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River flood seasonality in the Northeast United States: Characterization and trends

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Abstract

The New England and Mid-Atlantic regions of the Northeast United States have experienced climate-induced increases in both the magnitude and frequency of floods. However, a detailed understanding of flood seasonality across these regions, and how flood seasonality may have changed over the instrumental record, has not been established. The annual timing of river floods reflects the flood-generating mechanisms operating in a basin, and many aquatic and riparian organisms are adapted to flood seasonality, as are human uses of river channels and flood plains. Changes in flood seasonality may indicate changes in flood-generating mechanisms, and their interactions, with important implications for habitats, flood plain infrastructure, and human communities. I applied a probabilistic method for identifying flood seasons at a monthly resolution for 90 Northeast U.S. watersheds with natural, or near-natural, flood-generating conditions. Historical trends in flood seasonality were also investigated. Analyses were based on peaks-over-threshold flood records that have, on average, 85 years of data and three peaks per year—thus providing more information about flood seasonality than annual maximums. The results show rich detail about annual flood timing across the region with each site having a unique pattern of monthly flood occurrence. However, a much smaller number of dominant seasonal patterns emerged when contiguous flood-rich months were classified into commonly recognized seasons (e.g., Mar–May, spring). The dominant seasonal patterns identified by manual classification were corroborated by unsupervised classification methods (i.e., cluster analyses). Trend analyses indicated that the annual timing of flood-rich seasons has generally not shifted over the period of record, but 65 sites with data from 1941 to 2013 revealed increased numbers of June–October floods—a trend driving previously documented increases in Northeast U.S. flood counts per year. These months have been historically flood-poor at the sites examined, so warm-season flood potential has increased with possible implications for aquatic and riparian organisms.

KEYWORDS

climate, flooding, hydrology, Northeast United States, seasonality, trends

1 | INTRODUCTION

River flood seasonality reflects the hydroclimatic flood-generating mechanisms operating in a basin (Berghuijs, Woods, Hutton, & Sivapalan, 2016; Collins et al., 2014; Hirschboeck, 1988). Many aquatic and riparian area organisms are adapted to flood seasonality as are human uses of river channels and flood plains (Arias, Cochrane, Norton, Killeen, & Khon, 2013; Gardiner, 1994; Næsje, Jonssons, & Skurdal, 1995; Robertson, Bacon, & Heagney, 2001). Changes in flood seasonality may indicate changes in flood-generating mechanisms (Cunderlik & Ouarda, 2009; Ye et al., 2017), and their interactions, with implications for habitats, flood plain infrastructure, and human communities.

With detailed information on flood seasonality and how it has changed, in conjunction with information about hydroclimatic changes to Northeast streamflow more broadly (e.g., Berton, Driscoll, & Chandler, 2016; Hodgkins & Dudley, 2011; Huntington & Billmire, 2014), fisheries biologists can better understand migratory fish spawning habitats, rearing habitats, and migration conditions (e.g., Goode et al., 2013; Kynard, 1997; Lapointe, Eaton, Driscoll, & Latulippe, 2000). This kind of information is also useful for interpreting how ongoing and future climate change may affect anticipated flood trends. For example, the late winter and early spring (Mar–May) are commonly flood-rich months in New England (Collins et al., 2014). Because these same months are projected to have increased precipitation with global warming (Easterling et al., 2017), it is commonly assumed that flood magnitudes and frequencies will also increase. However, this may not happen if, as the changing phenology of deciduous plants brings earlier leaf-out (Hibbard, Hoffman, Huntzinger, & West, 2017; Peñuelas & Filella, 2001), floods also occur later in the Mar–May period when full foliage can damp their magnitudes.

Lins and Slack (2005) very generally characterized flood seasonality for water-resource regions across the United States, reporting that the largest number of annual maximum daily discharges occurred in March for the Mid-Atlantic and April for New England. Magilligan and Graber (1996) presented a more detailed study of flood seasonality for the New England region. They employed directional (circular) statistics to quantify mean date of annual occurrence, a circular variable with no true zero, and a measure of annual timing variability. They showed that the average time of occurrence for annual maximum floods—the largest floods of each year at a station—ranged from the beginning of March in south-western Connecticut (CT) to the end of April in northern Maine (ME). But, for many of their gages, the annual timing variability was large, indicating floods happen throughout the year in New England. Circular statistics, however, are unable to adequately characterize the seasonality of watersheds with more than one flood season (hereafter referred to as "multimodal" flood seasonality) or no defined flood season (Cunderlik, Ouarda, & Bobée, 2004a).

Collins et al. (2014) described flood seasonality for 22 gages across New England and Atlantic Canada with near-natural flood-generating conditions by computing the relative frequencies of annual maximum floods in four seasonal groups: Dec–Feb (DJF; winter); Mar–May (MAM; spring); Jun–Aug (JJA; summer); and Sep–Nov (SON; fall). They found that MAM accounted for nearly 60% of all annual floods and had the largest seasonal proportion of flood occurrence at 19 watersheds. MAM was especially important at northern and interior sites. DJF was also important—22% of all annual floods occur in winter—especially in coastal areas. SON was secondary to spring and/or winter in some areas of their study region (14% of annual floods), and annual floods infrequently occurred in summer (JJA; 5%). Collins et al. (2014) also plotted day-of-year relative frequencies of annual floods that suggest bimodal seasonal distributions characterize many sites, supporting conclusions of Caissie and Robichaud (2009) and Cunderlik and Ouarda (2009) for the Canadian Maritimes.

Villarini (2016) recently addressed the seasonality of annual maximum floods across the United States. His results were equivocal for the New England and Mid-Atlantic regions, predictably given the multimodal flood seasons in the Northeast and the circular statistics he employed. While advancing the application of circular statistics to flood seasonality by testing whether records of annual floods were statistically different from the circular uniform distribution and a symmetric nonseasonal circular distribution, his methods were still incapable of characterizing in detail the multimodal seasonal distributions common across the region (see Cunderlik et al., 2004a). Villarini (2016) also investigated temporal trends in flood seasons, but the methods he employed did not assess trend direction. Ye et al. (2017) improved the characterization of annual maximum flood seasonality in the United States, and associated interpretations of generating mechanisms, by focusing on a circular statistics measure of annual timing variability and comparing it with the annual timing variability of annual maximum rainfall. While not fully capturing the multimodal distributions of Northeast U.S. floods, their methods yielded valuable insights about the importance of antecedent soil moisture to flood generation in this region. They also analysed temporal trends in annual timing variability, including trend direction (Ye et al., 2017).

