal differences in evapotranspiration and soil moisture.

Antecedent precipitation was only significant across the runoff metrics in one~~two~~ very arid watershed~~s~~, ~~Arroyo Seco and~~ Clear Creek (Fig.~~ure~~ 7; Fig. S8). These ~~This finding indicates a complexity in this time varying hydrologic control as these~~ findings contrast with our expectation that antecedent precipitation, as a proxy for antecedent soil moisture, would be a control on rainfall-runoff patterns. Antecedent precipitation has been used has a proxy for antecedent soil moisture in several studies (Jahanshahi and Booij, 2024; Long ~~&~~and Chang, 2022; Merz et al., 2006; Tarasova~~, Basso, Zink,~~ et al., 2018b) and in the SCS curve method for runoff generation (Mishra ~~&~~and Singh, 2003). Past studies have found conflicting results in the significance of antecedent precipitation. Both 10-day antecedent precipitation ~~in Italy~~ (Merz et al., 2006) and antecedent soil moisture in Italy (Merz ~~&~~and Blöschl, 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b) and 5-day antecedent precipitation in Iran (Jahanshahi and Booij, 2024) have been found to influence event runoff response. However, 10-day antecedent precipitation in Germany (Tarasova~~, Basso, Zink,~~ et al., 2018b) and 3-day antecedent precipitation in Oregon, U.S.~~A~~ (Long ~~&~~and Chang, 2022) were not significant controls at the event scale. A possible reason why antecedent precipitation was not ~~identified as~~ significant in most~~eightseven~~ study watersheds may be the dominance of the seasonal water balance (Jahanshahi and Booij, 2024; Merz et al., 2006) which may not be captured in short window (<10 day) antecedent precipitation (Tarasova~~, Basso, Zink,~~ et al., 2018b). To mitigate this, Tarasova~~, Basso, Zink,~~ et al. (2018b) suggested applying a longer antecedent precipitation window (30-60 days) to better account for seasonal changes in the water balance.

~~In both Arroyo Seco and Clear Creek, significant condition groups revealed distinct trends within the storm depth and runoff peak relationship (Figure 8). In Arroyo Seco, the runoff peak for a given storm was lower in significant condition groups with dry condition events than those with wet condition events. Further, with increasing storm depth, the dry significant condition group trend deviated further below the all-events trend. A possible reason for the divergence between the wet and dry significant group trends is differences in dominant runoff processes (Bart, 2016; Biederman et al., 2022) driven by strong interannual variation in wetness conditions (Merz & Blöschl, 2009; Tarasova, Basso, Zink, et al., 2018). Antecedent precipitation was important during wet years in Arroyo Seco. Interestingly, high antecedent precipitation mattered more at low storm depths, where the high wet significant condition group trend returned to the all-events trend with increasing storm depth. This may be due to an increasingly overwhelming overland runoff response to larger storms that diminishes the influence of antecedent precipitation. Too few events in the dry significant condition group limited separation of antecedent precipitation so this remains inconclusive.~~

~~In Clear Creek, season was the primary driver separating the significant condition groups (Figure 8). This aligns with findings in other snow-dominated watersheds where the seasonal water balance was the primary driver of differences in rainfall-runoff patterns (Merz et al., 2006). This dominance of seasonal water balance over event antecedent precipitation likely explains why antecedent precipitation was not significant in the Clear Creek significant condition groups. Similar to other snow-dominated watersheds, the peak runoff response was highest during the melt and lower in the summer (Merz & Blöschl, 2009). Separation of wet and dry years was only significant during melt, likely due to the dominance of winter precipitation and interannual variance in snowpack in this watershed (Arriaga-Ramierez & Cavazos, 2010; Cayan, 1995). Summer was the most responsive season to increasing storm depth. Without the influence of the snowpack during summer, this responsiveness is consistent with the findings in rain-dominated Arroyo Seco.~~

5.3. Wildfire-effects on rainfall-runoff patterns~~Hydrologic variability in wildfire disturbed watersheds~~

Consideration of WYT and seasonality was critical to discerning the influence of wildfire disturbance on event runoff response. The influence of wildfire was most apparent in the winter in Arroyo Seco and summer in Clear Creek (Fig.~~ure~~ 8). The differences in~~between~~ post-fire response between~~in~~ Arroyo Seco and Clear Creek is consistent with the large range of post-fire responses observed across western U.S.~~A~~ watersheds (Hallema et al., 2017; Saxe et al., 2018). In Arroyo Seco, for each year post-fire the ~~pe~~event~~ak~~ runoff peak magnitudes~~events~~ were greater than expected based on the undisturbed rainfall-runoff event distribution. This post-fire increase in runoff peak is consistent with previously observed increases in total annual flow in the watershed (Bart, 2016; Beyene et al., 2021). In Arroyo Seco, the first two years post-fire were wet~~ years~~ and the subsequent years were dry. Without considering the dry years separately, the influence of the fire would have been obscured within the full undisturbed rainfall-runoff event distribution. Distilling disturbed event runoff response from natural WYT variability has been identified as a challenge by other studies (Biederman et al., 2022; Hallema et al., 2017; Long ~~&~~and Chang, 2022; Mahat et al., 2016; Newcomer et al., 2023; Owens et al., 2013). Without consideration of WYT, interannual hydrologic variability may obscure changes in post-fire rainfall-runoff patterns (Mahat et al., 2016; Newcomer et al., 2023; Owens et al., 2013) or falsely exaggerate the impact of wildfire if, for example, a fire is followed by very wet years as occurred in Arroyo Seco and Clear Creek~~ Clear Creek~~.

