Leveraging a time-series event separation method to untangle time-varying hydrologic controls ~~influence~~ on ~~wildfire disturbed~~ streamflow

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Abstract. Watershed disturbances can have broad, long-lasting impacts that result in a range of streamflow response. Increasing disturbance regimes, particularly from wildfire, is a growing concern for watershed management. The influence of watershed disturbances on rainfall-runoff patterns has proved challenging to untangle~~isolate~~ from undisturbed streamflow variability, driving the need to increase the understanding of hydrologic controls on event runoff response. We 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 controls~~watershed disturbance~~ on rainfall-runoff event patterns, we developed the Rainfall-Runoff Event Detection and Identification (RREDI) toolkit. The RREDI toolkit is a novel time-series event separation method that automates the pairing and attribution of precipitation and streamflow events, leveraging and building on existing rainfall-runoff event separation methods. A rainfall-runoff event dataset of 5042 events was generated by the RREDI toolkit from a collection of nine western USA study watersheds spanning a range of ~~streamflow regimes,~~ watershed characteristics~~properties, and burn characteristics~~. Through analyzing the rainfall-runoff event dataset, ~~we found that w~~water year type and season were identified as significant controls on ~~rainfall~~ runoff ~~metrics~~response. 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 influence of wildfire disturbance on event runoff response in two case study burned watersheds. 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 isolating~~untangling~~ the influence of wildfire on the rainfall-runoff patterns. The RREDI toolkit can be further applied to investigate the influence of other ~~watershed disturbances and~~hydrologic controls to increase understanding of rainfall-runoff patterns across the landscape.

1. Introduction

Watershed disturbances can have broad, long lasting, and variable impacts on watershed hydrology (Ebel & 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 & Mirus, 2014; Goeking & Tarboton, 2020; Hopkins et al., 2015; Kelly et al., 2017; Miller & Zégre, 2016). Wildfire is particularly impactful: since 2000 an average of 7.0 million acres has burned annually in the United States~~S~~ (Hoover & Hanson, 2021). Further, with~~in~~ a changing climate the observed occurrence and severity of wildfire has ~~is~~ increased in the western USA in recent decades~~ing~~, presenting growing challenges for human and water security (Abatzoglou et al., 2021; Abatzoglou & 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 & Hogue, 2015; Long & Chang, 2022; Newcomer et al., 2023; Saxe et al., 2018; Wine et al., 2018; Wine & 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 WYT wet and dry years may result in differences in runoff response (Biederman et al., 2022; Null & 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 differences 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 & Blöschl, 2009; Norbiato et al., 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b, Zheng et al., 2023). Finally, antecedent precipitation and antecedent moisture have been found to alter event runoff response (Jahanshahi and Booij, 2024; Merz et al., 2006; Merz & 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.

~~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 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 & 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 USA watersheds evaluated only static controls on event runoff response, and identified aridity, topographic slope, soil permeability, rock type, and vegetation density as significant (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 & Hogue, 2015; Long & Chang, 2022; Saxe et al., 2018; Wine et al., 2018; Wine & Cadol, 2016). Long & 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, USA.

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, a novel time-series event separation method (Canham & 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 on event runoff response. The specific ~~aims of the investigation into time-varying hydrologic controls were to~~research questions were to: (1) explore rainfall-runoff patterns and~~,~~ (2) identify significant time-varying hydrologic controls on event runoff response. The~~, an~~n~~,d~~ (3) explore the findings from research questions 1 and 2 in two case study ~~evaluate how time-varying hydrologic controls influence event runoff response in~~ wildfire disturbed watersheds. We hypothesize that ~~-~~accounting for ~~these~~ significant time-varying hydrologic controls will ~~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 were hand-selected to satisfy a wide range of ~~based on~~ watershed properties and streamflow regimes ~~, 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 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, 2011~~MTBS, 2023). ~~-~~The selected nine study watersheds spanned a large range of ~~contributing areas, streamflow regimes, and burn~~watershed characteristics~~ conditions~~ (Table 1). ~~-~~The 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 12.1 m^{3}s^{-1} in Thompson River to 0.03 m^{3}s^{-1} in Camp Creek. The mean annual precipitation ranged from 157 cm in Shitike Creek to 53 cm in Cache La Poudre River (Falcone, 2011) and the mean annual potential evapotranspiration ranged from 780 cm in Wet Bottom Creek and 401 cm in Valley Creek (Falcone, 2011). 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.

Two of the nine study watersheds were selected for a more in-depth exploration of watershed disturbance 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 wildfires during the period of available streamflow record that burned a significant 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)~~.~~. Additionally, these two case studies provided an

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~~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).~~

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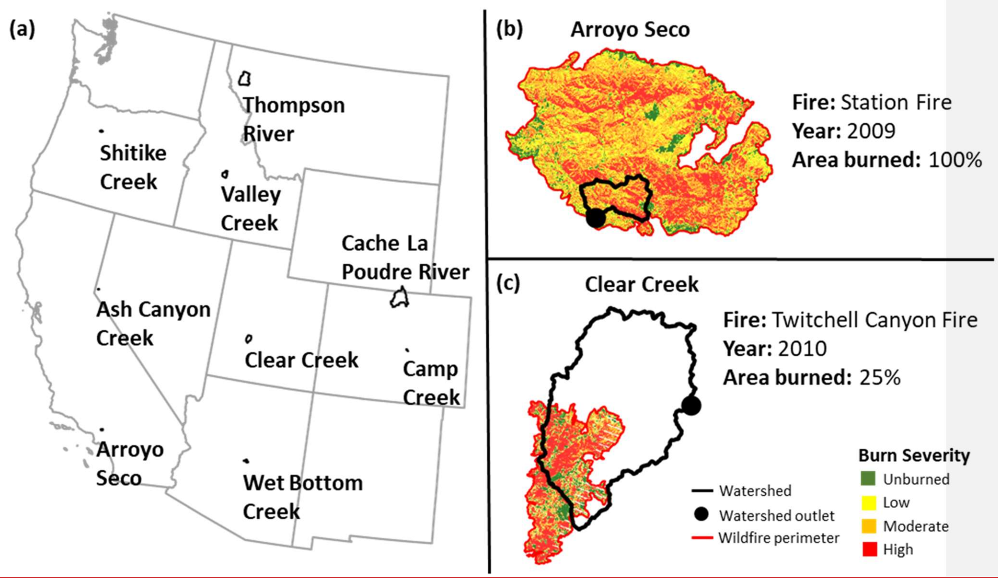