Frei, Kunkel, and Matonse (2015) investigated the seasonality of trends in Northeast U.S. precipitation and streamflow extremes. To do so, they computed and compared trends in magnitude and frequency for cold season (Nov–May), warm season (Jun–Oct), and full year extremes—defined as the 90th, 95th, and 99th percentile of daily values in each time period. They found the strongest changes since 1935 have been increases in the *frequency* of warm season precipitation and streamflow extremes, a result that is consistent with studies by Armstrong, Collins, and Snyder (2012, 2014) that showed historical increases in flood frequency across the region were stronger and more widespread than increases in flood magnitude (see also Archfield, Hirsch, Viglione, & Blöschl, 2016). Their analysis also partially explains the well-documented phenomenon that upward trends in Northeast U.S. precipitation extremes are stronger than increasing flood trends when both are evaluated on an annual basis (Wehner, Arnold, Knutson, Kunkel, & LeGrande, 2017). Frei et al. (2015) showed that cold season (Nov–May) streamflow extremes, for which upward trends in magnitude and frequency have been weaker, are more numerous in this part of the country than warm season events and thus dominate the annual signal (Frei et al., 2015).

The goals of this study were to (1) define the multimodality of Northeast U.S. flood seasons with greater accuracy and detail than previously available; (2) evaluate trends in flood seasonality including, for the first time, the direction of any seasonal shifts; and (3) through these analyses potentially yield new insights about regional flood-generating mechanisms. I identified flood seasons using peaks-over-threshold

(POT) flood records and a method developed by Cunderlik, Ouarda, and Bobée (2004b) based on monthly relative frequencies. POT flood records include all events over a threshold discharge, and thus more than just the largest of the year, facilitating a more accurate and robust characterization of flood seasons compared with annual maximum records (Cunderlik et al., 2004a, 2004b). POT series are also better for characterizing flood seasons because they do not include low to moderate flows that can be found in annual maximum records that include the largest flow of the year regardless of magnitude (Cunderlik et al., 2004a).

After flood seasons were identified, I then investigated timing trends two ways: (1) within-season trend analyses to evaluate whether established flood seasons shifted earlier or later in the annual cycle (e.g., has a spring flood season arrived earlier or later in the year over the period of record?) and (2) decomposition of annual POT time series into cold (Nov–May) and warm (Jun–Oct) season subseries to examine the relative importance of each season to documented increases in POT per water year across the region (Armstrong, Collins, & Snyder, 2012, 2014). The second approach follows the analyses of Frei et al. (2015), but with a more restrictive definition of what constitutes a streamflow extreme as described below.

2 | METHODS

2.1 | Gage selection

I used 90 POT flood records identified by Armstrong et al. (2012, 2014) for investigating hydroclimatic trends in flood magnitude and annual frequency, updating the records to 2013 (Figure 1). These stations across the New England and Mid-Atlantic regions (Hydrologic Unit Codes 01 and 02) are part of the original U.S. Geological Survey (USGS) Hydro-climatic Data Network (HCDN) and were further vetted to assure minimal human influence on flood peaks (Armstrong et al., 2014; Slack & Landwehr, 1992). For example, gage metadata, including USGS annual water data reports and peak discharge qualification codes, were reviewed in detail. Gage records with evidence of peak flow regulation and/or diversion, or other unique disqualifiers, were removed (Armstrong et al., 2014). The POT time series include all instantaneous peaks over a "base," or threshold, discharge established by USGS, chosen with the expectation that approximately three to four flows per year would exceed the threshold (Langbein, 1949). Thus, many high flows in these POT series are not overbank floods (Wolman & Miller, 1960). Base discharges for each gage are published in USGS annual water data reports (https://wdr.water.usgs.gov/; accessed 30 Jul 2018). Armstrong et al. (2012, 2014) assured event independence by using a conservative measure of watershed response time to identify POT clusters that may be one event and retained only the largest. The mean record length is 85 years, and the number of observations averages about 240, or about three peaks per year. All 90 flood series begin by water year 1951 at the latest and have less than 5% missing data. Eighty sites have no missing data. The longest span of consecutive missing years is 3 years, occurring at only one gage.

The USGS updated the HCDN after Armstrong et al. (2012, 2014) chose their gages for near-natural flood conditions. HCDN-2009 is now a subset of the GAGES-II database, which is an update of the

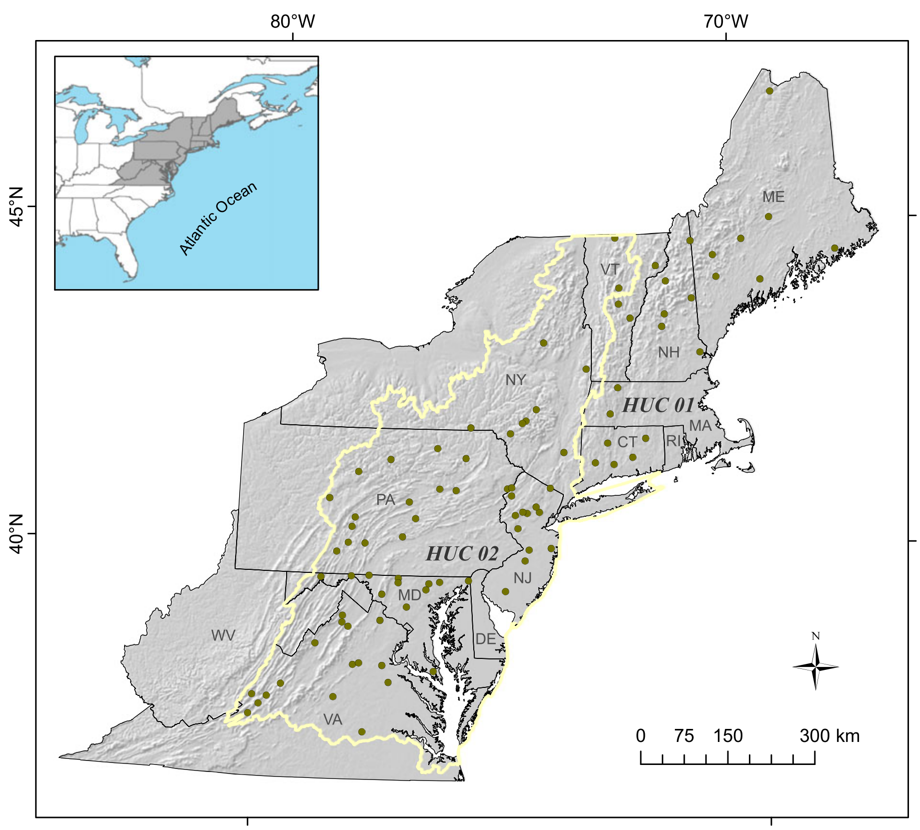

FIGURE 1 Hydrologic Unit Codes (HUC) 01 and 02 in the Northeast United States and 90 stream gages analysed for flood seasonality characterization and trends. Station details are available in Armstrong et al. (2012, 2014)

GAGES database described by Falcone, Carlisle, Wolock, and Meador (2010). HCDN-2009 gages have "reference conditions," meaning all attributes of streamflow are natural or "least-disturbed" (Lins, 2012). As noted by Lins (2012), "reference condition" can be unnecessarily restrictive for climate studies because all streamflow attributes at a site have to be near-natural for this status. A site could have natural or near-natural flood flows, or flood-producing conditions that have not changed over the period of record, and be excluded from HCDN-2009 because another flow attribute is influenced by human activity (e.g., water withdrawals affecting low flows).

