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Stochastic framework reveals the controls of forest treatment – peakflow causal relations in rain environment

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ABSTRACT

Decades of literature on forest treatment – peakflow relations have generated considerable disagreements and turned the topic into one regarded as enigmatic. Factors affecting peakflows are multiple and chancy and, hence, can only be investigated via a probabilistic approach. We analyze peakflow data using the peakflow frequency distribution framework in two pairs of control-treatment watersheds in the rain environment of an experimental forest in North Carolina. We demonstrate how a range of forest treatments can change the magnitude and frequency of all peakflows on record and how such effects can increase with increasing event size as a consequence of changes to the peakflow frequency distribution. Changes to the distribution's mean (−0.2 to +47.4 %) and variance (−30.9 to +162.1 %) resulted in a range of effects from no significant impacts on peakflows to making larger peakflows becoming even larger (up to 105 % increase) and more frequent (up to 18 times more frequent). Changes to peakflows are attributed to treatment-induced suppression of evapotranspiration and changes to non-vegetative factors, which can alter the soil storage capacity, moisture available for runoff, and the efficiency of runoff arriving to the outlet. The dominant topographical aspect of the watershed, seasonal differences in storm types, extent to which the storm events are in-phase or out-of-phase with high antecedent soil moisture, and lagged runoff responses with watershed memory emerged as key indicators of the sensitivity of peakflows to forest treatment. The application of the stochastic framework in forest hydrology can help fully understand forest treatment – peakflows relations.

1. Introduction

Sustainable forest management requires proper understanding of the relation between forest disturbances and the watershed peakflow response (or flood in the case of larger watersheds) in order to minimize potential negative impacts of forest disturbance on biotic and abiotic ecosystems. Although peakflows occur naturally, the magnitude and frequency of peakflow events can be altered by land use and management and/or climate change (e.g., Alfieri et al., 2016; Berghuijs et al., 2017; Blum et al., 2020; Hecht and Vogel, 2020; Oudin et al., 2018). Increased flood risk can negatively affect downstream communities, infrastructure and other assets, fluvial ecosystems, and water quality (e.g., Alexander et al., 2007; Ashley and Ashley, 2008; François et al., 2019; Kumar et al., 2021; Picchio et al., 2021; Talbot et al., 2018).

There are disagreements on how to investigate the relationship between forest treatment (a subset of forest disturbance which includes clearcutting, thinning, species conversions, and associated watershed alterations) and peakflows. Over the past century of forest hydrology literature using the paired watershed approach, the effect of forest treatment on peakflows has been defined as the difference in peakflow magnitudes between treated and control watersheds under the same storm input (rain environment) or freshet season (snow environment). This imposes a deterministic framework which does not account for the inherently stochastic peakflow response. Alila et al. (2009) refer to this as Chronological Pairing (CP), and instead argued that a stochastic framework is needed to properly investigate the effect of forest treatments on peakflows.

Under the CP framework, watershed peakflows were conceptualized through the scenario where a watershed's storage capacity along with the interception and transpiration by vegetation are limited, and can be overwhelmed by a large enough storm regardless of the presence of forests. In this line of reasoning, the specific peakflow event is indexed to the storm size under the assumption that if antecedent moisture conditions (AMC) are high and the storm is big enough, it does not matter

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whether or not forests are present. This line of reasoning is prominent in the peer-reviewed literature of the rain (e.g., Bathurst et al., 2020; Birkinshaw et al., 2014; DeWalle, 2003), snow (e.g., Bathurst et al., 2011b, Bathurst et al., 2011a), and rain-on-snow environments (e.g., Jones, 2000). It is also repeated in hydrology textbooks, such as Chang (2012, p. 403): "As the size or duration of storms increases … watersheds gradually become saturated, regardless of forested or bare ground, and the impact of forest cover on storm flow decreases to insignificant levels." This has been reinforced by decades of non-causal CP-based regression analysis where a quick convergence of pre- and post-treatment regressions at higher peakflows has been misinterpreted as an indication of decreasing effects of forests with an increase in event size (Alila et al., 2009 and references therein). However, a stochastic framework accounts for the fact that peakflows are controlled by multiple randomly occurring factors which interplay with each other affecting peakflows and possibly leading to no upper limit event size beyond which these factors cease affecting peakflows. This is only possible under the stochastic framework because it utilizes "the flood frequency curve [which] represents one of the most comprehensive and compact descriptions of a catchment's storm response…" (Robinson and Sivapalan, 1997, p. 2981). Pham & Alila (2024) discussed in-depth how the stochastic understanding of peakflows is necessary and the proper way of investigating the role of forests on peakflows as it more realistically resembles how peakflows occur in nature.

In rain-dominated environments, peakflows are influenced by two main hydro-meteorological factors: AMC and storm event inputs. Over time, every peakflow magnitude can be generated by many different combinations of these two randomly occurring factors, resulting in occurrence with a particular frequency. Past stochastic-based studies suggested that contrasting watershed topographic aspect (Moreno et al., 2016), seasonality (Basso et al., 2016), soil water storage (McCuen and Smith, 2008), and the prolonged impact of forest disturbance (Johnson and Alila, 2023) can affect peakflows. The frequency pairing (FP) approach, which compares pre- and post-treatment peakflow frequency distributions as described by Alila et al. (2009), is well-established in the wider hydrology, climatology, and other disciplines (e.g., Allen and Ingram, 2002; Blomberg, 2007; Gilli and Këllezi, 2006; Hoel et al., 2013; Howe et al., 1967; Katz, 1993; Katz et al., 2005; Lin and Neelin, 2000; Palmer, 2019; Possingham et al., 2013; Rivas et al., 2008; Stott et al., 2004; Sudakov et al., 2022; Van Kampen, 2007; Wigley, 1985), but has not been common practice in forest hydrology.

FP-based studies in snow environments have shown that i) forest treatment can affect not only small and medium but also the larger peakflows (return periods >10 years), ii) the effects can increase with event size, and iii) such effects can persist across a wide range of record lengths and hence return periods (e.g., Green and Alila, 2012; Johnson and Alila, 2023; Kuraś et al., 2012; Schnorbus and Alila, 2013, 2004). This newly emerging portrayal of the relation between forest treatments and especially the larger peakflows has been substantiated by other albeit rare FP-based studies in the rain and rain-on-snow environments in small and large watersheds (e.g., Birkinshaw et al., 2011; Brantley et al., 2015; Duncan, 1995; McEachran et al., 2021; Reynard et al., 2001; Verry et al., 1983). Moreover, it has been long-recognized and well-understood, outside of forest hydrology, that the frequency and magnitude of extreme events are sensitive to even tiny changes in the mean, variability, or skewness (Katz, 1993; Katz and Brown, 1992; Taleb and Douady, 2013; Wigley, 1985).

Reliable prediction of cause-effect relations between forest treatment and peakflows is predicated on sound understanding of the stochastic physics of peakflows. Stochastic hydrology and understanding the physical controls on the flood frequency distribution originated in the 1970s (Eagleson, 1972; Klemeš, 1978; Yevjevich, 1974). This involves evaluating how forest treatments may *physically* affect peakflows through its frequency distribution (*i.e.,* its mean, variance, and skewness parameters), as opposed to only observing and describing numerical changes, as emphasized by Dawdy and Gupta (1997, p. 274):

> "…our attempt goes far beyond a "statistics only approach" and tries to place the statistics in a physical framework to provide an understanding of those factors which govern the spatial [and temporal] structure of floods in a physical sense."

Using stochastic physics to understand the physical factors which govern peakflows under a stochastic framework is rarely, if ever, done in forest hydrology whereas the wider hydrology (e.g., Merz et al., 2022 and references therein) and other disciplines (e.g., Sudakov et al., 2022) readily use it to infer the stochastic physics in their research. Although forest treatment has been rarely studied in this framework of stochastic hydrology, one could infer how the flood frequency curve (FFC) might be affected by understanding the environmental controls of the FFC (Pham and Alila, 2024). Inferring the stochastic physics of peakflows reveal that it can be highly sensitive to slight changes in factors that generate peakflows and it is more likely than not that peakflows will be affected by forest treatment.

1.1. Stochastic understanding of how some physical processes can affect peakflows in past studies

Out of the two main hydro-meteorological factors previously mentioned, the forest treatment effect on AMC most directly affects peakflows. As AMC fluctuates through time, varying in wetness and the probabilities of being in any given state, studies showed that the realistic dynamic nature of the AMC state led to significant increases in the mean and variance of floods (De-Michele and Salvadori, 2002; Sivapalan et al., 2005).

Forest treatment can reduce evapotranspiration, which in turn increases AMC. Increasing AMC allows for more efficient delivery of water to the watershed outlet which in turn increases the variability of peakflows. Increased peakflow variability from forest treatment will affect the frequency and magnitude for a wide range of peakflow events (Archer, 2007; Green and Alila, 2012; Johnson and Alila, 2023). Expansion of the contributing area of peakflows can lead to increases in variability and skewness, which has been seen in empirical and simulated floods (Fiorentino et al., 2007; Gioia et al., 2012; Rogger et al., 2012).

Very deep soil mantles might limit the amount of area that can be saturated at any given time compared to other areas with shallower soil as a result of forest treatment. Deep soils allow for large water storage capacity (Hewlett, 1961; Hewlett and Hibbert, 1963). These large storage potentials can lead to a non-linear catchment discharge response which results in heavier-tailed and increased skewness in the peakflow Probability Density Functions (PDF) (Basso et al., 2015). Higher nonlinear hydrologic responses lead to heavier-tailed FFCs resulting in higher likelihoods of more extreme floods (Wang et al., 2025). Forest treatment can decrease the available watershed moisture storage capacity, which can affect the shape of the cumulative distribution function (CDF). This is because watershed storage is a significant factor affecting the skewness of peakflows (McCuen, 2001; McCuen and Hromadka, 1988; McCuen and Smith, 2008). Also, watershed storage potential can shift peakflow skewness from being more influenced by AMC to rainfall instead. This leads to the FFC moving upwards and changing its shape when watershed storage decreases (Hashemi et al., 2000). In addition to soil depth, watershed aspect can influence peakflow responses. For example, a hurricane event resulted in different flood responses between contrasting aspects where one side of the 10,000 km^2 basin with less rainfall experienced larger floods compared to the opposite side, and this was attributed to higher AMC and lower soil moisture storage potential (Sturdevant-Rees et al., 2001).