Figure 1: Study watersheds. (a) Nine selected study watersheds (labeled). Case study burned watersheds (b) Arroyo Seco and (c) Clear Creek. Shown are watersheds (black), ~~and~~ fire perimeters (red), and burn severity mosaics (MTBS, 2023).

~~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 area (km^2)	Streamflow (mean annual) ($m^2\ s^{-1}$)	P (mean annual)* (cm)	PET (mean annual)* (cm)	Streamflow regime
Arroyo Seco	CA	11098000	42	0.27	79	777	Rain
Ash Canyon Creek	NV	10311200	14	0.10	76	479	Snow
Cache La Poudre	CO	06752260	2966	4.9	53	449	Snow
Camp Creek	CO	07103703	25	0.03	56	479	Snow
Clear Creek	UT	10194200	426	1.0	54	508	Snow
Shitike Creek	OR	14092750	57	2.2	157	492	Snow
Thompson River	MT	12389500	1652	12.1	76	476	Snow
Valley Creek	ID	13295000	376	5.7	88	401	Snow
Wet Bottom Creek	AZ	09508300	94	0.39	62	780	Rain

*(Falcone, 2011)

2.1. Hydrologic data inputs

Streamflow and precipitation data were obtained for each study watershed as follows. The 15-minute, daily, and total annual streamflow data for the full period of record were retrieved from the USGS streamflow gage. The total annual precipitation at the centroid of each study watershed for each year with available USGS annual streamflow~~used 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) 4km^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 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 & 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 USA watersheds (Fig.~~ure~~ 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 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 trends in two ~~contrasting~~ burned watersheds, Arroyo Seco and Clear Creek.

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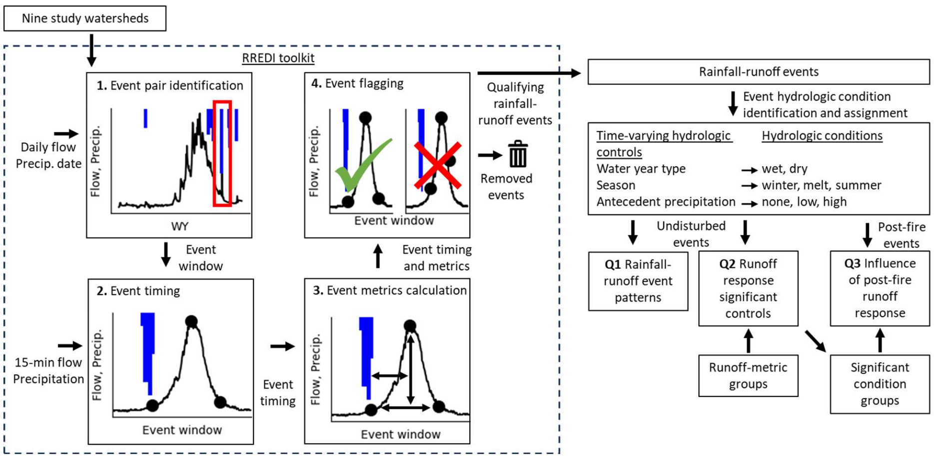

Figure 2: Methods workflow to explore the influence of time-varying hydrologic controls on rainfall-runoff event patterns as described in this paper. The four key steps of the RREDI toolkit (black dashed box) are outlined: Step 1. Event pair identification, Step 2. Event timing, Step 3. Event metrics calculation, and Step 4. Event flagging. Major connections between workflow steps and study research questions (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 & 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 events by separating precipitation time~~-~~series into rainfall ~~storms~~ and runoff 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. The runoff event start, peak, and end timing and magnitude and the runoff event volume were then

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identified using the~~n~~ 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 metrics were calculated using the rainfall and runoff event timings 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 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. The rainfall-runoff timing metric group included response time calculated as the difference between the rainfall~~storm~~ start time and the runoff start time. Metrics~~s~~ were also normalized by dividing metric values by the 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~~From 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.~~

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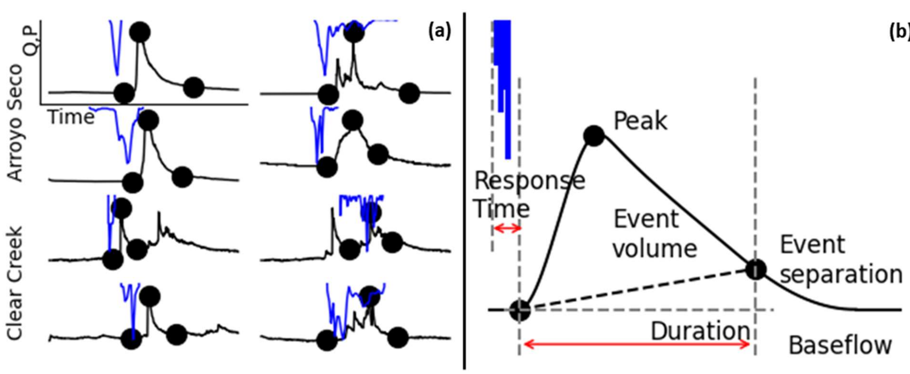