Only 42 of the 90 HCDN gages identified by Armstrong et al. (2012, 2014) are included in HCDN-2009. Yet a reanalysis of their work using only the HCDN-2009 stations shows that the proportions of sites with increasing and decreasing trends in flood magnitude and frequency—and the proportions of sites with significant trends—are nearly unchanged. This underscores the value of carefully vetting each site to evaluate whether it is suitable for hydroclimatic studies of the flow attribute of interest so that important records that maximize spatial and temporal coverage are not needlessly excluded.

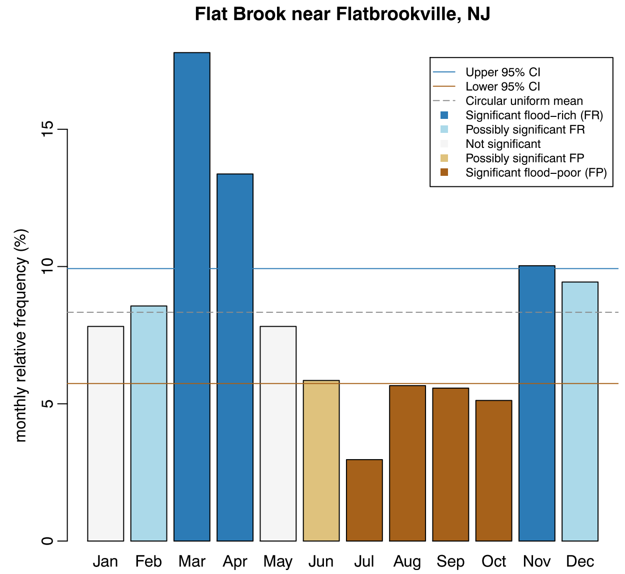

FIGURE 2 Flood seasonality at a monthly resolution for Flat Brook near Flatbrookville, New Jersey (NJ; site number 41 on Figures 4 and 6)

2.2 | Seasonality

Flood seasonality was assessed using a probabilistic method developed by Cunderlik et al. (2004b). Floods at each station were grouped by month, and then monthly relative frequencies were adjusted so that all months were 30 days (Mardia, 1972). Significant flood seasons were then identified by comparing observed monthly relative frequencies (i.e., probabilities) with the theoretical variability of a nonseasonal model—monthly relative frequencies estimated from 100,000 synthetic records generated from the circular uniform distribution with the same number of observations as the station record (Cunderlik et al., 2004b). One-sided $(1 - \alpha)\%$ confidence intervals were computed as the α $(1 - \alpha)$ empirical percentile intervals using models given by Cunderlik et al. (2004b). I used $\alpha = 0.05$. Observed monthly relative frequencies at a station above or below the one-sided confidence bounds were considered significant flood-rich or flood-poor months (Figure 2). Months not exceeding the confidence bounds were considered "possibly significant" if more than $\alpha^*\%$ of the same months did exceed them in 1,000 bootstrap resamples of the record—addressing sampling variability (Cunderlik et al., 2004b). I set α^* to 10%.

Contiguous, significant flood-rich months at a site were then manually classified within, or spanning, these commonly recognized seasons: DJF (winter), MAM (spring), JJA (summer), and SON (fall). For example, sites with only two significant flood-rich months occurring in March and April were classified as having a spring flood season. Sites with three significant flood-rich months in February, March, and April were classified as having a winter–spring flood season. Some sites had multiple flood seasons, meaning that contiguous, significant flood-rich months were separated by one or more flood-poor months and/or months not exceeding the confidence bounds. All sites were thus further classified by multimodality, or lack thereof. For example, sites were classified as "unimodal spring," "unimodal winter–spring," "bimodal spring, fall," or "bimodal spring, fall–winter."

Manual classification of flood seasonality for all sites was compared with two unsupervised classification methods (i.e., cluster analyses): partitioning around medoids (PAM) and agglomerative hierarchical clustering via the R packages "fpc" and "cluster" (Hennig, 2015; Maechler, Rousseeuw, Struyf, Hubert, & Hornik, 2017; R Core Team, 2017). The clustering objects were the monthly relative frequencies for each site, schematized as 12 asymmetric binary variables; that is, months were coded as either significant flood-rich (1) or not (0). I created a dissimilarity matrix using the DAISY function in the "cluster" package and used a "Gower" distance function that is appropriate for all data types. When all clustering variables are binary, as in this case, Gower's distance is equivalent to Jaccard distance (Dunn & Everitt, 2004). I then did PAM on the Gower dissimilarity matrix via the function PAMK, which estimates an optimal number of clusters from a user-specified range. I specified between 2 and 10. The number of clusters was estimated via the average silhouette width criterion (Hennig, 2015; Kaufman & Rousseeuw, 1990). Agglomerative hierarchical clustering on the Gower dissimilarity matrix was accomplished through AGNES (Kaufman & Rousseeuw, 1990). The clustering method was Ward's (Olden, Kennard, & Pusey, 2012).

PAM was chosen in favour of *k*-means clustering, a widely used partitional clustering method, because it iteratively forms clusters by minimizing a distance function between representative clustering objects ("medoids") and other similar clustering objects (Kaufman & Rousseeuw, 1990; Tan, Steinbach, & Kumar, 2006). Because medoids are members of the clustering data set (i.e., schematized monthly relative frequencies for each site), they have unambiguous hydrologic interpretations. *K*-means clustering, which forms clusters around means of the clustering objects, would not be appropriate in this case because the means of the binary clustering variables (i.e., averages of months coded as "1" if they are significantly flood-rich or "0" if not; e.g., 0.5) are not defined or physically meaningful.