Seasonal differences in solar insolation and precipitation can affect peakflow sensitivity to forest treatment. Differences in storm types between seasons help explain the shape of the CDF. FFC modelling has shown that rare high-intensity and shorter duration storms, such as convective types, produced steeper and accentuated CDF while low-intensity and longer duration storms, such as frontal stratiform types, produced flatter and milder-shaped CDFs (Hashemi et al., 2000; Kusumastuti et al., 2007; Sivapalan et al., 2005, 1990; Smith et al., 2018). Also, it has been shown that higher rainfall skewness increases peakflow skewness and that rainfall skewness acts as the upper bound of peakflow skewness (McCuen, 2001; McCuen and Smith, 2008). Derived seasonal FFC, through modelling, revealed that more persistent flow seasons produced flatter and milder-shaped CDF whereas more erratic flow seasons produced steeper accentuated CDF (Basso et al., 2016). Also, removing the dominant tree species within the riparian zone has led to higher increases in peakflows and water yield in the dormant season compared to the growing season in the southeastern US (Brantley et al., 2015). Convective storms can cover a larger proportional area of the smaller watersheds where they dominate the annual FFC for watersheds less than 100 km^2 (Bates et al., 2015; Sturdevant-Rees et al., 2001).

Changes and interactions between the aforementioned physical processes may compound their effects on peakflows. Aggregation and/or transformation of these processes are more likely than not to lead to heavy-tailed peakflow PDFs (Merz et al., 2022). Moreover, it is easier to propagate heavy-tailed behaviors than to maintain light-tailedness (Merz et al., 2022). Therefore, changing even one peakflow-generating factor from light-tailed to heavy-tailed due to forest treatment, will likely lead to peakflows becoming more heavy-tailed and increasing skewness. This phenomenon is further amplified if forest treatment changes more than one peakflow-generating factor. Previous FP-based studies usually focused on investigating the effect of the various aforementioned processes on peakflows one-at-a-time. This study will build upon previous work by examining how the interaction of these factors influence peakflows, which is rarely done but more closely represents reality (Pham and Alila, 2024).

1.2. Objectives and hypotheses

This study has two overarching objectives: i) investigate the cause-effect relation between forest treatment and peakflows using FP in two pairs of control-treatment watersheds in the rain environment, and ii) explain the differences in peakflow response between the treated and control (*i.e.*, reference) watersheds with a stochastic understanding to examine four proposed hypotheses:

Forest treatment can continue to affect peakflows unchecked with increasing event size. When it is the case, there appears to be no apparent “no effect” threshold at which forest treatment ceases affecting peakflows, at least within the observed peakflow record length. This may be due to the changes in the mean and variability of the peakflows caused by forest treatment.

Watershed topographic aspect plays a distinct role in peakflow response to forest treatment. Processes on contrasting aspects can modulate peakflow response where northern aspects can amplify while southern aspects can mute the effects of forest treatment on the mean and variance of peakflows within the Northern Hemisphere.

Seasonality of AMC and storm characteristics results in different peakflow magnitude-frequency responses to forest treatment. Different seasonal processes can result in differences in the mean, variability, and skewness of peakflows. Moreover, lagged interactions can shift peakflow responses where changes that would normally be expected in a specific season to instead affect the subsequent season.

Changing dominant forest species can lead to changes in the mean and variance of peakflows. Converting forests from deciduous to coniferous species can lower peakflows across a range of return periods.

This study aims to investigate if these hypotheses can apply to the experimentally unique dataset analyzed in this study, and infer how physical changes in various hydrological processes can manifest to changes in peakflows in a rain-dominated environment.

2. Methods

2.1. Study site

This study evaluated the effects of forest treatment on peakflows in the rain environment in two sets of paired watersheds at the Coweeta Hydrologic Laboratory, a United States Department of Agriculture (USDA) Forest Service experimental forest situated in North Carolina, southeastern United States of America. Coweeta was established in 1934 and is one of the oldest experimental forests with a continuous record of ongoing and completed experiments and treatments performed in the basin (Elliott and Vose, 2011). The availability of extensive records provides a unique opportunity to examine the effects of forest treatment on the peakflows at Coweeta using observed flows. This study focused on treatment watersheds WS1 and WS17 and their paired control watersheds WS2 and WS18, respectively, as they were the most similar in terms of physiography (besides aspect) and final treatments (Fig. 1).

2.2. Climate

The climate at Coweeta is classified as a marine, humid temperate to humid subtropical (Köppen classification: Cfb to Cfa) (Swift et al., 1988). Coweeta experiences more than 130 storm events throughout the year producing approximately 1800 mm yr^{-1} of precipitation on average at 685 m elevation and 32 % more at 1385 m elevation (Laseter et al., 2012). Precipitation and storm events are uniformly distributed throughout the year with slightly higher amounts (10–14 %) of precipitation in the winter, and almost all of the precipitation comes in the form of rain as there is very little to no snow even at high elevations (Nippgen et al., 2016). High precipitation brought by frequent storm events and high evaporative energy promote high evapotranspiration rates ranging between 352 and 1030 mm yr^{-1} on average in reference watersheds depending on elevation (17 to 56 % of precipitation) (Caldwell et al., 2016) while sustaining perennial streams even in relatively dry years (Swift et al., 1988). In general, there are more high intensity convective storms in the growing season whereas there are more low intensity stratiform storms in the dormant season (Gaffin and Hotz, 2000; Patric, 1978). Coweeta’s long-term precipitation regime has become more variable over time, resulting in more frequent wetter and drier years (Ford et al., 2011b), fewer small storms and increasing number of days between storms (Elliott et al., 2015), and changing seasonal daily rainfall distribution (Burt et al., 2017).

2.3. Physical and soil characteristics

Coweeta is a bowl-shaped, 1626 ha basin. Watershed slopes range from 30 % to over 100 % and elevation ranges from 675 m to 1592 m (Elliott and Vose, 2011; Nippgen et al., 2016). Forest soils belong to two general soil orders: young Inceptisols and weathered Ultisoils (Elliott and Vose, 2011). The soil profile consists of deep, friable, and uncompact sandy loams (Nippgen et al., 2016). The average depth to the regolith is approximately seven meters (Swank and Douglass, 1975). Undisturbed forest soils have infiltration rates that exceed 50 in. per hour (Hewlett and Helvey, 1970) due to thick, intact forest floor and network of large macropores. These soil characteristics result in very little to no overland flow during precipitation events and also provide a large soil water storage capacity (Amatya et al., 2016). The deep soil mantle is underlain by impermeable quartz diorite gneiss, folded peltic schist, and quartzose metasandstone bedrock (Serengil et al., 2011). It is commonly assumed that water percolation below the bedrock is very small due to the impermeable granitic bedrock (Douglass and Swank, 1972).

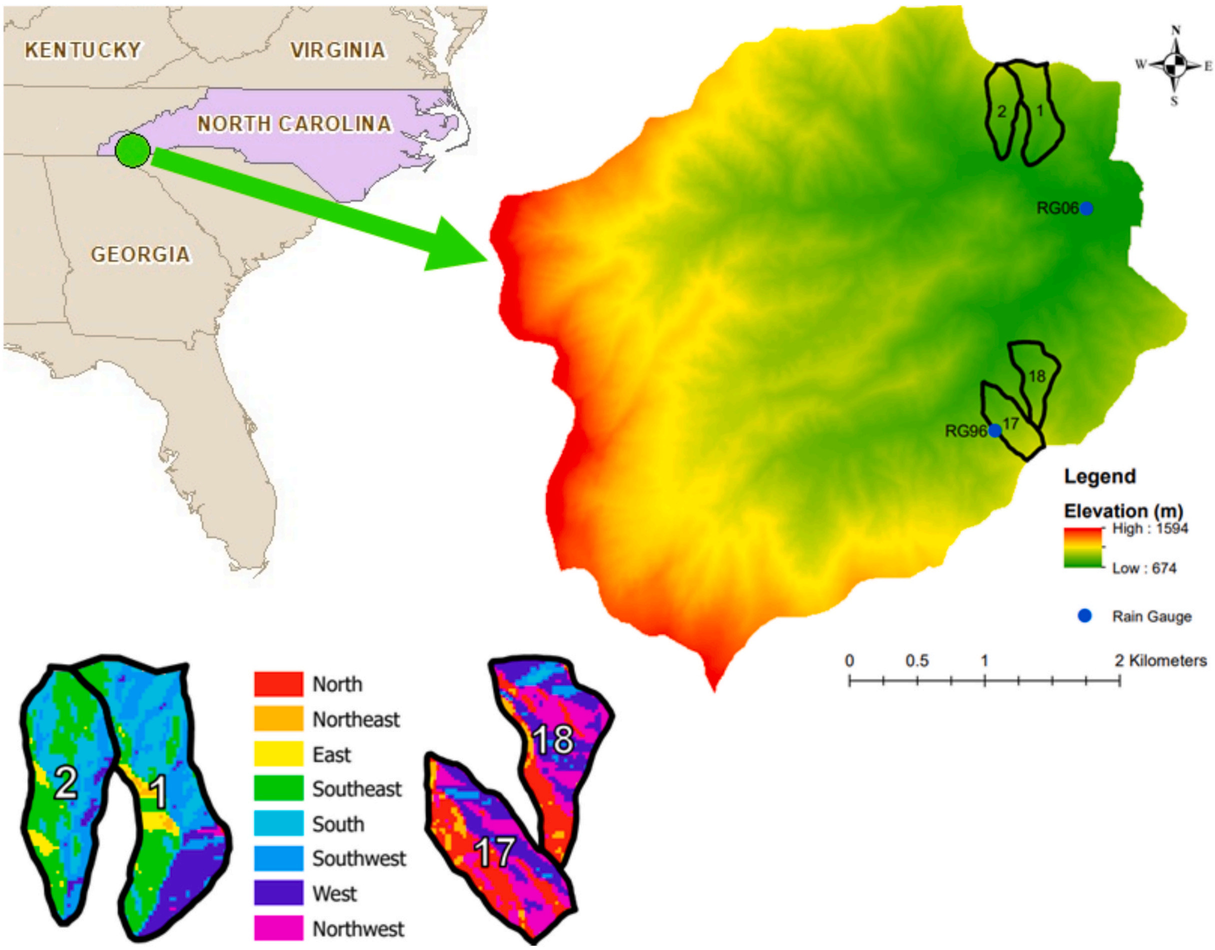

Fig. 1. Top left: The general area of the US and Coweeta (green dot). Top right: The Coweeta basin and sub-basins used in this study are outlined and numbered along with the associated rain gauges. Bottom left: Detailed aspect map of the two watershed pairs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.4. Vegetation and treatment

Coweeta has complex phenological patterns due to stand composition varying along environmental gradients and different growing season lengths in different parts of the basin depending on elevation (Elliott and Vose, 2011). The basin has experienced multiple disturbances caused by human activity and other disturbances which have affected historical vegetation patterns. At the time of this study, unmanaged watersheds were mixed deciduous forests that consist of mature oaks (*Quercus* spp.), hickory (*Carya* spp.), and maple (*Acer* spp.) along with yellow birch (*Betula lutea*), basswood (*Tilia heterophylla*), tulip poplar (*Liriodendron tulipifera*), with an increasing portion of the forest made up of fire-intolerant mesophytic species (Caldwell et al., 2016; Elliott and Vose, 2011). In the two control watersheds (WS02 and WS18), the average basal area was 25.6 m^2 per hectare with approximately 3044.3 stems per hectare and chestnut oak (*Quercus prinus*) accounted for approximately 21.3 % of the basal area (Serengil et al., 2011).