Altered post-fire rainfall-runoff patterns also appear~~ed~~ to be seasonal~~, as observed in Clear Creek~~ (Fig.~~ure~~ 8). In Clear Creek, post-fire peak runoff was greater than expected every year in summer, but the trend was inconsistent in winter and melt seasons. Biederman et al. (2022) similarly observed ~~identified a similar trend,~~ greater post-fire changes observed in ~~the~~ summer than ~~the w~~winter~~,~~ in watersheds in the southwest U.S~~A~~. Wildfire has also been found to influence snow accumulation and melt timing (Ebel~~, Hinckley,~~ et al., 2012; Gleason et al., 2019; Kampf et al., 2022; Maina ~~&~~and Siirila-Woodburn, 2020). However, less wildfire influence on event runoff response in the winter and melt seasons in snow-dominated watersheds like Clear Creek makes sense because snow accumulation and melt dynamics likely dominate runoff response during these periods~~seasons~~. The altered post-fire summer rainfall-runoff events would have been obscured by the larger snowmelt ~~runoff~~ events without considering ~~the~~ seasonality ~~of rainfall-runoff events~~ in Clear Creek. In Oregon, where Long ~~&~~and Chang (2022) found no significant change between pre- and post-fire rainfall-runoff patterns despite comparing two dry years, ~~the~~ seasonality ~~of rainfall-runoff events~~ may have similarly obscured post-fire~~ impacts as~~ effects~~ they did in Clear Creek~~.

6. Conclusions

This study presents and utilizes the RREDI toolkit, a transferable ~~novel~~ time-series signal processing based event separation and attribution algorithm~~method~~, to disentangle~~to investigate untangle~~ the influence of time-varying hydrologic controls~~ including WYT, season, and antecedent~~ on~~ wildfire disturbed~~ event runoff response. ~~A rainfall-run~~A~~off event~~ dataset~~,~~ ~~consisting~~ of 5042 rainfall-runoff events was generated by applying the RREDI toolkit to nine study watersheds in the western U.S~~A~~. This dataset was used to investigate rainfall-runoff event patterns~~ (Q1)~~, identify significant time-varying hydrologic controls by watershed and runoff metric group, ~~(Q2),~~ and evaluate how the identified controls influence event runoff response and the effects of wildfire in ~~in~~ two case study burned ~~wildfire~~

~~disturbed~~ watersheds~~ (Q3)~~. ~~Results revealed in generalacross the nine watersheds ,~~ Water Year Type and season were generally found to be significant ~~time-varying~~ hydrologic controls, but results ~~however significant controls~~ varied between~~across~~ watersheds and runoff metrics. Antecedent ~~The significance of antecedent~~ precipitation was generally less significant, ~~varied betweenacross watersheds,~~ indicating a more complex influence ~~relationship fo~~on runoff response ~~r this control~~ consistent with the literature. ~~The identified significant controls were used to explore the influence of wildfire disturbance Unique trends were identified within significant condition groups in two burned contrasting watersheds,~~In Arroyo Seco and Clear Creek, post-fire ~~. Within each of the identified significant condition groups, the portion of post-fire~~ rainfall-runoff events ~~that fell above t~~generally exhibited higher peak runoff for a given rainfall depth than expected based on the undisturbed trends. Grouping rainfall-runoff events into significant hydrologic condition groups helped to reveal the effects of wildfire on event runoff response. Study findings improve fundamental understanding of multiple, confounding controls on event rainfall-runoff patterns and emphasize the need to consider the influence of interannual and seasonal variability to better isolate watershed disturbance effects. Better understanding the effects of watershed disturbances on streamflow patterns is ~~he significant condition group trend was generally greater than expected for peak runoff. Consideration of the significantse time-varying controls promoted the isolation untangling of wildfire disturbance on event runoff response. This analysis has increased the understanding of controls on rainfall-runoff patterns on streamflow and emphasized the importance of consideration of significant hydrologic controls in in undisturbed and disturbed watersheds. This~~critical to managing our natural resources ~~elevates the ability to prepare for watershed manag~~under ~~ement in a future with~~ increasing disturbance regimes.

Code and Data Availability: All code for data processing and visualization is available upon request from the author. The RREDI Toolkit python code and documentation for creation of the rainfall-runoff event dataset used in this study can be accessed via H~~h~~ydroshare at https://www.hydroshare.org/resource/797fe26dfefb4d658b8f8bc898b320de/~~/~~ (Canham ~~&~~and Lane, 2022). Streamflow data from the USGS is publicly available at https://dashboard.waterdata.usgs.gov/ and the AORC precipitation gridded dataset is publicly available at https://hydrology.nws.noaa.gov/aorc-historic/. Wildfire perimeters and burn severity mosaics are available at https://www.mtbs.gov/ and PRISM gridded precipitation data are available at https://prism.oregonstate.edu/.

Author Contributions: HC and BL designed the study. HC performed the analyses with input from BL, CP, and BM. The first draft of the paper was written by HC and reviewed by all co-authors.

Competing Interests: The authors declare that they have no conflict of interest.

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