2.3 | Temporal trends

Within-season flood timing trends were assessed via methods adapted from Cunderlik and Ouarda (2009). For each site, Julian dates of flood occurrence (JD_i) were converted to angular values (θ_i) as

$$\theta_i = JD_i \frac{2\pi}{D} \quad 0 \leq \theta_i \leq 2\pi. \tag{1}$$

D = 365 or 366 for leap years. The Mann–Kendall nonparametric trend test, implemented via the R package "zyp" (Bronaugh & Werner, 2013), was then used to assess whether angular values for a season increased (floods occurred later) or decreased (earlier). Flood seasons for these analyses were defined as contiguous, significant flood-rich months and included 1 month before and after to capture the potential time transgressions being investigated. Serial correlation in the seasonal time series was addressed, as necessary, via an effective trend-free prewhitening routine implemented in "zyp" where the trend residuals used to compute significance are multiplied by a magnification factor (Bronaugh & Werner, 2013; Serinaldi & Kilsby, 2016; Yue, Pilon, Phinney, & Cavadias, 2002). If a site had more than one flood season (i.e., contiguous, significant flood-rich months were separated by one or more months not identified as such), they were analysed separately because they likely arise from different hydroclimatic mechanisms (e.g., Figure 3a; Cunderlik & Ouarda, 2009). If a flood season spanned the New Year, the angular values were increased or decreased by a constant so that all flood dates had their relative positions in the annual cycle preserved and also represented correctly in Cartesian space for trend analyses (e.g., Figure 3b). That is, the transformations assured that Dec floods plotted adjacent to Jan floods on the ordinate axis and not at opposite ends that would generate spurious trends (Cunderlik & Ouarda, 2009).

To investigate whether previously documented regional trends in annual flood counts (Armstrong et al., 2012, 2014) were driven by changes in frequency during one time of year, I decomposed annual POT flood series into cold (Nov–May) and warm (Jun–Oct) season counts for 65 gages with no missing data from 1941 to 2013. This time period was chosen for comparability with the analyses of Frei et al. (2015) while also including a majority of the 90 study gages (i.e., less than half of the gages have data going back to 1935). The count series were then pooled across sites, and regional trends for the three series (water year, Nov–May, and Jun–Oct) were assessed by the Regional Kendall test via the R package "rkt" (Helsel & Frans, 2006; Marchetto, 2017). Data were pooled and evaluated by a single test to address two issues: (1) small sample sizes, especially for the Jun–Oct series, at some sites and (2) spatial correlation. The Regional

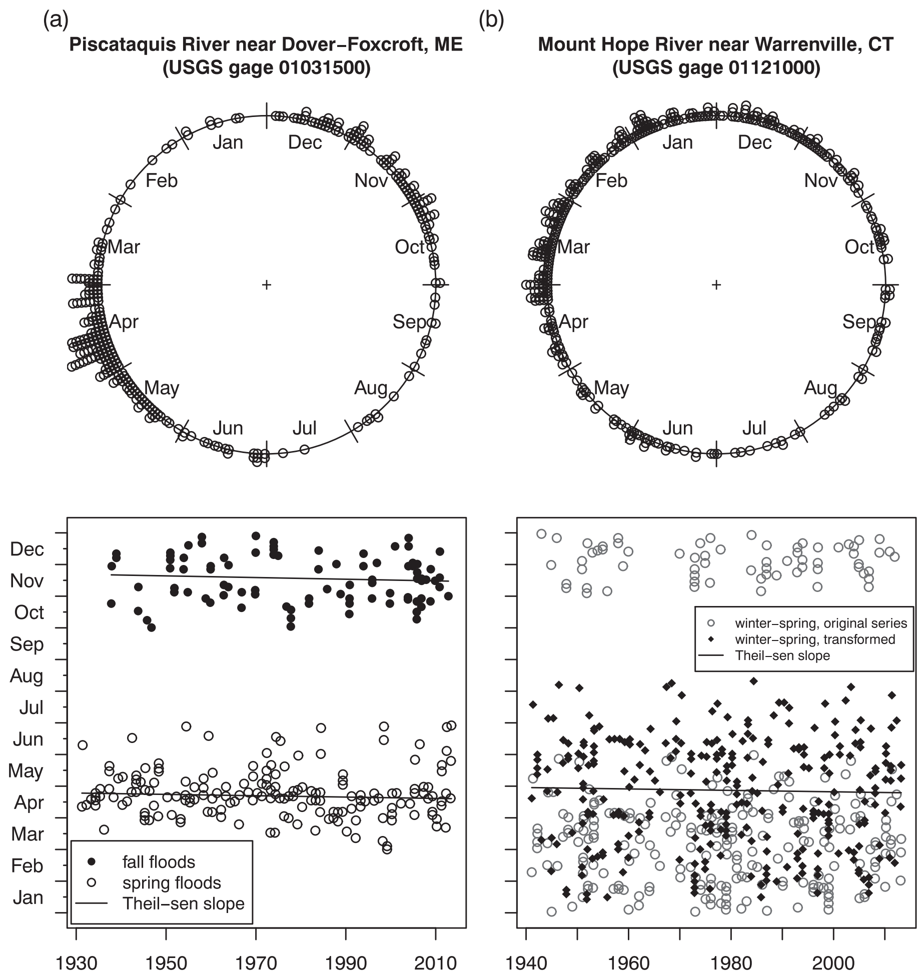

FIGURE 3 (a) Bimodal flood seasonality shown in a circular, or polar coordinate, plot (top) and trend analyses for the spring and fall modes (bottom). Trend slopes are negative and not significant at $p < 0.05$. (b) Unimodal winter–spring flood seasonality spanning the New Year (top) and associated transformation of original time series necessary for trend analysis (bottom). Trend slope is negative and not significant

Kendall test implemented via “rkt” explicitly accounts for spatial correlation. Before data were pooled, serial correlation was investigated for all three count series at every site and found insignificant.