The Coweeta basin has been divided into smaller watersheds in which various forest treatments have been carried out with control watersheds used for comparison. The control and treatment watersheds pairs used in this study are WS17 (treatment)/WS18 (control) (northern aspects) and WS1 (treatment)/WS2 (control) (southern aspects) (Table 1). These treated watersheds have experienced multiple experimental treatments since stream flow measurements began (Table 1). After Eastern White Pine (*Pinus strobus*) was planted, leaf area index increased and levelled off approximately 12 years after planting (Swank et al., 1988). The treatment/control watershed pairs share similar physical characteristics and climatic settings which reduces potential confounding factors that could obscure the interpretations of the results (Table 1). In 2001, preventive logging and basal area losses occurred within WS1 and WS17 due to a southern pine beetle (*Dendroctonus frontalis* Zimmerman) infestation (Ford et al., 2011a; Nowak et al., 2008).

2.5. Flow measurements

All watersheds were instrumented with permanent v-notch weir structures to measure stage above the weir notch on 5-minute intervals over the period of record. The measured stage was used to calculate streamflow using rating equations dependent on the geometry of each weir (Reinhart and Pierce, 1964). The flow time series began in 1935 for WS1, 1936 for WS2, and 1937 for WS17 and 18. The pre-treatment calibration period between treatment and control watersheds was therefore 1936–1941 for WS1/WS2, and 1937–1939 for WS17/WS18. Event peakflow magnitudes were identified and extracted from the 5-minute flow time series using methods of Hibbert and Cunningham (1966). The calibration dataset included 22 events for WS1/WS2 with an R^2 of 0.95 and 15 events for WS17/WS18 with an R^2 of 0.92.

2.6. Data analyses

Extreme events can be analyzed via either annual maxima series (AMS) or peak-over-threshold (POT) time series. We analyzed peakflow values using POT extracted from the data for each watershed. We used

Table 1
Summary table of physical characteristics and treatment history for watersheds WS1, WS2, WS17, and WS18. and

Watershed #	Area (ha)	Maximum elevation (m)	Aspect	Elevation at Weir (m)	Treatment description
1	16	988	S	705	Entire watershed treated with prescribed fire in Apr 1942. Riparian shrubs and trees (25 % of watershed area) were treated with herbicide in 1954, and again in 1955–1957 growing seasons. Full clearcut (hand-felled) and entire watershed burned in 1956–1957 without removing products to minimize soil disturbance. Watershed was subsequently converted to an eastern white pine plantation (*Pinus strobus*) in 1957 (hand-planted). In the following years, hardwood species competition with *P. strobus* was suppressed with cutting and herbicide as necessary.
2	12	1004	SSE	709	Control (no treatment)
17	13	1021	NW	760	Full woody vegetation removal (hand-felled) in Jan–Mar 1940. Vegetation regrowth were cut annually afterwards until 1955 with no products removed from the watershed to minimize soil disturbance. Watershed was subsequently converted to an eastern white pine plantation (*Pinus strobus*) with a 2 × 2 m spacing in 1956 (hand-planted). In the following years, hardwood species competition with *P. strobus* was suppressed with cutting and herbicide as necessary. Afterwards, the watershed was left unmanaged until 2001 when ~2 ha of the watershed was cut to impede the spread of southern pine beetle (*Dendroctonus frontalis* Z.).
18	13	993	NW	726	Control (no treatment)

Adapted from Ford et al. (2011a); Ford et al. (2011b)Hewlett and Hibbert (1961).

the lowest annual maximum peakflow value as the threshold for each watershed independently as used in previous studies (Bezak et al., 2014; Fischer and Schumann, 2016; Langbein, 1949). The next step involved ensuring that each peakflow event was an independent event; independence was assumed to occur when there was at least five days between peakflow events based on stormflow duration (Scaife and Band, 2017). We used data up to year 2000 to minimize any confounding factors that the southern pine beetle infestation and the associated forest operations may introduce; the resulting record was deemed sufficient as it contained 40+ years of observed data. We applied the frequency pairing method outlined in Alila et al. (2009) and Green and Alila (2012), and this involved three major steps: estimating the expected discharge, peakflow frequency analyses, and adjusting for nonstationarity within the peakflow time series. We developed linear regressions between the treatment and control watersheds (e.g., Hewlett and Helvey, 1970; Hoover, 1944) only for the calibration period prior to the treatment, and then used this model to predict the peakflow that was expected to have occurred if no treatment was applied:

$$\widehat{Y}_i = b_1 X_i + b_0 \quad (1)$$

where X_i is the peakflow in the control watershed and $\widehat{Y}_i$ is the expected peakflow in the treatment watershed.

We estimated the exceedance probability of the j^{th} largest peakflow event (Y_j) using the approximately quantile-unbiased Cunnane plotting position equation (Stedinger et al., 1993):

$$1 - F_y[Y_j] = \frac{j - 0.40}{n + 0.20} \quad (2)$$

where F_y represents the CDF for n peakflows events over the threshold. As we used POT analysis, we obtained the return period by converting each peakflow to its associated annual exceedance probability and return period (Stedinger et al., 1993). We developed the 95 % confidence intervals for expected peakflows to account for the loss of variance and predictive uncertainty of the calibration regression in equation (1) through 10,000 Monte Carlo simulations assuming that the overall uncertainties are normally distributed with the methods described in Alila et al. (2009).

We used four statistical tests to detect possible change points or trends within the peakflow time series: Wilcoxon-Mann-Whitney, Pettitt, Spearman rank correlation, and Mann-Kendall. We selected these tests based on previous studies that also investigated forest peakflows (Alila et al., 2009; Villarini et al., 2009) and applied them to the raw observed peakflows. We used multiple tests because inferences from one test may not be supported with other tests. Detailed descriptions and discussions about these tests can be found in Villarini et al. (2009).

We adjusted the observed peakflow time series for non-stationarity which might be induced by the vegetation regrowth to meet the stationarity assumption for conventional frequency analyses. We detrended the peakflow time series with linear modelling as a function of the time since forest treatment ended as a surrogate for non-stationary trends. We added the time since treatment ended ($t_{treatment}$) as a covariate into a linear regression model:

$$\widehat{Y_a} = b_2 Y_i + b_3 * t_{treatment} + b_4 \quad (3)$$

where $\widehat{Y_a}$ is the observed peakflow in the treatment watershed that has been adjusted for vegetation regrowth and hydrological recovery and Y_i is the observed peakflow prior to adjustment. This detrending procedure has been applied in FP- (Alila et al., 2009; Green and Alila, 2012) and CP-based (Thomas and Megahan, 1998) studies and is also well-established in hydrology literature (Khaliq et al., 2009; Koutsoyiannis, 2006). The 'time since treatment ended' covariate was found to be statistically significant ($p < 0.01$) for the post-white pine treatment period. The regrowth suppression period was essentially stationary as there should be no vegetation recovery during this time period to affect peakflows. This period represents the hydrological effects immediately after tree removal, and the continuous suppression provided an extended record length. This is a unique dataset as this type of treatment is rarely done experimentally to provide empirical data and is mostly done with modelling simulations due to the effort and resources required to carry out regrowth suppression for an extended period of time.

We performed additional analyses on the study watershed pairs to examine the effects of forest treatments on peakflows at different time scales. We performed analyses on a seasonal scale based on the growing (April 15-October 14) and dormant (October 15-April 14) seasons established at Coweeta (Hibbert and Cunningham, 1966; Nippgen et al., 2016). We examined the effects of record length on the peakflow magnitude-frequency relation using FP analyses of varying record lengths by partitioning the time series in 10-year increments, each beginning after the final treatment: 10, 20, 30, 40, and ~44 years.

We investigated the influences of antecedent soil moisture and storm size on peakflows through both deterministic and stochastic approaches. We used Antecedent Precipitation Index (API) as a surrogate for AMC. Several API intervals were tested such as 5, 10, 30, 90, 180, and 365 days. We used a 30-day duration API based on literature of nearby areas (e.g., Epps et al., 2013) and lagged runoff response to precipitation at Coweeta (e.g., Nippgen et al., 2016). API was calculated as the running sum of precipitation preceding the event as was similarly done in a previous study within the same area (Singh et al., 2021). We separated storm events based on a minimum of six hours of no precipitation between consecutive storm events (Chouaib et al., 2018). We calculated API and storm depths for each annual maximum peakflow event for the entire record length. We separated and ranked the events into 'below median' and 'above median' categories. We paired precipitation data using rain gauge RG96 for WS18 and rain gauge RG06 for WS2 (Fig. 1). We used control watershed peakflows to avoid confounding factors that may arise from forest treatments.

Understanding and predicting the effects of forest treatment on peakflows require evaluating changes to the form of the peakflow frequency distributions in terms of the location, scale, and shape parameters of the CDF and PDF. These parameters were empirically obtained to avoid additional uncertainties associated with fitting a distribution. The increasing uncertainties associated with higher order moments make it hard to make definitive inferences and this is why there is not a heavy focus on numerical changes to skewness but instead an examination of general patterns to the shape of the CDF that can be inferred from the observed peakflows. This was achieved by examining repeated patterns of such tail behaviors in a *meta*-analysis context across the two pairs of watersheds during different seasons, treatments, and record lengths. Furthermore, inferences on skew were based on the physical understanding of what controls the skew more so than blindly relying on a quantitative estimate of skew within short record lengths.

3. Results

3.1. Change point and trend test analyses and expected peakflow

Out of the four change point and trend tests used in this study, three tests (Pettitt, Spearman rank correlation, and Mann-Kendall) found no significant change points or trends (p-values > 0.12) for peakflows in either of the treated watersheds post-treatment. The only test that detected a potentially significant change point was the Wilcoxon-Mann-Whitney Test for WS17 (1997, $p = 0.02$). Further analyses were performed to reaffirm the stationarity of the peakflow time series in addition to the previously mentioned statistical tests. The de-trending procedure resulted in only minor adjustments (~10 % change) to the peakflows during the first 15 years post-white pine planting. Different sets of record lengths, 0–15 and 16–44 years post-white pine FFC revealed very similar patterns to the 0–44 years post-white pine FFC (not shown for conciseness). Collectively, these outcomes suggest that there were no major change points or trends throughout the peakflow time series.

3.2. CDF analysis during WS17 regrowth suppression period

Deciduous tree removal and regrowth suppression resulted in a 33.7 % increase in the peakflow mean and a 162.1 % increase in the variance for WS17 (Fig. 2). The inset PDF shows that the upper tail was extended, which implies that there were more frequent and larger extreme events as a result of treatment. The forest treatment increased the magnitude of larger peakflow events and the effect increased with event size as seen by the increasing vertical difference between the expected and observed peakflow CDFs (Fig. 2). For example, the 26-year peakflow event prior to treatment (~$4.9 * 10^{-3}$ m^3 sec^{-1} ha^{-1}) was predicted to increase by 50 % to ~$9.8 * 10^{-3}$ (m^3 sec^{-1} ha^{-1}) and would become a 3-year event after treatment.