Figure 3. RREDI toolkit rainfall-runoff event examples and metrics. (a) Eight example rainfall-runoff events identified using the RREDI toolkit. Shown are the rainfall event (blue), the paired runoff event hydrograph (black), and the identified runoff start, peak, and end times and magnitudes (black 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 magnitude~~ose~~ independently identified by visual inspection for each rainfall-runoff event following similar performance assessment methods used for 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~~vents 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 and precipitation were plotted for the undisturbed period of record to visually identify the annual precipitation threshold 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 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 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 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 started the month ~~where~~ that baseflow dominated over winter rainfall ~~storm~~ peaks in the mean annual hydrograph. Rainfall-runoff e~~E~~vent antecedent precipitation was assigned as none (<1mm), low (1-25mm), and high (>25mm) based on the cumulative precipitation depth over the six days prior to the rainfall~~precipitation~~ event start time (Long & Chang, 2022; Merz et al., 2006; Merz & Blöschl, 2009; Tarasova~~, Basso, Zink,~~ et al., 2018b) (Fig~~ure~~. 4 c). Only 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 using methods other than those described here to adjust the thresholds to re-assign rainfall-runoff events would substantially alter our proposed approach or findings in this study.

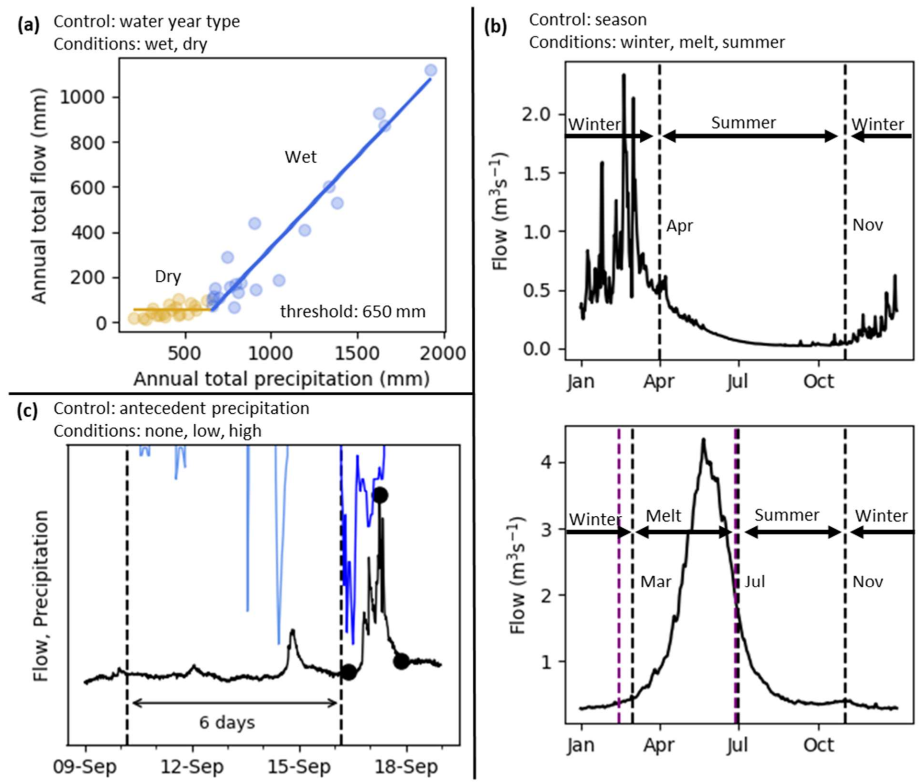


Figure 4: Example hydrologic condition identification for time-varying hydrologic controls. (a) Water year type wet (blue) and dry (orange) years for Arroyo Seco. The ordinary least squares linear regression lines for above and below the threshold are shown. (b) Seasons (vertical dashed) delineated from 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

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)~~, trends in undisturbed rainfall-runoff patterns were first evaluated using a LOWESS curve. 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 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 Test results and the Eta squared test for the Kruskal Wallis 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 ~~identify~~ highlight ~~significant~~ important hydrologic controls on event runoff response. The use of the relative significance~~t~~ rate reduced the issue of multiple comparisons and reduced the emphasis on specific metric calculation methods. ~~S~~Summarizing by area-normalized runoff metrics facilitated comparison between different sized watersheds while ~~. S~~summarizing 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, 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 significant rainfall-runoff event metrics (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 significance~~t~~ rate for this~~e~~ 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 assessment in wildfire disturbed watersheds

Additional statistical methods were performed on two burned study watersheds, Arroyo Seco and Clear Creek, 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~~W~~atersheds, specific significant condition groups were identified for the rainfall ~~storm~~ depth and 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.

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 rainfall-runoff events above the significant group trend and one standard deviation was calculated for all post-fire years combined and individually. The calculated post-fire rainfall-runoff event percents were compared to the expected 50% above the trend and 16% above the standard deviation.