3 | RESULTS

3.1 | Seasonality

Figure 4 shows flood seasonality at a monthly resolution, providing detail about flood timing across the region. Each of the 90 sites has a nearly unique pattern of monthly relative frequencies as well as significant flood-rich and flood-poor months. Yet a relatively small number of general patterns emerge when contiguous flood-rich months are manually classified within, or spanning, commonly recognized seasons (e.g., spring or winter–spring). All sites can be classified in 11 seasonal patterns: four unimodal, six bimodal, and one trimodal (Table 1). These further reduce to just three dominant types accounting for over 90% of sites (Table 1 and Figure 5). Forty percent of sites (36) have a unimodal spring pattern with floods occurring Mar–May (Type I). Another 20 sites have a unimodal winter–spring pattern when a significant quantity of floods occur anytime between Dec and May (Type II). The Type III pattern, bimodal with a primary season in the spring and a secondary season sometime in the fall–winter period, characterizes another 26 sites (Table 1). Only eight sites are not classifiable as Type I, II, or III, having unique, or nearly unique, relative

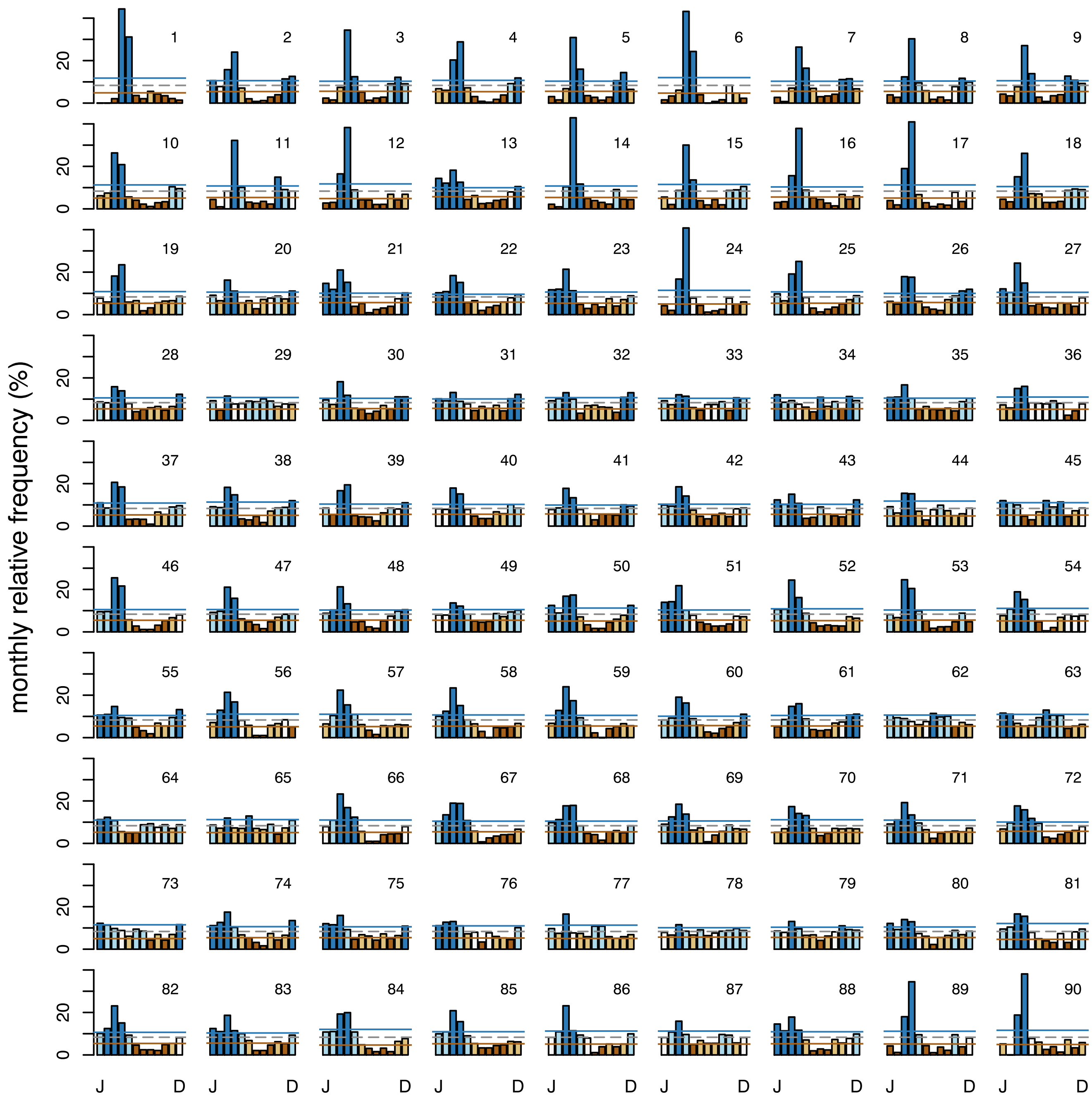

FIGURE 4 Flood seasonality for the 90 HUC 01 and 02 stations. Each bar chart has a number that corresponds to the site location shown in Figure 6. See Figure 2 for detailed bar chart legend

TABLE 1 Patterns of flood seasonality across the Northeast United States

	SON	DJF	MAM	JJA	Stations	Type
Unimodal						
Spring					36	I
Winter–spring					20	II
Winter					2	
Summer					1	
Bimodal						
Spring, winter					11	III
Spring, fall					9	III
Spring, fall–winter					6	III
Spring, summer					1	
Winter, summer					1	
Winter–spring, winter					1	
Trimodal						
Winter, summer, fall					2	

Note. For the general Types I–III, green = spring mode; blue = winter–spring mode; orange = fall, winter, or fall–winter modes. Grey indicates patterns not classified (NC) as Types I–III. SON: Sep, Oct, Nov; DJF: Dec, Jan, Feb; MAM: Mar, Apr, May; JJA: Jun, Jul, Aug.

frequency patterns and are hereafter referred to as "NC" sites, or not classified. Figure 6 shows the spatial distribution of the dominant seasonal patterns across the region.

The two unsupervised classifications corroborated the dominant seasonal patterns identified by manual classification, but also supported choosing the manual classification to generalize flood seasonality for the region. Each of these methods performed poorer than the manual classification partly because they forcibly assigned the relatively unique NC sites to clusters. See the Supporting Information for further discussion of the unsupervised classification results.

3.2 | Temporal trends

All sites have at least one flood season. Table 2 shows a mix of earlier and later within-season trends for season 1 with very few that are statistically significant. Results are similar for sites that have a second (n = 31) and third (n = 2) flood season. Figure 3a,b shows examples of sites with bimodal and unimodal flood seasonality, respectively, with no evidence for significant shifts in annual timing. These results demonstrate that established flood seasons have been stable in the annual cycle across the region over the historical period.