3.3. CDF analysis for WS1 and WS17 over complete record of the post-white pine period

Forest treatment resulted in changes to the mean and variance of the peakflow frequency distribution on an annual basis based on 43 and 44 years of observed peakflows for WS1 and WS17, respectively. Overall, WS17 experienced larger increases to the peakflow mean and variance after treatment than WS1. WS17 experienced significant changes after treatment with increases of 47.4 % and 67.8 % in the peakflow mean and variance, respectively. Further, the magnitude of all peakflow events increased after treatment and the effect increased with event size as seen by the increasing vertical difference between the expected and observed peakflow CDFs (Fig. 3A). For example, peakflows return periods in WS17 changed from 16- to 3-year, 26- to 6-year, and 70- to 9-year events, and that the 16-, 26-, and 70-year events increased by 2.5–3.4 (m^3 sec^{-1} ha^{-1}, 10^{-3}) (38–63 % increases) (Fig. 3). This shows that extreme events making up the upper tails of the CDF are not only increasing in magnitude but are also becoming ~4 to 7 times more frequent in the north facing watershed. On the other hand, WS1 experienced almost no change in peakflow mean and a decrease of 30.9 % in variance after treatment. These changes manifested as relatively small shifts in the CDF and were not statistically significant from expected peakflows. WS1 peakflows were not significantly affected by forest treatment across the entire range of peakflow magnitudes and return periods. Detrending had very little effect on peakflows in either watershed which is to be expected based on the inferences in section 3.1.

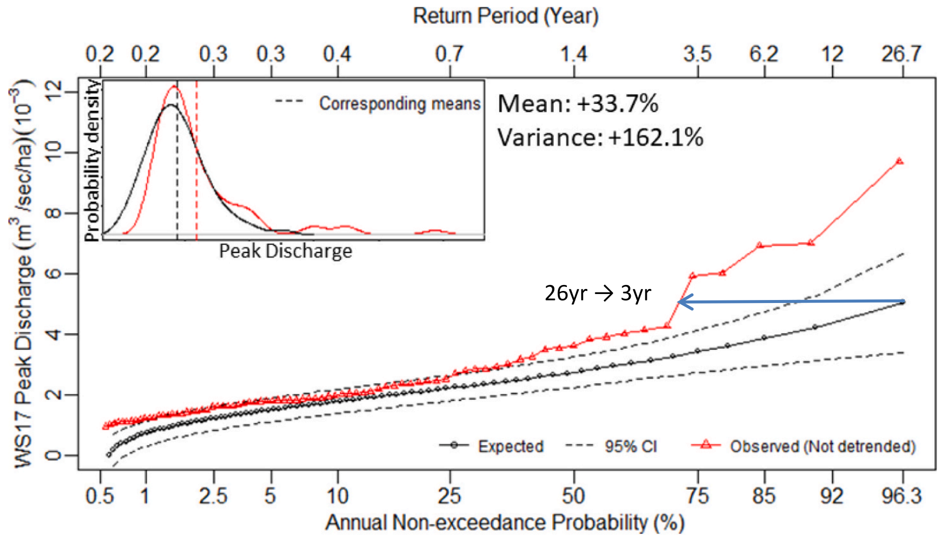

Fig. 2. The annual Cumulative Distribution Function (CDF) of the regrowth suppression period peakflows for the north-facing watershed (WS17). The Probability Distribution Function (PDF) is shown as the inset graph with the associated changes in mean and variability.

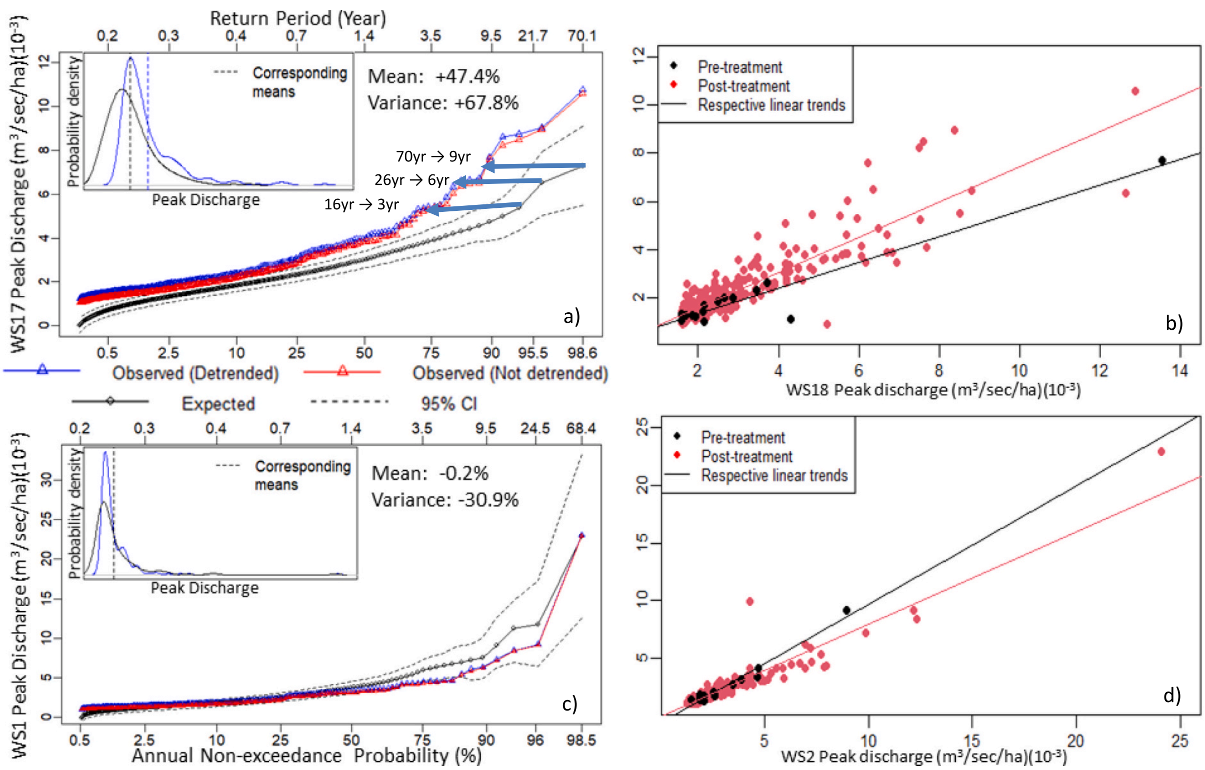

Fig. 3. The Cumulative Distribution Function (CDF) of annual post-white pine peakflows for the north-facing watershed WS17 (A) and the south-facing watershed WS01 (C). The Probability Distribution Function (PDF) is shown as the inset graph with the associated changes in mean and variability around the mean of the peakflow distribution. Regression peakflow plots for WS17/WS18 (B) and WS1/WS2 (D) are included. This consists of 43 and 44 years of data for WS1 and WS17, respectively.

3.4. CDF analysis for WS1 and WS17 over complete record of the post-white pine period by season

The south-facing watershed WS1 exhibited peakflow frequency curves with similar seasonal shape as the north-facing watershed WS17. The growing season CDF at non-exceedance probabilities greater than 50 % is characterized by a steep accentuated shape while the dormant season is characterized by a flat shape in both watersheds (Fig. 4). The post-treatment mean and variance of WS17 growing season peakflows increased by 23.9 % and 52.8 % compared to pre-treatment, respectively, whereas the dormant season peakflow mean and variance increased by 54.6 % and 128.8 %, respectively. As a result, the 73-year dormant season peakflow return period decreased to 4-year and the 28-year decreased to 3-year, and magnitude increased by 4.1 and 4.4 (m^3 sec^{-1} ha^{-1}, 10^{-3}) (93 % and 105 % increases) for the 73- and 28-year events, respectively. Growing season peakflows changed from 70- to 19-year and from 26- to 17-year events and magnitude increased by 3.4 and 2.3 (m^3 sec^{-1} ha^{-1}, 10^{-3}) (46 % and 35 % increases) for the 70- and

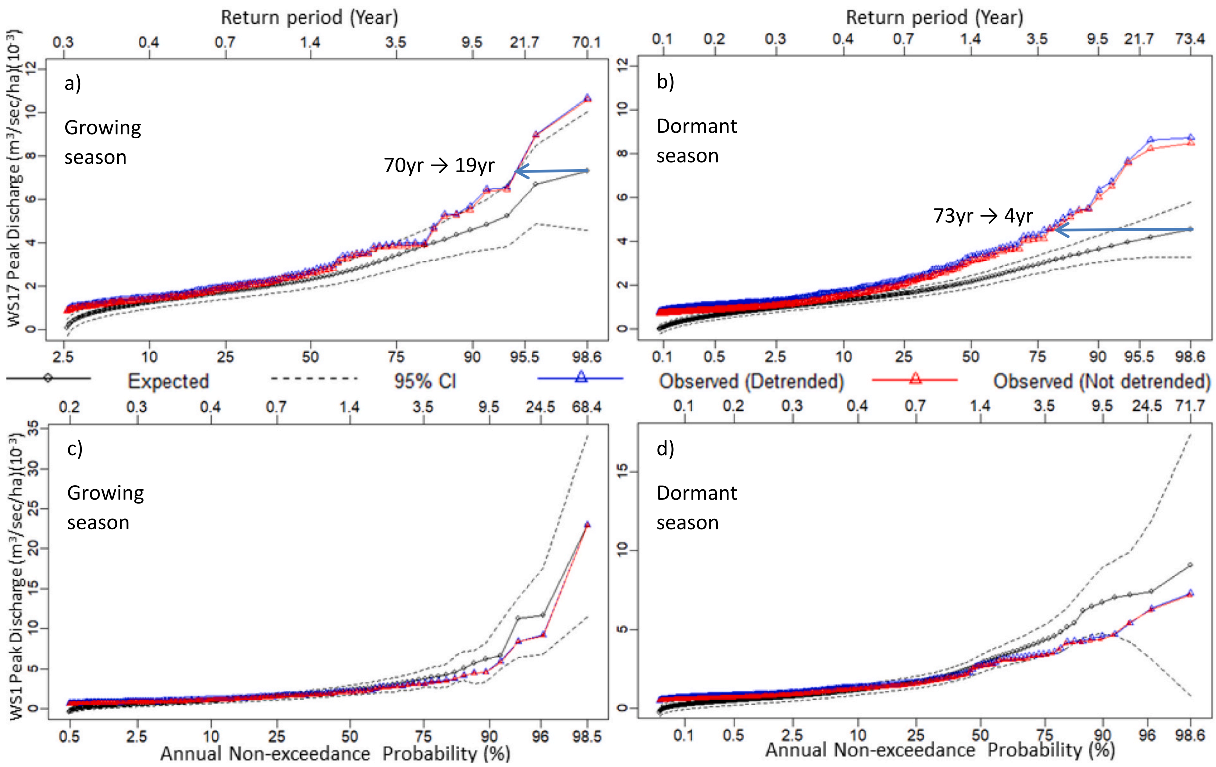

Fig. 4. The Cumulative Distribution Function (CDF) during different seasons for the north- and south-facing watersheds post-white pine peakflows. This consists of 43 and 44 years of data for WS1 (C, D) and WS17 (A, B), respectively.

