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Key Points:
- We introduce a flood connectedness measure enabling the mapping of spatial flood dependence
- The spatial dependence of floods varies regionally and seasonally and is generally highest in winter and spring
- Land-surface conditions modulate the direct influence of extreme precipitation upon spatial flood dependence.

Supporting Information:
- Supporting Information S1
- Figure S1

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Spatial Dependence of Floods Shaped by Spatiotemporal Variations in Meteorological and Land-Surface Processes

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Abstract Floods often affect large regions and cause adverse societal impacts. Regional flood hazard and risk assessments therefore require a realistic representation of spatial flood dependencies to avoid the overestimation or underestimation of risk. However, it is not yet well understood how spatial flood dependence, that is, the degree of co-occurrence of floods at different locations, varies in space and time and which processes influence the strength of this dependence. We identify regions in the United States with seasonally similar flood behavior and analyze processes governing spatial dependence. We find that spatial flood dependence varies regionally and seasonally and is generally strongest in winter and spring and weakest in summer and fall. Moreover, we find that land-surface processes are crucial in shaping the spatiotemporal characteristics of flood events. We conclude that the regional and seasonal variations in spatial flood dependencies must be considered when conducting current and future flood risk assessments.

Plain Language Summary Floods often affect large regions and cause adverse societal impacts. Regional flood hazard and risk assessments require a realistic representation of spatial flood dependencies to avoid the overestimation or underestimation of regional flood risk. However, it is not yet well understood how the spatial dependence of floods, that is, the degree of co-occurrence of floods at different locations, varies in space and time and which physical processes influence the strength of this dependence. We identify regions in the United States with seasonally similar flood behavior and analyze processes governing spatial dependence. We find that spatial flood dependence varies regionally and seasonally and is generally strongest in winter and spring and weakest in summer and fall. Moreover, we find that land-surface processes play a critical role in shaping the spatiotemporal characteristics of flood events. We conclude that to quantify shifts in flood risk in a warming climate one must not only understand land-surface processes and extreme precipitation increases but also consider the regional and seasonal deviations in spatial flood dependencies.

1. Introduction

Floods occur at least periodically across most regions on Earth and represent a large fraction of all natural disasters worldwide, accounting for 43% of all recorded events and affecting nearly 2.5 billion people in the period 1994-2013 (CRED, 2015). Per year, floods cause insured damages totaling 50 billion dollars globally, 7.7 billion dollars in Europe, and 4.5 billion dollars in the United States (Aon Benfield, 2016).

The costs associated with such events can be reduced by implementing adequate flood adaptation measures and by increasing flood preparedness. The implementation of such measures requires reliable estimates of the frequency and magnitude of flood events (O'Connor & Costa, 2003). In many studies, the focus is on a single location because flood risk estimation procedures are straightforward if only one location is of interest (Brunner et al., 2016). Yet flood events are inherently spatial phenomena—in that the spatial structure of floods can be a key factor determining flood severity—and the most severe floods often affect large regions. Recent examples of such widespread floods include the lower Mississippi flood in 2019 (NOAA, 2019) or the California floods in 2017 (NASA, 2017), which mainly affected the Sacramento and Feather rivers. Geographically widespread floods, in particular, can be “surprising” (Kjeldsen & Prosdocimi, 2018) and cause damages over a large region, which can amplify societal costs. Flood hazard and risk estimates should therefore capture the regional dimension of flooding.

State-of-the-art regional flood risk estimates are commonly derived using a model chain comprised of a stochastic event generation model and a flood impact model allowing for the aggregation of loss indices over an area (Serinaldi & Kilsby, 2017; Thieken et al., 2015). A large set of spatially consistent flood events can be generated either through a continuous approach combining a stochastic rainfall generator with a hydrological model (Winter et al., 2019) or an event-based approach simulating flood events directly from spatial extreme value models such as the conditional exceedance model by (Heffernan & Tawn, 2004) (Keef et al., 2013; Tawn et al., 2018; Towe et al., 2016). Understanding the nature of spatial dependencies, that is, the degree to which floods at a specific location are related to floods at other locations, is crucial for developing suitable simulation approaches as a mischaracterization of dependence will result in an underestimation or overestimation of regional damage, respectively (Lamb et al., 2010; Metin et al., 2020). As different models are able to capture different types of dependencies, knowledge on the type of spatial dependence over a region can inform suitable model choice.