Despite the stability of the established flood seasons shown via the within-season trend analyses, the investigation of whether previously documented regional trends in annual flood counts are driven by changes in frequency during one time of year revealed that flood seasonality in the region is nonetheless changing. Figure 7 shows the total annual POT for 65 sites across the region with data from 1941 to 2013, as well as the cold (Nov–May) and warm (Jun–Oct) season subseries. Comparing LOESS smooth trend lines and Regional Kendall test p values for the full water year (black) with the Nov–May subseries (blue), the trend magnitude diminishes and changes

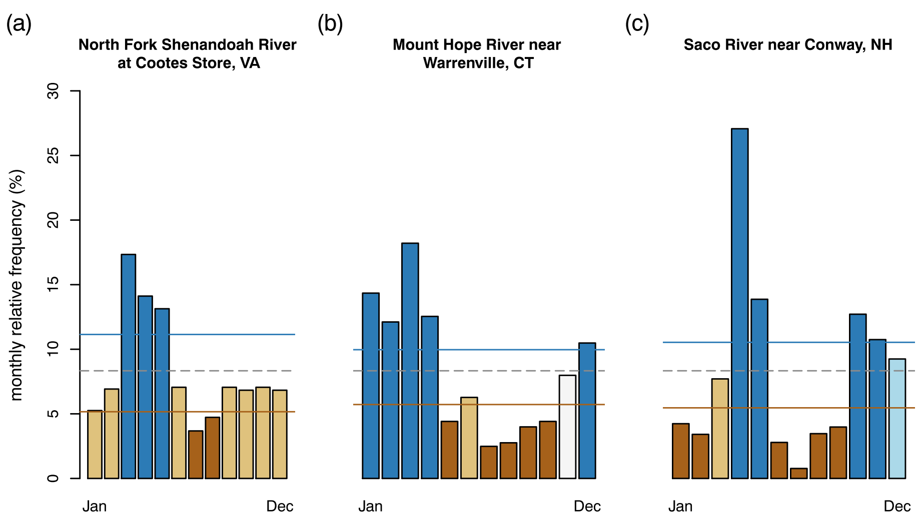

FIGURE 5 Examples of the three dominant flood seasonalities in the Northeast United States: (a) Type I, unimodal spring; (b) Type II, unimodal winter–spring; and (c) Type III, bimodal with a dominant spring season and subdominant fall and/or winter. Types I–III characterize 40%, 22%, and 29% of all sites, respectively

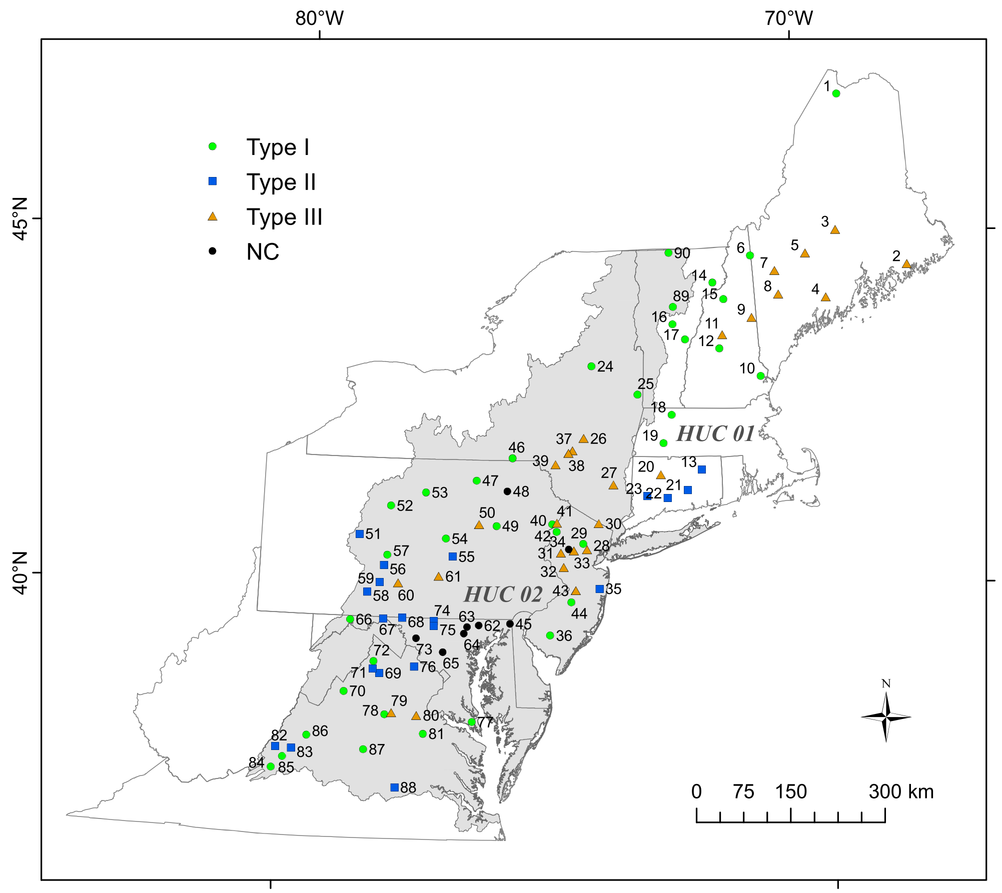

FIGURE 6 Spatial distribution of flood seasonality types. Type I: unimodal spring (Mar–May); Type II: unimodal winter–spring (Dec–May); Type III: bimodal with primary spring (Mar–May) mode and secondary fall and/or winter mode (SON and/or DJF)

from highly significant at $p < 0.01$ to not significant at $\alpha = 0.05$. The coefficient of variation (CV) for the respective subseries is 0.461 and 0.458. The upward trend in the Jun–Oct subseries (CV = 0.867) is highly significant and apparently an important driver of increasing trends in POT per water year documented by Armstrong et al. (2012, 2014).

TABLE 2 Within-season temporal trends (i.e., changes in timing during the annual cycle) for all identified flood seasons and all sites

	Season 1			Season 2			Season 3		
	n	Later	Earlier	*n*	Later	Earlier	*n*	Later	Earlier
Spring	63	41 (2)	22 (1)						
Winter–spring	21	14 (0)	7 (1)						
Winter	5	0 (0)	5 (2)	12	8 (0)	4 (1)			
Summer	1	0 (0)	1 (0)	4	1 (0)	3 (0)			
Fall				9	5 (0)	4 (0)	2	2 (1)	0 (0)
Fall–winter				6	2 (0)	4 (0)			
Total	90	55 (2)	35 (4)	31	16 (0)	15 (1)	2	2 (1)	0 (0)

Note. Values in parentheses indicate the number of stations with p values < 0.05.