4. Results

4.1. RREDI toolkit performance

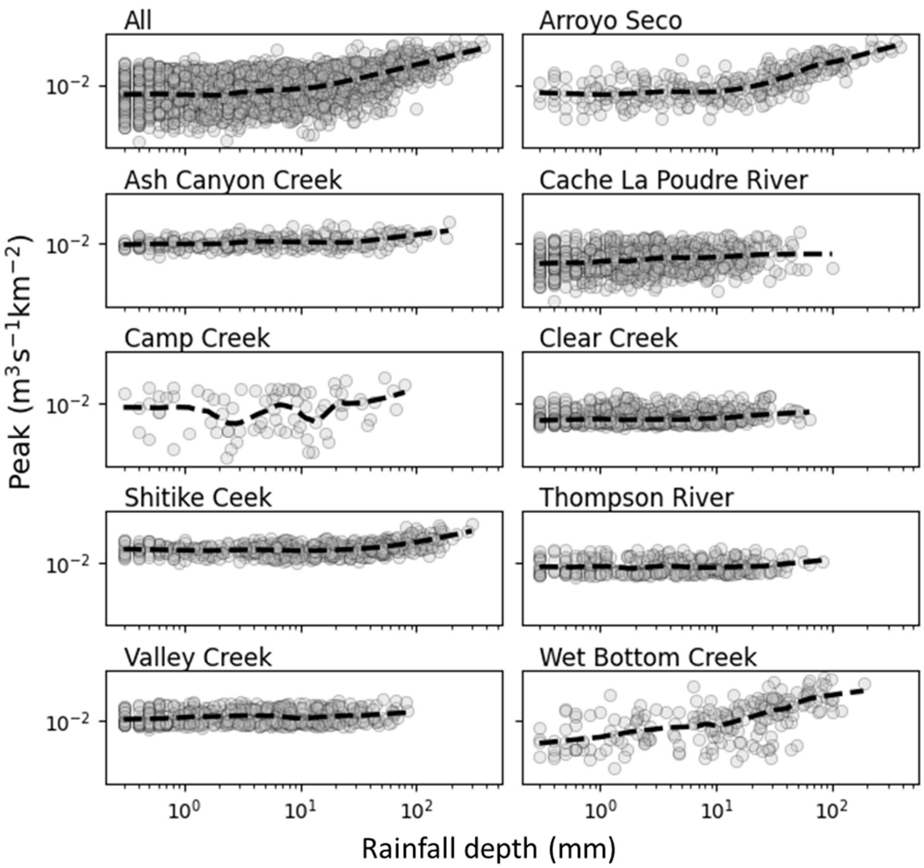
The RREDI toolkit ~~performed well across the nine study watersheds and~~ resulted in a rainfall-runoff event dataset of 5042 rainfall-runoff events across the nine study watersheds (Table S4). 7026 rainfall-runoff events were initially identified by the RREDI toolkit in step 2. Of these, 774 rainfall-runoff events (11% of total events, 5 to 34% range across study watersheds) 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 the accuracy rate rose to 90% after flagging (step 4). The identified occurrence rate for each of the four known issues across all watersheds was 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.

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

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 methods~~rainfall-runoff events were assigned to all hydrologic conditions in each watershed~~ (Table S6). For ~~undisturbed~~ rainfall-runoff events across all the study watersheds, there was an increasing trend in runoff peak with increasing rainfall~~storm~~ depth (Fig.~~ure~~ 5). A slope break 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 rainfall~~storm~~ depth existed across the watersheds. The identified slope break was most apparent in three watersheds: Arroyo Seco, Shitike Creek, and Wet Bottom Creek. Rainfall-runoff e~~E~~vents 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 large 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)

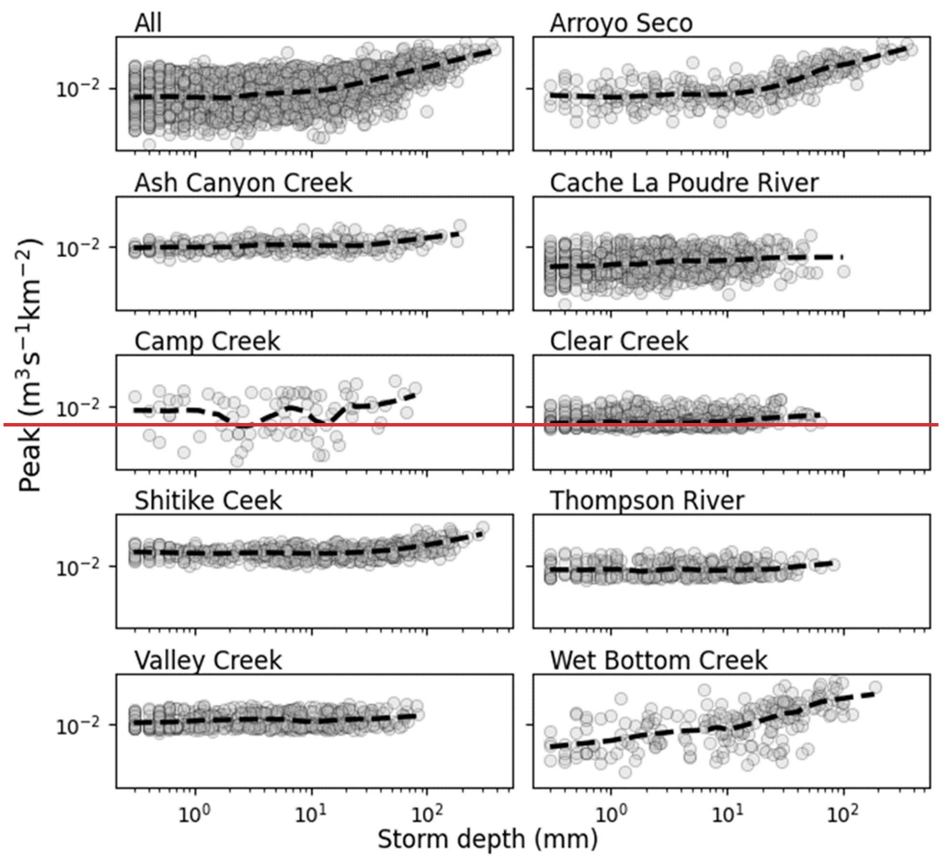
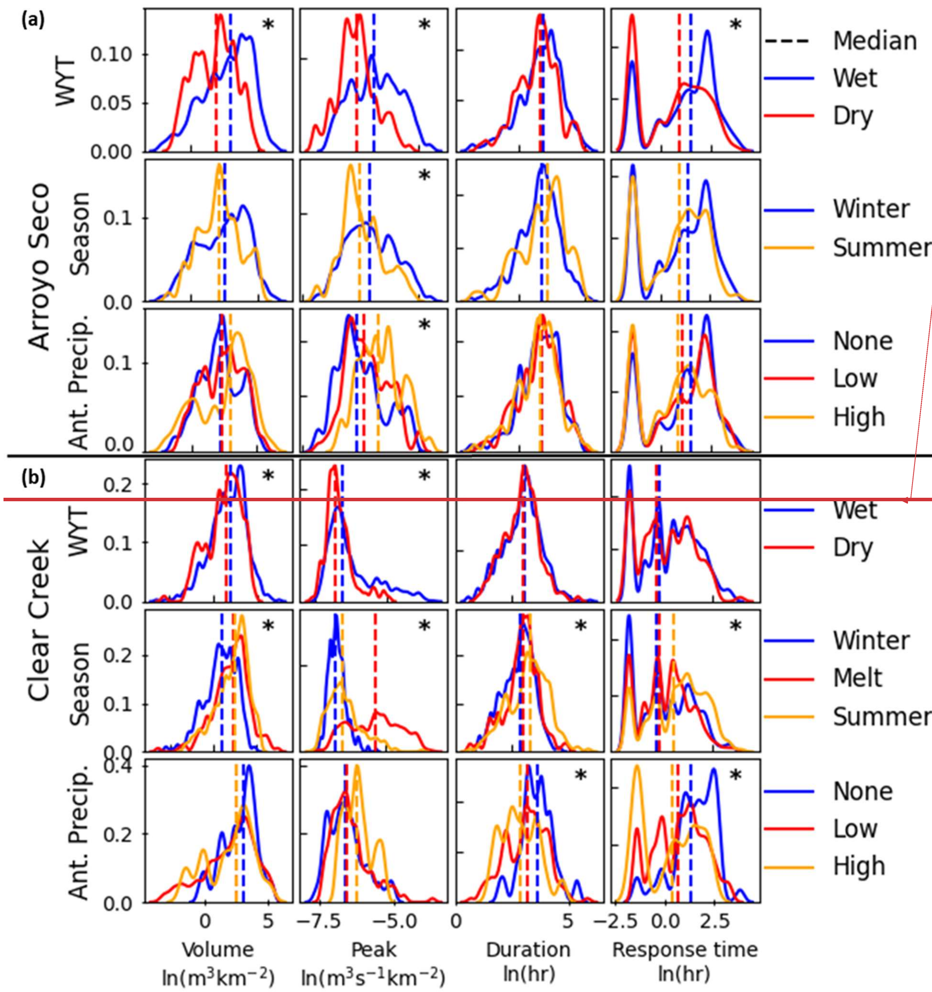