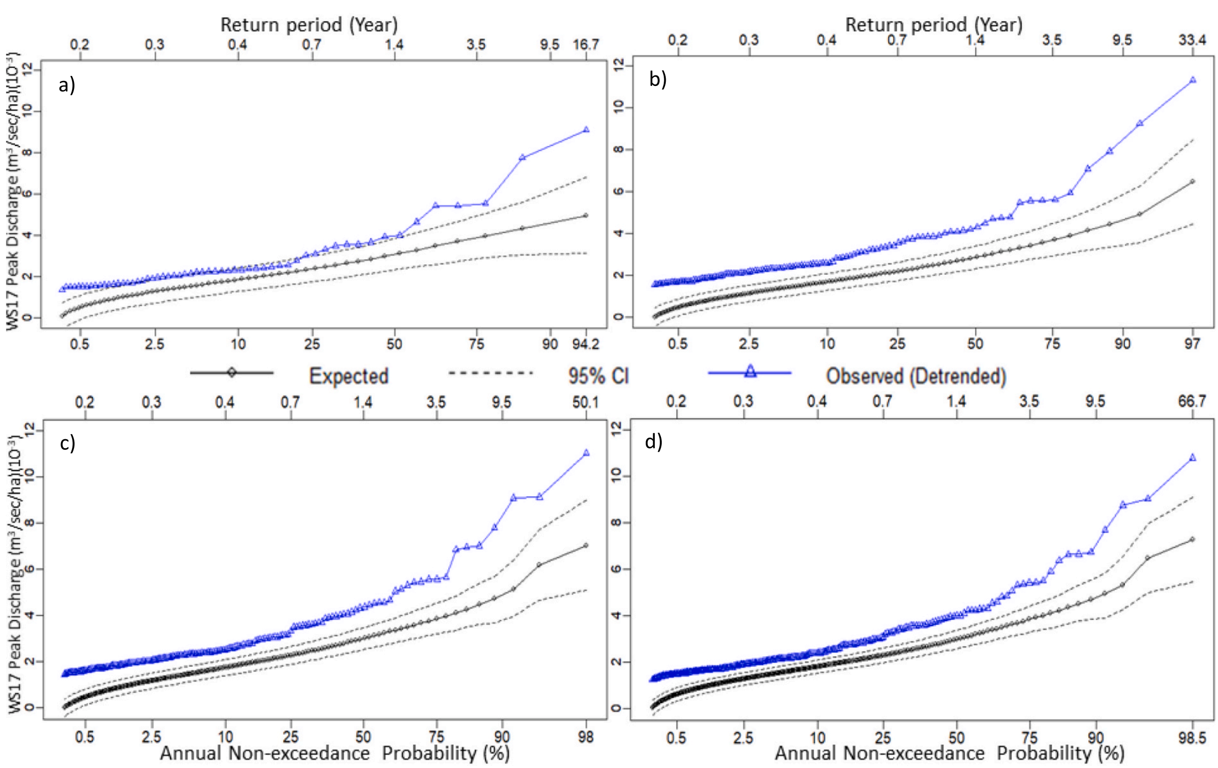

Fig. 5. The Cumulative Distribution Function (CDF) of annual (both growing and dormant seasons) post-treatment peakflows for the north-facing watershed (WS17) with varying data record lengths. The record lengths for each graph are A) 10, B) 20, C) 30, and D) 40 years of data. The full record length can be seen in the annual CDF found in Fig. 3.

26-year events, respectively (Fig. 4). For the WS1, mean and variance of peakflows in the growing season increased by 8.6 % and decreased by 23.8 %, respectively, whereas in the dormant season these increased by 13.2 % and decreased by 49.8 %, respectively. However, like annual peakflows, the WS1 seasonal peakflows were not significantly affected by forest treatment across the entire range of peakflow magnitudes and return periods. The largest event in WS1 (68-year return period) appears to have the observed and expected peakflows overlapping each other (Fig. 3C and 4C). However, inferences on the largest events in any FFC need to be cautiously done as indicated by the widening confidence bands associated with these events.

3.5. Effect of record length on CDF analyses

The entire usable record length for WS17 was partitioned into periods of different lengths to examine the effects of record length on the relation between forest treatment and the peakflow frequency distribution. The observed peakflow CDF continued to diverge from the expected peakflow CDF and this trend continued with increasing record length and hence return periods (Fig. 5). These results suggest that the no-effect threshold beyond which forest treatments has no effect on peakflows does not exist, at least not within the observed record length (44 years). Additionally, the observed peakflow CDF is outside the 95 % confidence interval at the upper tails suggesting that the difference is statistically significant. The continuing divergence between the observed and expected CDFs with increasing record length suggests that higher return period events are affected more than smaller events as the larger and rarer events experience larger changes in terms of magnitude and frequency than smaller events. A similar partition exercise was performed for WS1 and the observed peakflow CDFs for varying record lengths continued to exhibit similar patterns to the CDFs over the complete record of the post-white pine period of WS1 (not shown for conciseness).

3.6. Comparison of stochastic and deterministic analyses of the influence of AMC and storm depth on peakflows

We performed stochastic and deterministic analyses on the role of AMC and storm depth controlling peakflows in north facing control watershed WS18. Linear regressions fitted between peak discharge and both API and storm depth revealed a significant relationship between peak discharge and API ($p = 0.00726$) but not between peak discharge and storm depth ($p > 0.4$) (Fig. 6A & B). The stochastic analyses showed that there is a distinction between high and low API compared to storm depth (Fig. 6C & D). Also, for the few largest peakflow events at the upper tail of the curve, there was a switch from being above to below median storm controlled whereas this switch did not occur for API. Differences between below and above median API CDFs suggest that increasing AMC leads to increasing the mean and variability of peakflows due to the upward shift and divergence of the CDFs, respectively. The two CDFs also show larger divergence towards the upper tail, which suggests that AMC exerts more influence on the less frequent and higher magnitude events. Although other API intervals were considered, only the 30-day API is shown since it exhibited similar trends to longer intervals. Only data analyses from WS18 were presented for conciseness, as WS2 revealed similar patterns. These plots were based on data from the control watershed, as opposed to the treated watershed, in order to exclude possible confounding factors introduced by the treatments.

3.7. Comparison of undisturbed watershed CDFs on contrasting aspects

The dimensionless FFCs for the control watersheds (WS18/WS2) on contrasting aspects at low (*i.e.*, more frequent) return periods are very similar, but they start diverging at roughly the 3-year return period and generally continue to do so with larger divergences for higher return periods. Differences in the slope and shape of the control watershed FFCs are seen with a steeper accentuated south-facing watershed FFC contrasting with the flatter and milder-shaped north-facing watershed FFC when the two FFC diverge (Fig. 7).

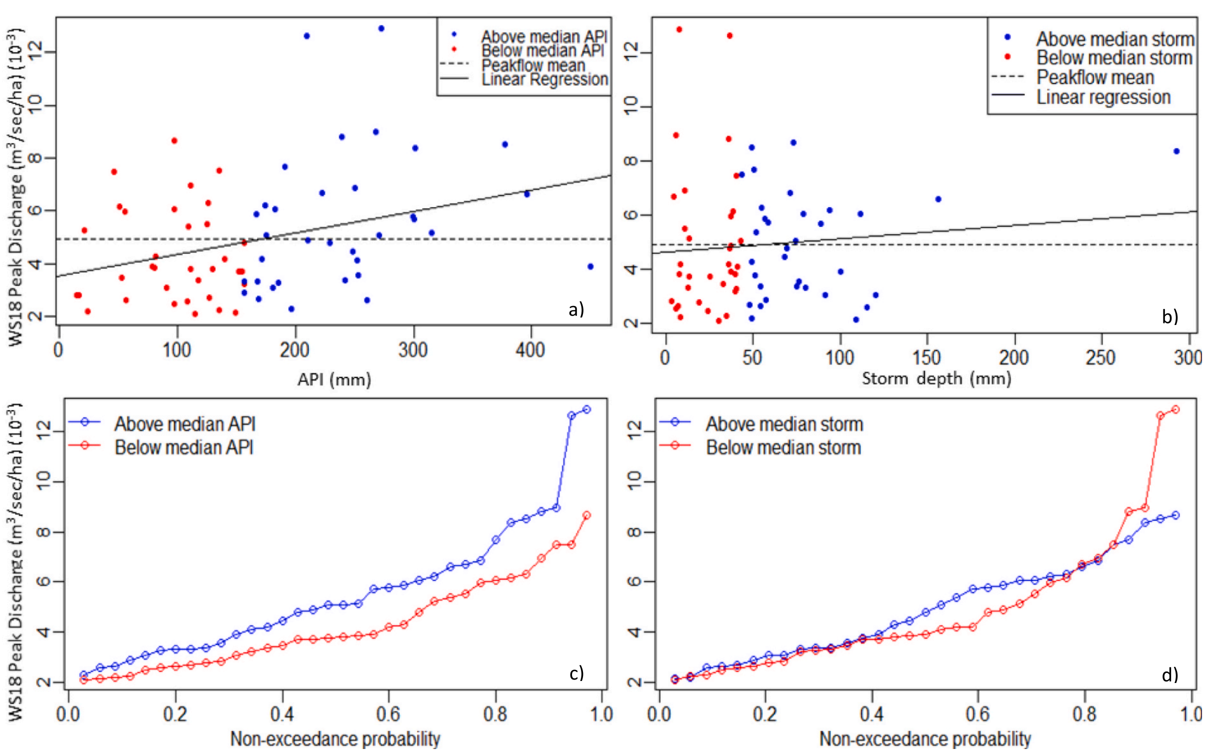

Fig. 6. Comparison of deterministic (A, B) and stochastic (C, D) approaches in analyzing the influence of antecedent precipitation index (API) (A, C) and storm depth (B, D) on peakflows for control watershed WS18.

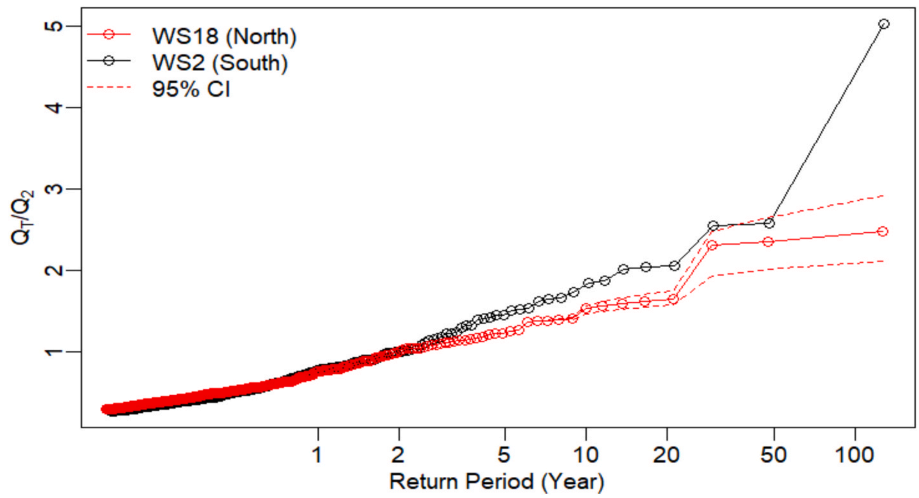

Fig. 7. The dimensionless flood frequency curve (FFC) for the north-facing (WS18) and south-facing (WS2) control watersheds.