4 | DISCUSSION

Northeast U.S. flood seasonality is revealed in this study in greater detail than previously known. Floods in the Northeast U.S. can happen

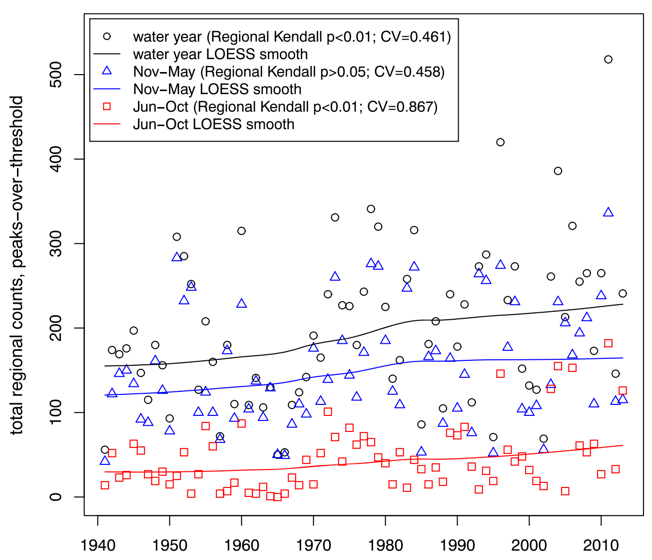

FIGURE 7 Total peaks-over-threshold for 65 sites with data from 1941 to 2013 for the cold season (Nov–May; blue), warm season (Jun–Oct; red), and the full water year (black)

any time of year, but three patterns—all of which include MAM—characterize more than 90% of sites (Table 1).

Forty percent of stations have a Type I pattern—unimodal MAM. It is widely believed that the prevalence of MAM floods in the Northeast United States, in association with a comparatively even annual precipitation distribution (Cowell & Urban, 2010; Huntington, Richardson, McGuire, & Hayhoe, 2009), indicates snowmelt is a dominant regional flood-generating mechanism (Berghuijs et al., 2016; Magilligan & Graber, 1996; Villarini, 2016). However, Dudley, Hodgkins, McHale, Kolian, and Renard (2017) found no HUC 02 watersheds south of New York State (NY) with greater than 30% of total precipitation falling as snow. Yet roughly equal proportions of HUC 01 and 02 gages in this study are unimodal MAM, with this pattern well represented as far south as Virginia (VA) from the coastal plain (e.g., site 81, Figure 6) to the higher elevations (e.g., site 86, Figure 6). Even in New England (HUC 01) and Atlantic Canada, where the assumption of snowmelt as a dominant mechanism is most intuitive, Collins et al. (2014) showed through detailed mechanistic studies that snowmelt contributes to less than 30% of all annual floods. Rain is the dominant precipitation mechanism that generates floods (72%) despite the MAM period accounting for nearly 60% of all annual floods.

Collins et al. (2014) concluded that rain falling during leaf-off conditions, when evapotranspiration is low and soil moisture relatively high, along with rain on frozen ground, are collectively at least as important as snowmelt at generating floods during MAM in HUC 01 and Atlantic Canada. Under these antecedent conditions, rainfall does not need to be extreme to produce flooding (and without these conditions, extreme rainfall often does not produce flooding; Ivancic & Shaw, 2015). This is likely true for HUC 02 watersheds too, although frozen ground and snow become even less significant factors further south in the Mid-Atlantic and high antecedent soil moisture associated with rainfall, and seasonally low evapotranspiration, become more important (Ye et al., 2017). Figure 8a shows how long-term median streamflow in southern VA increases steadily from late Oct through mid-late Mar. This time frame roughly corresponds to the annual dormant period for deciduous plants, highlighting how reduced transpiration increases ground water recharge and causes greater run-off through increased soil moisture and less available storage for rainfall (Cowell & Urban, 2010; Jasechko et al., 2014). This time of year also has the least daylight, further reducing evapotranspiration. Figure 8b shows the same general phenomenon operating at a site further north, although long-term median streamflow there begins increasing earlier in October and peaks later—early Apr—corresponding to the longer plant dormant period at that latitude. Although the western Massachusetts (MA) site also shows a clear influence of snow and cold typical for streams at this latitude (a decrease and/or stagnation in long-term median flow from mid-Dec through late Feb), the hydrograph rise between mid-Oct and mid-Dec that corresponds with the onset of the dormant period for deciduous plants (like the VA site) suggests soil moisture would be at a maximum in MAM in northern parts of the domain even in the absence of snow influence. This helps explain why Collins et al. (2014) could find rain without snowmelt commonly generating annual floods during MAM in HUC 01 and further highlights the importance of seasonally low evapotranspiration and high soil moisture for generating floods across the entire Northeast United States.

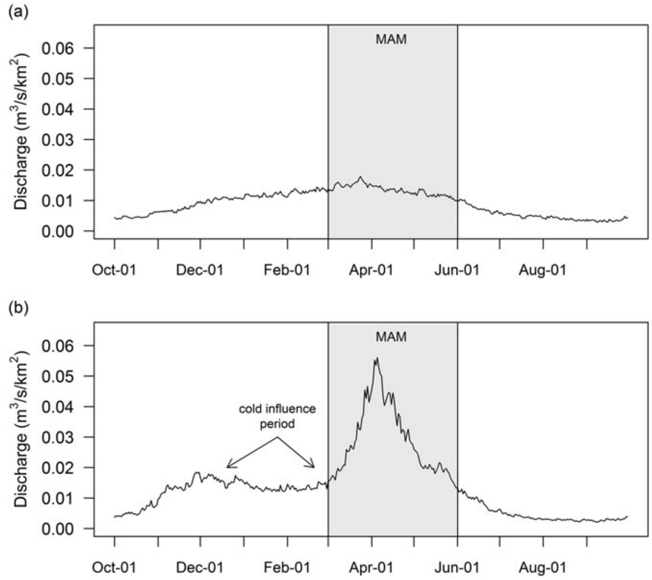

FIGURE 8 Long-term median streamflow for the (a) Robinson River near Locust Dale, VA (USGS 01666500; site 78, Figure 6) and (b) West Branch Westfield River at Huntington, MA (USGS 01181000; site 19, Figure 6). The periods of record are 74 and 81 years through 2017 and 2016, respectively. Both are HCDN-2009 stations

For further insight about mechanisms that give rise to the Type II and III patterns, which have significant flood-rich months in MAM and additional seasons (Figure 5), I did a limited investigation of whether the types differ by mean basin elevation of the member stations, drainage area, and/or distance to the coast. These geomorphic and climatic variables have been identified as important to Northeast U.S. flood seasonality (Collins et al., 2014; Magilligan & Graber, 1996). I did a Wilcoxon rank sum test on all pairwise comparisons between the three types and found no significant difference with respect to mean basin elevation or drainage area ($\alpha = 0.05$). The stations with a Type III pattern, however, are significantly closer to the coast than Type I and Type II stations ($p < 0.001$ and $p < 0.01$, respectively). Types I and II are not distinguished by distance to the coast.