Figure 5: Undisturbed rainfall-runoff events for rainfall~~storm~~ depth (mm) and runoff peak (m^3 s^{-1} km^{-2}). A LOWESS curve (dashed black line) for the undisturbed rainfall-runoff events for all study watersheds and each individual watershed is shown.

~~Clear d~~Directional shifts that varied by runoff metric and watershed were apparent in four selected runoff metric undisturbed rainfall-runoff event distributions for WYT, season, and antecedent precipitation. In both Arroyo Seco and Clear Creek, wet years had a higher median value than dry years for 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 consistent ~~in direction~~ in Clear Creek. ~~For~~ With respect to antecedent precipitation, ~~in both Arroyo Seco and Clear Creek~~, 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.



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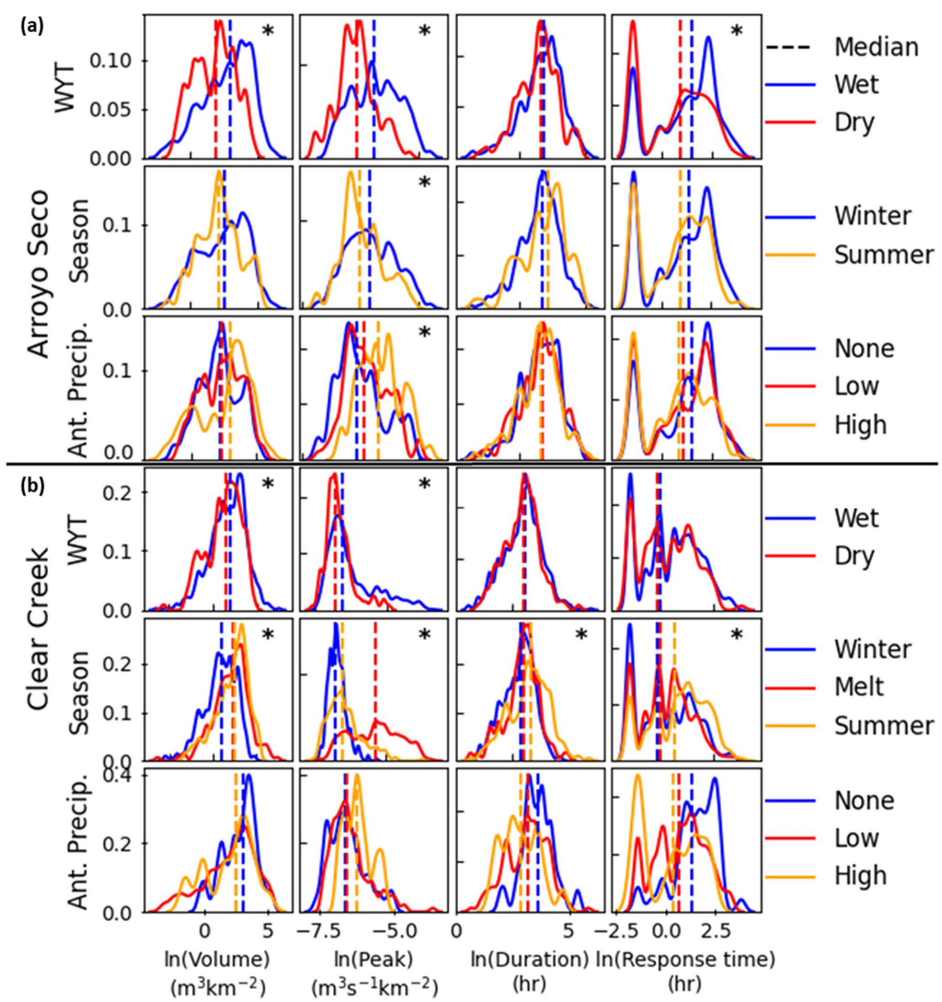