Despite the importance of understanding the spatial dependence of floods when deriving regional flood estimates, it has often been overlooked in practical applications and is not well understood. While the spatial dependence of precipitation has been investigated in several studies (e.g., Davison et al., 2012; Le et al., 2018; Thibaud et al., 2013; Touma et al., 2018), the spatial dependence of floods has been addressed in only a few studies primarily focused on modeling this spatial dependence under stationary conditions (Asadi et al., 2015; Bracken et al., 2016; Brunner et al., 2019; Diederen et al., 2019; Keef et al., 2009; Neal et al., 2013; Quinn et al., 2019). Asadi et al. (2015) and Brunner et al. (2019) have shown that the spatial dependence of floods at different locations decreases with the increase of the distance along the river network between these stations. These antecedent studies dealt with the analysis of the spatial dependence of floods focusing on one particular region. However, there has been little, if any, investigation to date regarding whether the spatial dependence of floods varies regionally or seasonally on larger spatial scales.

Two recent studies by Berghuijs et al. (2019) and Kemter et al. (2020) have shown for large sets of European catchments that the distance between catchments experiencing floods at the same time varies regionally and depends on the homogeneity of a particular region's flood generating mechanisms. While the authors looked at regional differences in this distance, seasonal differences were not considered because their analysis focused on annual maxima floods.

Not only has the detection of spatial dependence patterns received little attention, but also the factors and processes that influence the spatial dependence of floods at a seasonal scale have been largely overlooked. Thus, it is presently unclear which climatological and/or geographical factors influence spatial dependencies of floods besides the river network structure.

The aim of this study is threefold: we (1) propose a connectedness measure allowing for the mapping of regional differences in spatial flood dependence, (2) map regional and seasonal differences in spatial flood dependencies on a large scale for the continental United States, and (3) identify potential drivers of spatial flood connectedness patterns in a manner that accounts for regional and seasonal complexity. Increasing our process-level understanding of the spatial dependence of floods is a first step toward improving large-scale flood simulation models, as well as learning how changes in future flood risk may differ from changes in extreme precipitation in a warming world.

2. Data and Methods

We first map seasonal networks of flood co-occurrences and determine regions with similar flood behavior using events identified in the discharge records of 671 catchments in the United States. To do so, a connectedness measure is introduced, which quantifies the number of catchments with which a specific catchment co-experiences floods. We then evaluate to what degree the spatial dependence in floods can be explained by the spatial dependence in extreme precipitation in the different seasons and how other factors such as snowmelt and soil moisture might influence the spatial dependence of floods.

2.1. Data Set

The study relies on a large-scale data set in the contiguous United States (CONUS) consisting of 671 catchments covering a wide range of discharge regimes minimally influenced by human activity (Newman et al., 2015). Daily discharge data (ft^3/s; converted to m^3/s) for the 671 catchments in the Catchment Attributes and MEteorology for Large-sample Studies (CAMELS) data set (Newman et al., 2015) were downloaded for the period 1981–2018 from the USGS website https://waterdata.usgs.gov/nwis using the R-package dataRetrieval (De Cicco et al., 2018). Areal precipitation and mean daily temperature for the same period were computed using the Daymet data set which provides gridded estimates of daily precipitation (mm/d) and temperature (°C) at a 1-km spatial resolution (Thornton et al., 2012) and is in contrast to other gridded products (e.g., NLDAS-2 Xia et al., 2019) based on observations only. Snow-water equivalents (SWE; mm) and soil moisture values (mm) were derived from a modeled data set by Newman et al. (2015), who used the Snow–17 snow model coupled with the Sacramento Soil Moisture Accounting (SAC) Model to derive a set of hydro-meteorological variables. Catchment characteristics for the 671 catchments are available via the CAMELS dataset (Addor et al., 2017). Here, we focused on catchment area, elevation, mean potential evapotranspiration, fraction of snow, and aridity.