4. Discussion

This study used stochastically-based FP analyses to examine how peakflows changed as a result of forest treatment using long-term data at Coweeta. The high quality and unique treatments that were meticulously carried out within Coweeta provided an opportunity to better investigate the controls governing peakflows within the proper causal inference framework. The forest operations done manually by hand (Table 1), which is rarely done, reduced potential confounding factors to also affect peakflows that would normally arise as part of normal operations and allows us to better isolate the actual causes of hydrological changes. The mean and variability of peakflows increased due to forest treatment during the 14-year regrowth suppression period after clearcut in the north-facing watershed. Contrasting changes in peakflows between the watersheds of opposing north and south-facing aspects and different treatment histories were observed after forests were converted from deciduous to eastern white pine. Peakflows increased in the north-facing watershed throughout the recorded periods whereas peakflows decreased even immediately after treatment in the south-facing watershed. Peakflow response during the dormant and growing season also differed for the two watersheds. The proposed effects of past forest treatment, aspect, seasonality, and species conversion on peakflows could help explain these outcomes. These factors can affect and alter AMC which may heavily influence peakflows (Fig. 6C), along with other hydrological processes. Moreover, we found that it is possible for the effects of forest treatment to continue affecting peakflows with increasing return periods unchecked, *i.e.,* with no apparent threshold beyond which the effect ceases to occur, at least within the available record length in this study.

4.1. Inferring how forest treatment can influence hydro-meteorological factors that affect peakflows

The greater separation between below and above median API compared with storm depth corroborates the hypothesis that peakflow events are more controlled by AMC than storm size (Fig. 6C & D). This has been alluded to in the past (Gioia et al., 2012; Ledingham et al., 2019; Merz and Blöschl, 2009a, 2009b; Peskett et al., 2021; Sturdevant-Rees et al., 2001) and that storm size is neither the only nor the most important factor affecting peakflows as the return period of storms and peakflows can greatly differ (Viglione and Blöschl, 2009). Differences between below and above median API CDFs can be used as qualitative analogues for the effects of treatment in the watershed as forest treatment can lead to higher AMC. Past studies that investigated the role of API have rarely considered time periods longer than a few weeks or months prior to a hydrological event (Nippgen et al., 2016). However, the findings by Nippgen et al. (2016) suggest that antecedent conditions over different lengths of time need to be considered, which may mean that more than a year of precipitation history may have an effect on an event. Moreover, vegetation can use water deeper in the soil that can be a year old (e.g., McDonnell et al., 2018; Sprenger et al., 2019) or even up to several decades old in some cases (e.g., Zhang et al., 2017). This can have implications on soil water storage capacity as deforestation can significantly decrease water storage capacity in root-zone layer (Nijzink et al., 2016). The deep soils at Coweeta can influence various hydrological processes mentioned throughout the paper and not limited to only AMC. Investigating the effect of soil depth can be an avenue of future research. As such, short-term API measures, even the 30-day API that was used, may not fully capture the true effects of API/AMC on peakflows. Despite this potential limitation, the exploratory analyses revealed stark differences between the CP and FP frameworks. Future research can investigate and expand on this exploratory example in more depth.

CP-based inferences cannot be used as they are not similar or equivalent to FP-based inferences, even in instances where CP-based results seem to suggest similarity to FP-based results (e.g., Fig. 3). This is because only FP accounts for the random occurrence over time of all covariates affecting peakflows and, as a consequence, the fact that every peakflow occurs with a certain frequency (*i.e.,* classes of events and not a single event) (Pham and Alila, 2024). FP may also help in exploratory analyses more so than with CP (e.g., Fig. 6A-D). In the wider hydrology, however, it has long been recognized that "a causal relationship is not necessarily a deterministic one and a deterministic relationship is not necessarily causal" (Klemeš, 1978, p. 291).

Changes in peakflow skewness and/or variance were observed on the north-facing watershed where the observed post-treatment CDF became more accentuated compared to the expected pre-treatment CDF in the regrowth suppression, annual and seasonal post-white pine, and the partitioned record length analyses (Figs. 2–5). CDFs that are inherently milder in shape (less steep or relatively flatter) with lower skewness are more sensitive to forest treatment than CDFs that are accentuated with higher skewness, as slight shifts in mild-shaped CDFs result in much larger changes to peakflow frequencies than changes in accentuated CDFs (Pham and Alila, 2024). Moreover, as skewness and variance are mathematically related, factors that affect variance should also affect skewness albeit to different degrees. Therefore, CDFs that are inherently more sensitive to disturbances, due to lower variability and hence milder slopes, would also be similarly induced by lower skewness and milder shape (Allen and Ingram, 2002; Berris and Harr, 1987; Green and Alila, 2012; Pham and Alila, 2024; Taleb, 2012; Taleb et al., 2020; Taleb and Douady, 2013). As a consequence of the aforementioned rationales, peakflow sensitivity differed between seasons where the observed dormant and growing season CDFs portrayed contrasting shape (mild vs accentuate shape). For example, the 73-year dormant season event became a 4-year event (~ 18x more frequent) while the growing season 70-year event became a 19-year event (~ 3x more frequent) (Fig. 4).

As the peakflow sensitivities induced by skewness and variance more profoundly affects higher than lower return periods, the larger uncertainties associated with higher return periods may be of concern. Although the observed CDFs are statistically significantly different from the expected CDFs for the larger events, such as in Fig. 3A or Fig. 4B, we can further reaffirm the effects of forest treatment on peakflows by using Fig. 3A as an example. Assume that the expected peakflow FFC is increased up to the upper 95 % confidence band, the change in return period for the largest event would be from a 70- to 27-year event. Conversely, assuming instead that the observed peakflow FFC decreased down to the upper 95 % confidence band, the change in return period for the largest event would be from a 70- to 20-year event. In either case, the changes between the observed and expected peakflow FFCs are physically meaningful and practically significant.

4.2. *Does a threshold peakflow event size beyond which forest treatment ceases to have an effect exist?*

This study's investigation of the effects of the record length on the CDFs suggests that there is no clear upper limit event size at which point the forest treatments will have "no-effect" on peakflows as the divergence of the two CDFs continues to shift towards larger return periods with increasing record length (Fig. 5). Even though a threshold may seemingly exist, such as the largest event in WS1 (Fig. 3C and 4C), any inferences based only on the very few of the largest events should be avoided or have other supporting evidence due to the large uncertainties associated with these events. As such, our inferences focus on the overall patterns of the FFCs and can be corroborated with trends that are seen with other peakflow events while not relying solely on the very few of the largest events. However, there could be cases where the FFCs can converge and future research can investigate these potential cases. The lack of a "no-effect" threshold is consistent with other studies that have used FP, which involved *meta*-analyses of observed and model simulated peakflows (Alila et al., 2009; Birkinshaw et al., 2011; Green and Alila, 2012; Kuraś et al., 2011; Schnorbus and Alila, 2013). Despite extensive observed record lengths that are available at Coweeta, sample size can be an issue when analyzing extreme events. However, model simulations of 1000 years of peakflows also failed to reveal any indication of a "no-effect" threshold as the logged and forested CDF remain separated with no sign of convergence (Birkinshaw et al., 2011 in their Fig. 8). This is because treated and forested CDFs will remain separated and continue extending parallel to each other at higher return periods.

At higher return period peakflow events, the concept of gradient of extreme values (GRADEX) dictates the behavior of the extremely rare events where the peakflow CDF upper tail properties can be derived from the rainfall frequency curve and result in the upper tails of the pre- and post-treatment CDFs to have the same slope as the rainfall frequency distribution curve (Carré et al., 2016; Cœur and Lang, 2008; De-Michele and Salvadori, 2002; Gaume, 2006; Guillot, 1993; Guillot and Duband, 1967; Lawrence et al., 2014; McCuen and Smith, 2008; Mosquera-Machado and Ahmad, 2007; Naghettini et al., 1996, Naghettini et al., 2012). The parallel slopes of the two CDFs seen in Birkinshaw et al (2011, Fig. 8) are consistent with the GRADEX concept. Although previously mentioned "no-effect" threshold examples focused on the effects of forests on peakflows, the GRADEX concept applies regardless of land use scenarios within the watershed, with scenarios that have less available soil moisture storage potential becoming parallel to the rainfall curve sooner than scenarios with more moisture storage potential (Pham and Alila, 2024). This difference between the point at which the CDFs/FFCs run parallel to the rainfall curve creates a persistent gap between the two scenarios and implies that it is unlikely the two FFCs will converge even for higher return periods. More in-depth discussions on this can be found in Pham and Alila (2024). The GRADEX concept has been documented when rainfall skew becomes an increasing factor in determining peakflow skewness as the watershed becomes wetter (McCuen and Hromadka, 1988). The GRADEX concept is well-established in wider hydrology (e.g., Naghettini et al., 1996; Slimani and Lebel, 1987), but is seldomly used in forest hydrology. Although site-specific, GRADEX has been shown to provide good and reliable agreement with peakflow estimations made from reconstructed peakflow record lengths of almost 400 years with only 44–47 years observed records (Naulet et al., 2005).

4.3. *Effects of aspect on forest treatment – peakflow causal relationships*

The FP analyses from the north- and south-facing watershed pairs produced strikingly different outcomes. Some of these differences could be related to differences in the forest treatments between the two watersheds as described previously, but watershed aspect likely also played a role. Dimensionless FFC comparisons for the control watersheds (WS18/WS2) suggests the influence of aspect (Fig. 7) where differences in the FFC between the two contrasting aspects reveal inherent sensitivity in peakflows. The flatter slope of the north-facing watershed FFC suggests that peakflows in this watershed are inherently less variable and, as a consequence, more sensitive to changes in the FFC which extend for higher return periods. The differences in sensitivities between the two watersheds could suggest that north-facing watersheds may experience larger impacts to peakflows from forest treatment than south-facing watersheds. Focusing on the influence of aspect on peakflows automatically encompasses all other hydrological factors and processes (such as temperature, transpiration, evaporation, precipitation, vegetation growth, AMC, and so on) that are affected by aspect differences. Moreover, by focusing on wider-scale factors, such as aspect, it maintains the interactions among hydrological processes and how they may synergize (or antagonize) among each other to affect extremes such as peakflows (Pham and Alila, 2024; Runge et al., 2019). Pham and Alila (2024) discusses how investigating individual hydrological processes one-at-a-time in isolation may not reflect reality and Runge et al. (2019) discusses how the implications from multiple causal factors interacting among each other affect extremes.