Figure 6: Undisturbed rainfall-runoff event KDE distributions for hydrologic conditions for natural log transformed WYT, season, and antecedent precipitation in (a) Arroyo Seco and (b) Clear Creek for four selected runoff metrics: volume, peak, duration, and response time. Distributions are colored by hydrologic condition. The median value of each distribution is shown (dashed line). Significant difference between distributions is indicated (*). Note there is no melt season in Arroyo Seco.

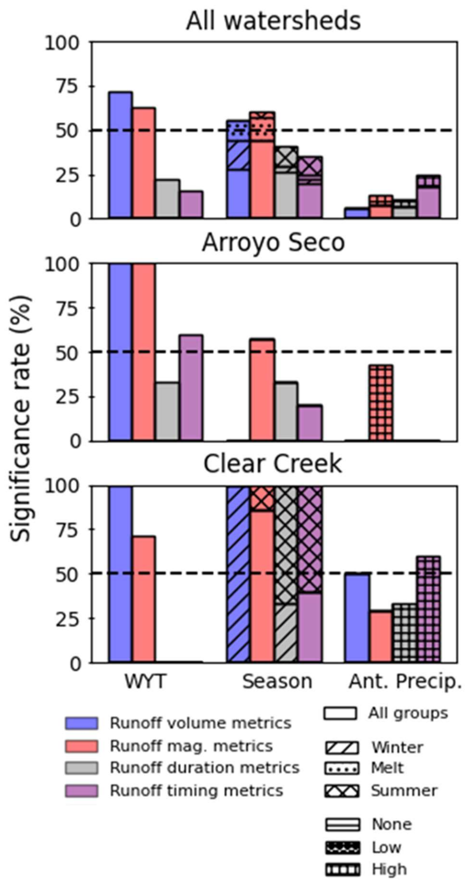
All time-varying hydrologic controls were found to be significant for the ~~in~~ undisturbed rainfall-runoff events in Arroyo Seco and Clear Creek, but significance varied by event runoff metric and watershed (Fig.~~ure~~ 6; Table 3). Water year type was the most often significant hydrologic control 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 in both watersheds and exhibited the most variation in significance between runoff metrics across the two watersheds. Of the four selected runoff metrics, peak runoff was most commonly significant across all the study watersheds for all three time-varying hydrologic controls (Tables S7, S8, S9). Peak runoff was also significant across the three time-varying hydrologic controls for both Arroyo Seco and Clear Creek except antecedent precipitation in Clear Creek (Fig.~~ure~~ 6; Table 3). Conversely, the ~~least common significant~~ runoff metric least frequently identified as significant varied across ~~all~~ the study watersheds ~~varied by runoff metric~~, including runoff duration and response time for WYT, duration for season, and volume for antecedent precipitation (Tables S7, S8, S9). Despite being least ~~commonly~~ frequently significant overall, WYT corresponded with significant differences in runoff response time ~~for WTY~~ in Arroyo Seco and season corresponded with 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-runoff ~~e~~Event metrics			
		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: &None, ~Low, +High

Water year type and season were generally ~~more important~~ differentiating (greater than 50% average 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, time-varying hydrologic control importance varied for individual watersheds and ~~area-normalized~~ runoff metric groups. For example, in Arroyo Seco, the relative significant rate for the WYT runoff volume metric group was 100%, as two out of the two metrics within this group, runoff volume and runoff ratio (Table S3), were found to be significant by the Mann Whitney U Test (Table S7) while the significance rate for the runoff duration metric group with respect to WYT was 33% because only one out of three metrics was significant. The 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 f~~the average significance rates of all metric groups exceeded those calculated across watersheds ~~or all metric groups in Arroyo Seco~~ (Fig.~~gure~~ 7 b) and ~~for runoff magnitude and runoff volume metrics group~~s in Clear Creek the average significance rates of runoff magnitude and volume metric groups exceeded those calculated across watersheds (Fig.~~ure~~ 7 c). Water 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 in Cache La Poudre River and Thompson River to the average significance across watersheds (Fig. S8).



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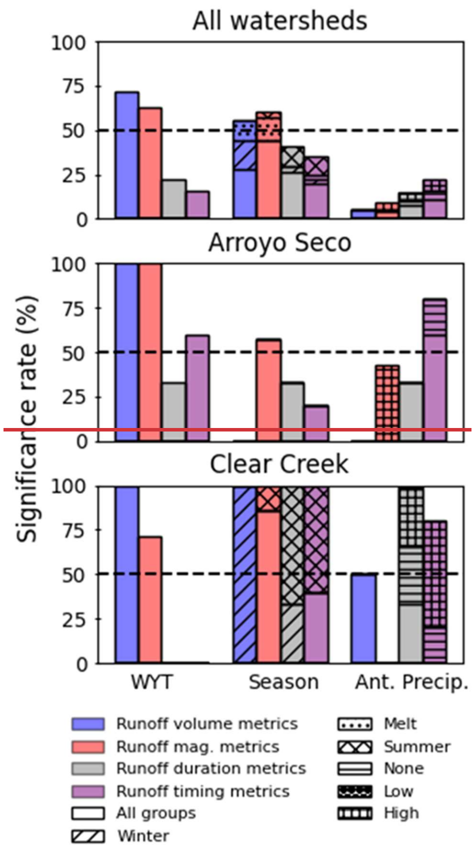