2.2. Flood Event Identification

Floods in this study are defined as events where discharge exceeds a certain threshold. We use a set of flood events identified using a peak-over-threshold (POT) approach similar to the one used in Brunner et al. (2019) consisting of three main steps and resulting in three data sets: (1) POT events in individual catchments, (2) event occurrences across all catchments, and (3) a regional event set (Figure S1).

- Step 1: Independent POT events are identified in the daily discharge time series of the individual catchments using the 25th percentile of the corresponding time series of annual maxima as a threshold and by prescribing a minimum time lag of 10 days between events (Diederen et al., 2019). Using this threshold resulted in 1.5 extracted events per catchment and year, on average, and a more comparable number of events identified across catchments as compared to using a quantile threshold based on the daily, instead of the annual maxima values.
- Step 2: A data set consisting of the dates of flood occurrences across all catchments is compiled. This set is converted into a binary matrix which specifies for each catchment whether or not it is affected by a certain event.
- Step 3: A set of *regional* events is identified consisting of events relevant at a number of stations and of a certain severity. To qualify for a regional event, the two criteria used in Brunner et al. (2019) must be fulfilled: (i) the event must be of similar importance in the individual catchments affected, and (ii) over all catchments, the event has to be of sufficiently high magnitude. The regional event set is finally set up by summarizing the magnitudes corresponding to the dates of the regional events for each of the catchments in a matrix. The set contains 1,164 events among which 258 occur in winter, 291 in spring, 324 in summer, and 291 in fall.

In addition to the three flood data sets, a binary precipitation event set is composed based on the overall dates of occurrence of floods determined in step 2 in order to enable the establishment of direct links between precipitation and flood spatial dependence. For each date of occurrence and each station, we check whether the same station experienced a POT precipitation event. The precipitation thresholds for the individual stations are defined in the same way as the discharge thresholds.

2.3. Spatial Patterns of Flood Occurrence

The three flood data sets described above are used to look at different aspects of floods. We use the first set, the POT events in individual catchments, to describe the seasonality of flood occurrence by circular statistics which are suitable for describing variables measured on a cyclical timescale (Burn, 1997). We then use the second set, the binary matrix of overall flood occurrences, to map networks of flood co-occurrences and to quantify the flood *connectedness* of a station with other stations.

Flood connectedness is defined here as the number of catchments with which certain catchments co-experience flood events. In addition to overall flood connectedness, we quantify seasonal flood connectedness using a calendar month subset of events given by seasonal matrices of flood occurrences (winter: November–January; spring: February–April; summer: May–August; and fall: September–November). We