The bimodal Type III flood seasonality pattern found at stations more proximal to the coast (Figure 6) corresponds well to a daily and extreme precipitation climatology recently established for New York and New England (Agel et al., 2015). Despite the Northeast having a relatively even precipitation distribution throughout the year compared with other parts of the world, Agel et al. (2015) found significant differences between inland and coastal stations in seasonal patterns of daily and extreme precipitation. Although inland precipitation stations show a single peak in late summer for daily and extreme precipitation intensity and totals, coastal stations have a bimodal distribution with spring and fall maxima. Importantly, the fall peaks are larger for daily and extreme precipitation intensity and extreme totals (Agel et al., 2015). Multiday events at coastal stations show the same bimodal pattern with fall maxima in daily and extreme precipitation totals. Storm-related extreme days at coastal precipitation stations are most often associated with a storm track that extends along the eastern seaboard just offshore. Collins et al. (2014) identified storms along this track as disproportionally affecting stream gages more proximal to the coast and producing larger magnitude annual floods across the region. The track occurs all year, but has the greatest track density in MAM and SON (Agel et al., 2015).

The coastal precipitation climatology described above, in combination with the concurrent start of the plant dormant period and shorter day lengths, may explain why regional stream gages more proximal to the coast often register a subdominant flood season in the fall-early winter (i.e., a Type III pattern). Despite antecedent ground water and stream flow levels being near annual lows (Figure 8), the opposite of MAM conditions, fall precipitation in coastal areas can be intense enough, and/or of long enough duration, to produce saturated conditions and overland flow.

The Type II pattern may not be a distinct pattern at all, but may instead suggest a possible failure of the classification. Nine Type III sites would be Type II except for a single "possibly significant" flood-rich month breaking an otherwise unimodal winter–spring pattern (sites 27, 31, 32, 37, 38, 43, 50, 60, and 80; Figures 4 and 6). The majority of these are more proximal to the coast. Sampling variability may thus, in these areas, lead to confusing a variant of the Type III pattern with a separate pattern altogether (i.e., Type II). In southwestern, inland areas of HUC02, the Type II pattern may be a variant of Type I shifted 1 month earlier—reflecting the more southerly location and earlier median streamflow peak (Figures 6 and 8a). Sites 56, 58, 59, 67, 68, 69, 71, and 82 exemplify this shift (Figures 4 and 6). Giving support to the idea that Type II in this geography may instead be a variant of Type I are the classifications of three nearby stations on the Shenandoah River in VA (sites 69, 70, and 71). Two are classified as Type II and the other as Type I. But their proximity and location within the same river basin (Figure 6), and the similarity of their monthly relative frequency patterns (Figure 4), suggest they should have the same classification.

There is little evidence across the region to suggest that historically flood-rich seasons are occurring earlier or later in the year (Table 2 and Figure 3). However, there is an increased frequency of floods in the warm season (Jun–Oct)—historically flood-poor months at nearly all gages (Figures 3 and 4). This trend generally matches the seasonality of regional upward trends in precipitation totals, extremes, and persistence (Frei et al., 2015; Guilbert, Betts, Rizzo, Beckage, & Bomblies, 2015; Huang, Winter, & Osterberg, 2018; Huang, Winter, Osterberg, Horton, & Beckage, 2017), indicating flooding is becoming more likely during a time of year when evapotranspiration and antecedent soil moisture conditions have historically not favoured flooding (Ivancic & Shaw, 2015). The increase in Jun–Oct flood counts also supports the findings of Frei et al. (2015) who found warm season high streamflow in the Northeast has increased in frequency. Interestingly, Mallakpour and Villarini (2015) showed an increased frequency of summer floods in the eastern part of the central United States—an area proximal to the Northeast United States that has a similar climate and where the summer season has historically been a minor contributor to flood occurrence.

5 | CONCLUSIONS

This study employed POT flood records having an average of 85 years of data and three peaks per year to characterize Northeast U.S. river flood seasonality in greater detail than available before. Flood occurrence is not limited to a specific season, although spring (MAM) is important at nearly all sites, and it is common throughout the region for a site to have more than one flood season (e.g., spring and fall or spring and fall–winter).

In addition to practical advantages for planning and risk reduction, knowing a region's flood seasonality is an entry point to understanding the mechanisms that generate floods—requisite knowledge for predicting how floods will change in the future. Although this study did not generate new insights about regional flood-generating mechanisms (the third study goal), it did yield new evidence to support recent research that challenges a common assumption: that spring floods in the Northeast derive primarily from snowmelt. Collins et al. (2014) showed evidence suggesting evapotranspiration and associated soil moisture conditions during MAM are at least as important as snowmelt for generating floods in New England and Atlantic Canada. In this study, I have documented how MAM is also a dominant period for flood occurrence across the Mid-Atlantic region where snow is less prevalent. This finding further highlights the importance of seasonal evapotranspiration and soil moisture conditions for spring flood generation across the Northeast.

Although the seasonality data are compelling for process inference, further detailed studies of flood-generating mechanisms that identify the synoptic climatology, precipitation, and antecedent conditions associated with individual events are warranted. Such analyses, in turn, may clarify the general seasonal patterns described here. Although the physical basis for the unimodal Type I pattern and the bimodal Type III pattern is reasonably clear, the Type II pattern is ambiguous. Further elucidating flood-generating processes at stations across the region will help address this ambiguity and provide more detail about the mechanisms producing Types I and III.

The Northeast U.S. flood seasons defined here show no evidence for shifts earlier or later in the year. MAM remains a significant flood-generating period at nearly all sites, regardless of snow influence. Because climate model projections indicate the late winter and early spring will have increased precipitation in coming decades (Easterling et al., 2017; Lynch, Seth, & Thibeault, 2016) and evapotranspiration and soil moisture conditions during MAM often favour run-off, the Northeast United States has ongoing vulnerability to increased magnitude and/or frequency of river floods (Douglas et al., 2016). Recent increases in warm season (Jun–Oct) flood occurrence documented by this study may have implications for the region's aquatic and riparian organisms, but it is unclear if these trends will continue in a warming climate. There is evidence that recent increasing trends in warm season precipitation in the region are strongly influenced by internal climate variability, expected increases in extreme precipitation are not seasonally specified, and how anthropogenic forcing may affect large-scale, multidecadal, ocean–atmosphere anomalies is not well understood (Easterling et al., 2017; Hoerling et al., 2016; Huang et al., 2018; Yu, Zhong, Pei, Bian, & Heilman, 2016).

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SUPPORTING INFORMATION

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