Figure 7: Summary plots of statistical significance rates of a~~A~~rea-normalized event runoff metrics averaged by runoff metric group (bars) with respect to three time-varying hydrologic controls (x-axis) ~~significance summary rates for statistical test results~~. Individual plots ~~for~~ show results for~~the watershed-average~~All Watersheds (a), Arroyo Seco (b), and Clear Creek (c) under undisturbed conditions. ~~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 bars represents statistically different individual hydrologic conditions from the Dunn Test,

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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 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 Arroyo Seco, the runoff magnitude~~, duration, and timing~~ metric group~~s~~ was~~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 Clear Creek ~~for~~ all four ~~runoff volume, runoff duration, and rainfall-runoff timing~~ metric groups ~~in Clear Creek~~were better differentiated (Fig.~~ure~~ 7 c). 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).

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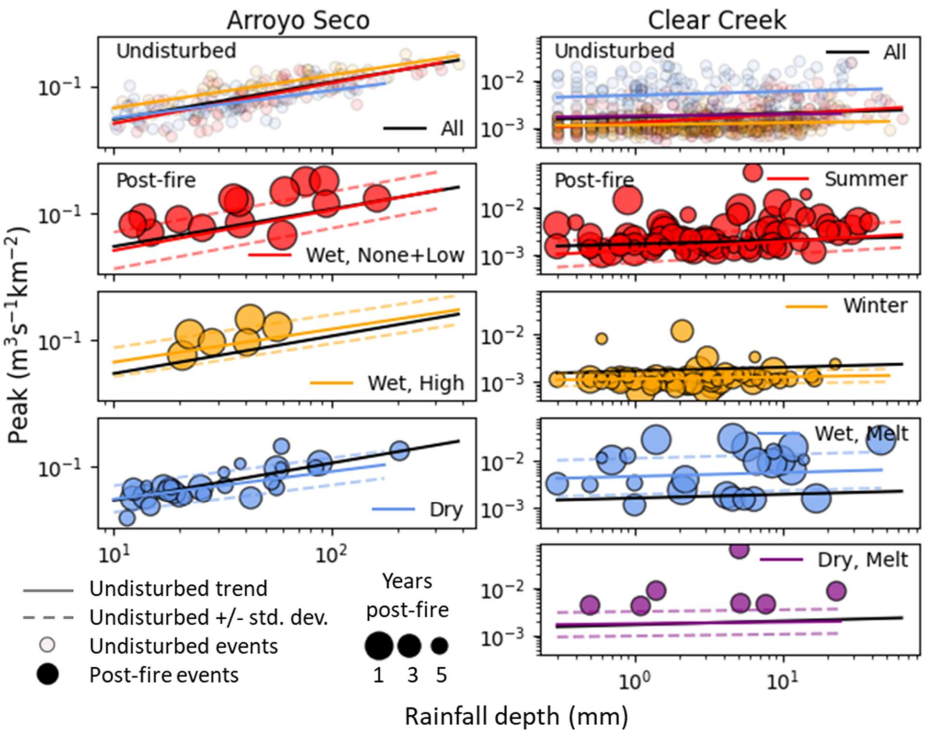
4.3. Hydrologic variability in wildfire disturbed watersheds

~~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 within a different portion of the un-grouped rainfall-runoff ~~all~~ events distribution (Fig.~~ure~~ 8; Table S10).


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

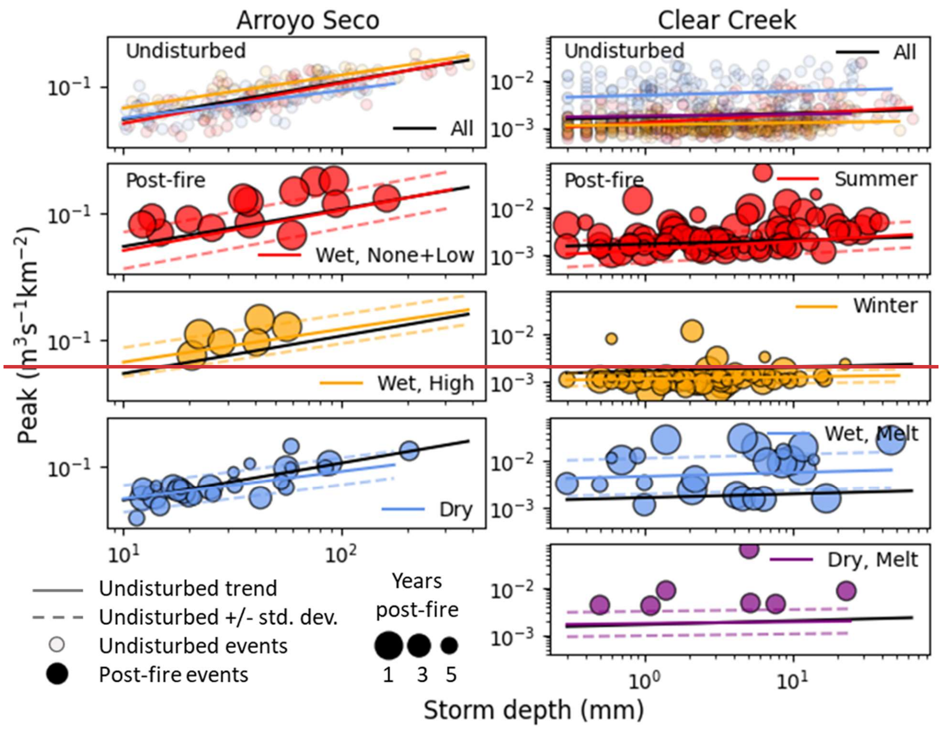


Figure 8: Significant condition groups for Arroyo Seco and Clear Creek for rainfall~~storm~~ depth (mm) and runoff peak (m^3 s^{-1} km^{-2}). Shown are the significant group trends and one standard deviation for each of the significant condition group (colored) and the un-grouped rainfall-runoff~~all~~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

The portion of post-fire rainfall-runoff events that fell above the significant condition group trend 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 except winter in Clear Creek (Table S11). 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 (Fig.~~ure~~ 8; Table S11).