Higher vegetation productivity on north-facing compared to south-facing (Coble et al., 2001; Måren et al., 2015; Yang et al., 2020) could help explain the difference in peakflow response between north- and south-facing watersheds as removing more productive vegetation has been shown to have a greater effect on peakflows (Figs. 2 & 3). Vegetation removal and regrowth suppression was maintained for four years on south-facing watershed (WS1) at Coweeta but it was found that water losses to the atmosphere were only marginally affected (Hewlett and Hibbert, 1961), suggesting that soil evaporation compensated for transpiration and canopy interception after treatment. Also, north-facing aspects have been shown to have higher increases in water yield due to forest treatment than south-facing aspects at Coweeta (Hibbert, 1967), and these increases persisted for longer on the north-facing watershed (WS17) compared with the south-facing watershed (WS1) (Swank et al., 1988, 1982; Swank and Miner, 1968). Differences in non-vegetative factors between aspect could also amplify differences in peakflow response after forest treatment such as differences in solar insolation. South-facing watersheds at Coweeta receive more insolation than north-facing watersheds throughout the year with south-facing watersheds receiving 79 % and 16 % more insolation in the dormant and growing season, respectively (Nippgen et al., 2016). Long-term data from control watersheds within Coweeta show that watersheds on contrasting aspects have different AMC levels year-round, with higher AMC on north-facing watersheds compared to south-facing ones (Bolstad, 2019) (Appendix A). Differences in soil water storage affects the nonlinearity of hydrologic responses which in turn affect the heavytailedness of the FFC and the likelihood of extreme floods (Wang et al., 2025). This can be further corroborated as it has been demonstrated that increasing baseflow always decreases flood variability, and this effect becomes even more significant as watershed size increases (Blöschl and Sivapalan, 1997). Collectively, the influence of contrasting aspects can have an effect on various hydrological processes which can in turn translate to having an effect on peakflows. Investigating the influence of contrasting aspects and its role on peakflows is another venue for future research.

4.4. Effects of season on forest treatment – peakflow causal relationships

Seasonal analysis of peakflows reveals consistently distinct patterns between growing and dormant seasons despite changes to the peakflow mean and variance that differ between north- and south-facing watershed aspects. Peakflows in the dormant season appear to be more sensitive to treatment than in the growing season for the north-facing watershed. This suggests that higher amounts of insolation in the growing season can help decrease changes in peakflows following forest treatment. The growing season CDF exhibits steeper and accentuated trends, whereas the dormant season was a flatter and mild curve. These patterns are consistent between the north and south aspects (Fig. 4). These seasonal patterns have been documented at Coweeta where the frequency curves for monthly flows showed similar seasonal differences in shape between growing and dormant season months (Elliott et al., 2017). This pattern has also been seen in other studies and regions as described in the introduction (e.g., Basso et al., 2016; Brantley et al., 2015; Wang et al., 2025). Differences in steepness and shape between the CDFs resulted in the dormant season experiencing larger changes in the return period and frequency of the peakflows than in the growing season with an increasing effect at higher return periods, and manifested as larger horizontal differences between the observed and expected peakflow CDFs (Fig. 4). Moreover, precipitation frequency curves from rain gauges within the basin (Fig. 1) showed stark differences between growing and dormant season precipitation (Appendix B). These differences should naturally translate to differences in seasonal peakflows. This is as a result of GRADEX and aggregation of hydrological processes (Merz et al., 2022; Pham and Alila, 2024). Despite seasonal differences in FFC observed in some past studies (e.g., Basso et al., 2016; Brantley et al., 2015; Wang et al., 2025), linking these differences to possible causes has rarely been done. This study attempts to explain why these differences should not be surprising and illuminate possible underlying processes that could be at play.

Results from the seasonal analysis initially seem counterintuitive as it appears that dormant season peakflows are affected more by forest treatment than growing season peakflows (Fig. 4). However, these seemingly counterintuitive findings can be physically explained. The very deep soils at Coweeta allow for large amounts of soil water to be stored which can persist for an extended period of time across seasons. Differences between seasonal peakflows are likely due to, in part, the delayed runoff response to changes in AMC resulting in 'watershed memory' (Nippgen et al., 2016). Extensive samplings of soil moisture in Coweeta have shown that there is available moisture within the tree root zone of the soil mantle even after periods of summer drought (Hewlett and Hibbert, 1961). Lagged responses in the watershed means that large increases in peakflow, as a result of forest treatment, typically expected in the growing season can actually be shifted to the dormant season and vice-versa.

Forest treatments can suppress the soil's ability to buffer seasonal fluctuations in AMC and runoff, and can lead to more extreme and variable seasonal fluctuations and result in increased runoff. This is due to the nonlinear relationship between AMC and runoff (Grayson et al., 1997; Yokoo et al., 2008). AMC seasonality can also affect the shape of the CDF. Seasonal changes in soil moisture storage potential will affect the nonlinearity of streamflow responses. During the growing season, there will be more soil moisture storage potential which leads to more nonlinear hydrologic responses and heavier-tailed FFCs while the dormant season will have less moisture storage potential leading to less nonlinear responses and lighter-tailed FFCs (Wang et al., 2025). Wet regimes tend to exhibit lower variance and skewness whereas drier regimes exhibit larger variance and skewness (Merz and Blöschl, 2009b). This helps explain the differences in shape and steepness between seasons as the dormant season would be a wetter regime compared to the drier growing season (Fig. 4). Moreover, the shape and steepness between seasonal FFCs are consistent with the expected effects of different dominant storm types (e.g., steep with convective in the growing and mild with frontal in the dormant seasons) as explained previously.

The timing of rain events coinciding with high AMC could also be a factor causing seasonal peakflow differences. These two processes occur with probabilities for any given magnitude. When these two processes coincide, they are in-phase with each other which creates resonance in the peakflow event and causes significant increases in the CDF, and this resonance effect on the CDF can be further amplified by nonlinear runoff generation processes (Sivapalan et al., 2005). Collectively with all the previously mentioned factors, lagged responses coupled with AMC seasonality would translate into the dormant season experiencing an increased likelihood of in-phase resonance conditions with increased AMC compared with the growing season as a result of forest disturbance.

4.5. Effects of vegetative non-stationarity and species conversion on forest treatment – peakflow causal relationships

Shifting from dominantly deciduous to coniferous trees would be expected to increase available soil water storage and affect the CDF by decreasing both the mean and variability of peakflows. This may partly explain what was seen in the south-facing watershed (WS1) CDFs where the observed CDF dipped below the expected CDF due to the decreases in mean and variance (Fig. 3). However, the dip of the observed CDF was not apparent for the north-facing watershed, possibly due to previously mentioned factors counteracting the expected decreases.

Vegetation growth and hydrological recovery may lead to nonstationary peakflows which needs to be detrended because stationarity of peakflows is required for conventional frequency analysis (Alila et al., 2009; Green and Alila, 2012). The change point and trend test analyses collectively failed to detect any significant non-stationarity within the time series of peakflows during the white pine growth period in both treatment watersheds. We hypothesize this to be a consequence of how evapotranspiration (ET) varies with age within the same tree species and the influence of past treatment effects being carried over to the white pine growth period. Eastern white pine grows remarkably quickly, being one of the fastest compared with other coniferous or deciduous trees in the southern Appalachians (Doolittle, 1958). The highest rate of growth for eastern white pine occurs within the first 10–15 years and tapers off afterwards (Beck, 1971; Hepp et al., 2015). Moreover, young and actively growing coniferous trees can have as much or more ET than mature deciduous trees. Helvey (1967) calculated that in Coweeta, 10-year old eastern white pine trees already had higher annual interception rates than mature hardwoods. Observed streamflow using the same species conversion experiment as the one examined in this study saw decreases in streamflow from the young white pine stands when compared to streamflow when the watersheds were originally covered with mature deciduous forests, and this indicated that ET losses were much higher with young white pine than with mature deciduous trees (Swank and Douglass, 1974; Swank and Miner, 1968). The difference in ET between pine and deciduous trees remain even during the growing season where ET from pine were double that of deciduous trees (Ford et al., 2011a). While ET from young forests can increase rapidly with age, ET rates will eventually level off as the trees mature to old-growths (Brantley et al., 2019). Hence, the expected non-stationarity caused by the initial increases in ET of white pine is short lived and is muted in the long time series as the majority of peakflows occur during the steady and 'mature' white pine phase, and therefore, not much detrending is needed to create a stationary peakflow time series.

Further investigations were done to support the statistical tests and the lack of large detrending adjustments. For the north-facing watershed, post-white pine adjustments for the first 15 years, on average, increased peakflows by ~10 %. This is consistent with past CP-based peakflow studies out of Coweeta, which revealed minor peakflow increases immediately after treatment in various watersheds (7–15 %) (e.g., Hewlett and Helvey, 1970; Swank et al., 2014, Swank et al., 2001, Swank et al., 1982). The subsequent 15–44 years post-white pine FFC (not shown for conciseness) behaved similarly to the 0–44 years post-white pine FFC. As such, runoff responsible for peakflow generation during this period is hypothesized to be mostly controlled by the influence of past treatments on non-vegetative factors, which makes runoff somewhat 'blind' to the higher ET during this period.

This study utilized empirical data from unique watershed pairs as the level of experimental detail within the pairs is rarely achieved, owing to the intense resources required to carry out such an experiment. The paired watershed approach decreases the influence of climate on peakflows because the control-treatment watershed pair experience the same climate. The extended period of vegetative suppression (Table 1) provides empirical flow data of vegetation removal as opposed to simulating the effects or relying on shorter periods of vegetation suppression.

4.6. Why did forest treatment effects on peakflows persist long after vegetation recovery and species conversion?

The north-facing watershed (WS17) provided a unique opportunity to analyze data where vegetation was physically suppressed for an extended period. By keeping vegetation suppressed for 14 years throughout the entire watershed, the time series effectively mimicked peakflow conditions that would have occurred immediately after tree removal. The flatter slope of the expected CDF for the regrowth suppression period implies that the expected peakflows are highly sensitive to treatment, and the large divergence of the observed CDF from the flatter slope expected CDF resulted in much larger changes in return period especially with larger events. Moreover, the increases in peakflows during the regrowth suppression period (Fig. 2) persisted to the post-white pine period FFC (Fig. 3), even when analyzing the two treatment periods separately.