5. Discussion

5.1. RREDI toolkit

The RREDI toolkit was developed to automatically separate co-varying streamflow and precipitation time-series ~~in a method~~ using an approach that ~~could be applied in any watershed~~ 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 90% rainfall-runoff event accuracy rate, ranging from 78 to 100% across study watersheds. There were no clear 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 factors including poor quantification of rainfall ~~storm~~ timing, water withdrawals, temporally aggregated streamflow, and extended periods of diurnal cycling. The rainfall-runoff event accuracy increased after 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. This resulted in several identified rainfall-runoff event pairs where the event runoff response was outside of the allowable response window.

Quantification of rainfall~~storm~~ events influenced the RREDI toolkit performance, where rainfall~~storm~~ timing was a common reason for poor rainfall-runoff event identification. A gridded precipitation data product was used to overcome sparse rain gage density and limited or sporadic periods of record in the mountainous western USA. 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 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 here as the best available method given the large computational requirement for additional watershed ~~summary~~analysis, but future work could incorporate watershed averaged precipitation or other methods to 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 & 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 is~~was~~ transferable across diverse watersheds using only two watershed specific parameters, and addresses~~d~~ several common issues identified by past studies. 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, Giani~~a~~ 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 (Gian~~a~~i 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 by using 15-minute streamflow the RREDI toolkit could identify and characterize sub-daily rainfall-runoff events. The use of time-series signal processing also allowed for the identification of rainfall events with no runoff response, providing more information about the rainfall thresholds and antecedent 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 & Mirus, 2014; Goeking & 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. 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 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 & 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 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 in six of the seven snow-dominated watersheds. Water year type was significant for one of the two rain dominated watersheds, Arroyo Seco. In Arroyo Seco, extreme interannual variability in the ~~interannual~~ frequency and intensity of atmospheric rivers that ~~bring~~ generate a majority 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 & Cavazos, 2010; Pascolini-Campbell et al., 2015). This may be because, despite the monsoon influence, the majority of precipitation in this watershed instead comes from winter rainfall events~~storms~~ (Arriaga-Ramierez & 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 a variety of watersheds with a range of precipitation and streamflow regimes and watershed properties (Jahanshahi and Booij, 2024; Merz et al., 2006; Merz & 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 & 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 & Kampf, 2020; Jahanshahi and Booij, 2024; Merz et al., 2006; Merz & 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 & 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 watersheds, ~~Arroyo Seco and~~ Clear Creek (Fig.~~ure~~ 7; Fig. S8). 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 & Chang, 2022; Merz et al., 2006; Tarasova~~, Basso, Zink,~~ et al., 2018b) and in the SCS curve method for runoff generation (Mishra & 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 & 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, USA (Long & Chang, 2022) were not significant controls at the event scale. A possible reason why antecedent precipitation was not identified as significant in eight~~seven~~ 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. 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 between post-fire response in Arroyo Seco and Clear Creek is consistent with the large range of post-fire responses observed across western USA watersheds (Hallema et al., 2017; Saxe et al., 2018). In Arroyo Seco, for each year post-fire the peak runoff 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 & 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 Clear Creek.

Altered post-fire rainfall-runoff patterns also appeared 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. Biederman et al. (2022) identified a similar trend, greater post-fire change observed in the summer than the winter, in watersheds in the southwest USA. 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 & Siirila-Woodburn, 2020). However, less wildfire influence on event runoff response in the winter and melt in snow-dominated watersheds like Clear Creek makes sense because snow accumulation and melt likely dominate runoff response during these seasons. The altered post-fire summer rainfall-runoff events would have been obscured by the larger melt runoff events without considering the seasonality of rainfall-runoff events in Clear Creek. In Oregon, where Long & 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 obscured post-fire impacts as they did in Clear Creek.

6. Conclusions

This study presents and utilizes the RREDI toolkit, a novel time-series event separation method, to ~~to investigate~~ untangle the influence of time-varying hydrologic controls including WYT, season, and antecedent on~~ wildfire disturbed~~ event runoff response. A rainfall-runoff event dataset~~,~~ consisting of 5042 rainfall-runoff events was generated by applying the RREDI toolkit to nine study watersheds in the western USA. This dataset was used to investigate rainfall-runoff event patterns (Q1), identify significant time-varying hydrologic controls (Q2), and evaluate how the identified controls influence event runoff response in two case study wildfire disturbed watersheds (Q3). Results revealed ~~in general~~across the nine watersheds ~~,~~WYT and season were significant time-varying hydrologic controls however significant controls varied between~~across~~ watersheds and runoff metrics. The significance of antecedent precipitation varied between~~across~~ watersheds, indicating a more complex relationship for 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, Arroyo Seco and Clear Creek. Within ~~each of~~ the identified significant condition groups, the portion of post-fire rainfall-runoff events that fell above the significant condition group trend was generally greater than expected for peak runoff. Consideration of the significant~~se~~ 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 elevates the ability to prepare for watershed management 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 hydroshare at https://www.hydroshare.org/resource/797fe26dfefb4d658b8f8bc898b320de/ (Canham & 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/.

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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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