The sustained increased peakflows after forest treatment in this watershed may be driven by factors other than reduced ET after harvesting. The 14 years of regrowth suppression could have induced unintended changes to non-vegetative factors in the watershed, such as soil properties, and their effects may have persisted long after the suppression ended. While the entire soil profile may have high storage potential, soil crusting and sealing might reduce the effective soil storage during peakflow events and allow more efficient water delivery to the outlet. Other changes to soil properties could have unintentionally occurred. For example, foot traffic during the regrowth suppression period in WS17 could have caused some soil compaction despite efforts to minimize soil disturbances by avoiding machinery and performing forest operations manually (Table 1). These changes could have resulted in changes to stormflow pathways in either the soil subsurface or surface layers. Future studies can report whether there were changes in surface or subsurface flow pathways. Changes in non-vegetative factors and soil characteristics may arise due to various factors. The lack of vegetative cover for 14 years meant that the soil was exposed to harsher conditions such as raindrops with higher kinetic energy, more wind, larger temperature fluctuations, and so on which can possibly lead to soil sealing or affect other soil properties (Armenise et al., 2018; Belnap, 2001). Moreover, something that might be seemingly irrelevant can actually affect soil properties, such as herbicide treatment which can enhance soil biocrust (Condon and Gray, 2020). WS1 also experienced a unique past treatment which involved herbiciding vegetation in the riparian area (25 % of the watershed area) for four years prior to complete watershed harvesting and planting white pine (Table 1). This could have affected peakflows similarly to the regrowth suppression period in WS17 through similar physical processes but to a lesser extent. Although the riparian zone only accounts for 25 % of the watershed area, riparian vegetation could have more influence on hydrological processes than non-riparian vegetation where, at Coweeta, hemlock loss in riparian areas had a detectable effect on water yield and peakflows (Brantley et al., 2015).

4.7. Implications for management

Despite the relatively small watersheds examined, findings from this study can relate to the topic of forest management and peakflows in larger watersheds. Forest treatment effects on higher peakflows has been documented via the few FP analyses in a wide range of watershed sizes, even in some as large as 1000 s to 10,000 s km^2 (e.g., Hurkmans et al., 2009; Kay et al., 2006; Preti et al., 2011; Reynard et al., 2001; Siriwardena et al., 2006; Svoboda, 1991; Te Linde et al., 2010; Zhang et al., 2018). While not every interpretation can be extrapolated to larger scales, some processes can occur regardless of the size of the watershed. For example, the influence of stratiform storms, seen during the dormant season, might apply to larger watersheds due to the large spatial coverage of stratiform storms compared to convective cell storms. The influence of baseflow and seasonality has been shown to play an increasingly bigger role on peakflow variability as watershed size increases (Blöschl and Sivapalan, 1997). Moreover, watersheds in areas with distinct seasonality and neutral propensity of flood tail behaviors tend to have increasing linear hydrological responses as watershed size increases (Wang et al., 2025). This suggests that these larger watersheds will exhibit less heavy-tailed FFCs, which in turn increases the sensitivity of these watersheds to forest treatment. This is because it is easier to shift towards heavier-tailed than to maintain lighter-tailed FFCs (Merz et al., 2022). Another example that could apply, and perhaps even more so, to larger watersheds would be watershed memory and lag effects as a result of larger soil storage potential and longer subsurface runoff travel times. Moreover, the potential for more above and below ground storage in larger watersheds can have profound impacts on the mean, variability, and skewness of peakflows which affect the sensitivity of peakflows and the "no-effect" threshold return period for previously mentioned reasons. FP-based studies have shown that larger watersheds tended to have lighter tails and smaller watersheds have heavier tails (Macdonald et al., 2022; Merz and Blöschl, 2009a; Villarini et al., 2011). This suggests that larger watersheds tend to be more sensitive to changes in the FFC than smaller watersheds due to differences in variability and skewness.

The effects of forest treatment in the headwaters can propagate downstream in larger watersheds. This idea was hinted to as early as in the 1970s where increased downstream flood risk might not be controlled by the timing and superposition of peakflows, but rather the increased accumulation of runoff volumes from smaller tributaries (Hewlett and Helvey, 1970). The increased runoff volume from headwater channels can also affect geomorphological processes. For example, it can carry more sediment to be deposited downstream which decreases channel capacity and, in turn, increases flood risk. These 'indirect' effects of forest management on sedimentation can substantially contribute to sediment yield (McEachran et al., 2020). These factors can lead to forest treatment resulting in reduced floodplain storage potential due to suppressed ET and changes in soil and geomorphological properties. In turn, this can result in losing the attenuating properties of these storages and lead to increasing the variability of peakflows and a steeper FFC downstream (Archer, 1989). While the effects of forest treatment on peakflows at the larger watershed scale will depend on the many factors considered in this study, it will also depend on the extent of forest treatment within the watershed. For example, the effect of forest treatment on annual water yield might not be detectable if only a small portion upstream watershed has been treated (Goeking and Tarboton, 2020; Hibbert, 1967).

The stochastic physics of peakflows derived from this study can help inform other disciplines such as engineering, geomorphology, ecology, and so on. Increased frequency and magnitude of peakflow events, as a result of forest treatment, can translate to increasing the risk to existing structures or new structures may need to be designed to withstand larger and more frequent peakflows. Changes in the hydrological regime can affect the nutrient and sediment environments for fluvial ecosystems, and change the hydrogeomorphological dynamics of the watershed. In turn, these changes can also affect sustainable harvest volumes and timber supply when considering the potential effects of forest treatment on the peakflow regime.

4.8. Limitations and future research

Despite analyzing data from the renowned Coweeta Hydrologic Laboratory, there will always be some experimental or technical limitations such as limited observed flow records or increasing uncertainties associated with higher statistical moments of flows and with higher return period and magnitude events. Differences in past treatment, prior to converting the watersheds to eastern white pine, between the north- and south-facing watersheds could have led to changes in soil properties or other non-vegetative factors which could affect peakflows differently within these watersheds. Although the calibration equation may introduce uncertainties, the outcomes from it are, at least qualitatively, physically plausible.

Future research can help advance our understanding of the relationship between forests and peakflows. Some nonstationary factors (such as vegetation growth) were controlled for, but others may have had an effect on peakflows such as climate. Future studies can utilize nonstationary analysis (Johnson and Alila, 2023) to assess hydrological recovery or other environmental factors that can change through time and bypass the need of a calibration equation. Hydrological modelling, such as Schnorbus and Alila (2013, 2004) and Birkinshaw et al. (2011) can be used to analyze longer record lengths, test various treatments, investigate different climatic conditions, analyze the influence of various physiographic characteristics of a watershed, and so on. The longer record lengths from modelling could also help to quantitatively assess the effect of forest treatment on skew due to the higher uncertainties, and consequently longer record lengths needed, with assessing higher order moments. Our study attributed observed peakflow changes to effects caused by larger macroscale factors (such as the dominant topographic aspect of the watershed) which encapsulates and considers all other processes that can affect hydrology (such as ET). Future studies can investigate the degree to which each of these processes affected peakflows and how they may interact among each other to synergize (or antagonize) the relative effects of the various processes under the proper FP framework such as the work done by Beckers and Alila (2004). Species conversion can become an important consideration in the future as preferential range for different tree species shifts in response to a changing climate or done for economic reasons (McKenney et al., 2011, 2007; Naudts et al., 2016). Future studies could consider climate change which can affect species composition, precipitation, and so on and understanding the effect of these changes on peakflows and the water supply. Another future research endeavor could examine how different types of forest management can leave prolonged impacts to hydrological processes, or on disentangling the contribution of the various factors found at play in this study and determine the degree of influence each factor played in peakflow generation.

5. Conclusion

This study took advantage of the stochastic hydrology literature to infer how forest treatment can affect the FFC. This allowed better understanding of the physical processes and watershed characteristics that affect peakflows through a stochastic framework by instilling physical meaning into the mean, variability, and skewness of peakflows and how they change in response to forest treatment. Frequency pairing framework is best suited to quantify the effects of forest treatment on the peakflow regime because the causes of peakflows are multiple and chancy and thus can only be evaluated in a probabilistic framework. By using the FP framework, it revealed that forest treatment can affect the mean and variability of peakflows which caused peakflows to be affected for a wide range of return periods. Forest treatment can also interact with other hydro-climate processes and physical characteristics of the watershed to further affect peakflows. Some of these include watershed topographic aspects, seasonality and lagged interactions, and a shift in dominant forest tree species. This results in peakflows being affected by multiple processes simultaneously and these processes can occur randomly. Therefore, proper understanding of peakflows, through FP, involves investigating these processes as how they would holistically occur as opposed to a reductionist approach by looking at these processes individually as what has been traditionally done (Pham and Alila, 2024). Moreover, the call for more rigorous applications of the stochastic framework has been echoed in other hydrological fields such as droughts (Vogel and Kroll, 2021).

CRediT authorship contribution statement

Henry C. Pham: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Younes Alila:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Peter V. Caldwell:** Writing – review & editing, Supervision, Resources, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Availability

Data supporting this research are available from the USDA Forest Service Coweeta Hydrologic Laboratory as they manage data from Coweeta. Data analyses were performed using R Statistical Software (v4.1.2; R Core Team, 2021).

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Appendix A. Soil moisture content

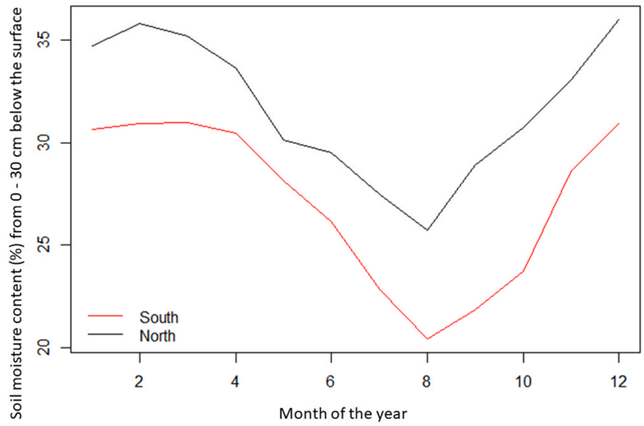

Fig. A1. Soil moisture content (%) from 0 to 30 cm below the surface for two control watersheds at Coweeta. Data from (Bolstad, 2019).

Appendix B. Rainfall intensity

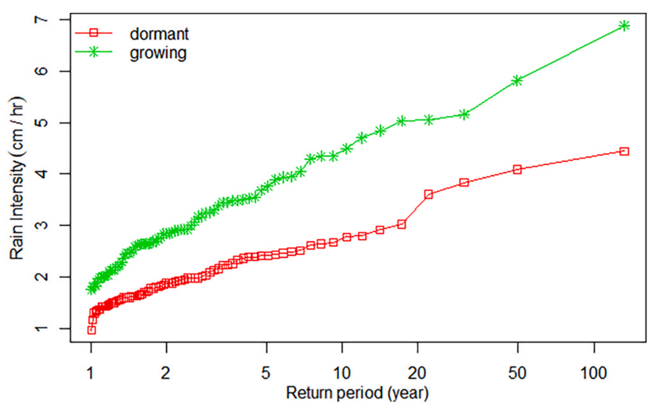

Fig. B1. Rainfall intensity experienced at Coweeta based on RG06.

Data availability

Data will be made available on request.

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