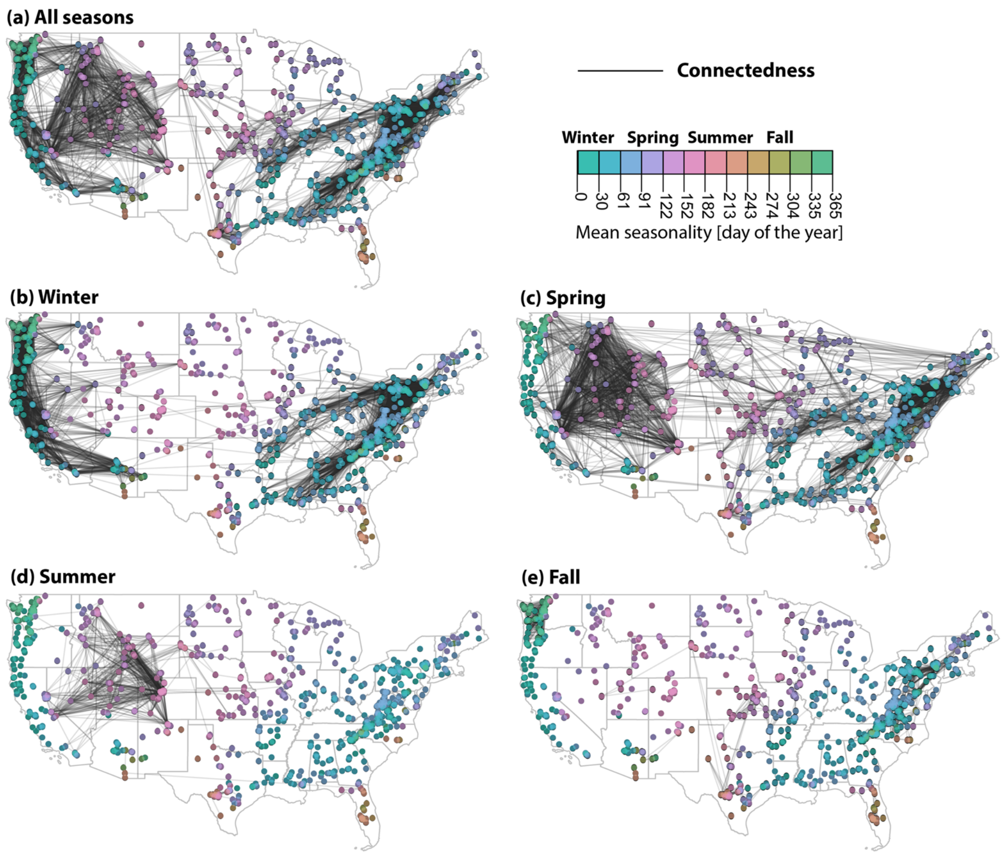

Figure 1. Networks of co-occurrence over (a) all seasons and (b–e) per season. Links indicate flood connectedness between stations, that is, highlight pairs of catchments which have at least 10 events in common over all seasons or five events in common per season. Stations are colored according to the mean day of flood occurrence, also in the seasonal plots.

then apply this procedure to the binary matrix of precipitation events to determine the connectedness in extreme precipitation. The connectedness measure allows for spatial mapping of regions with a high or low spatial dependence, respectively. It does not, however, in itself, allow for the identification of regions with similar flood behavior.

Therefore, to identify regions of catchments with similar flood behavior, a third set, the regional event set, is used in conjunction with a clustering procedure relying on the F-madogram as a distance measure as proposed by Bador et al. (2015) and Saunders et al. (2019). The F-madogram ν^F measures spatial dependence as a function of distance between a pair of stations (h; here Euclidean) by comparing the ordering of extreme events between two time series of extreme events ($Z(x)$ and $Z(x+h)$) (Cooley et al., 2006):

$$\nu^F(h) = \frac{1}{2}\,\mathrm{E}\left|\left|F[Z(x+h)] - F[Z(x)]\right|\right|, \tag{1}$$

where $Z(x)$ are transformed to have Fréchet margins so that $F(x) = \exp(-1/x)$. Here, we use the F-madogram distance computed using the regional flood event set as an input to a hierarchical clustering algorithm (Gordon, 1999) to define regions similar in terms of extreme flood events where catchments show a high spatial dependence. To identify a suitable number of clusters, the hierarchical clustering tree is cut at different levels (k = 2, 3, ..., 30) and we compute the average silhouette width, which represents a measure of clustering validity (Rousseeuw, 1987). We finally chose 15 clusters because the average silhouette width reached a plateau there.

2.4. Relationship of Spatial Dependence with Potential Hydro-Meteorological Drivers

We subsequently place annual and seasonal patterns in flood connectedness in the context of potential hydro-meteorological drivers. To do so, the seasonal connectedness of flood events is compared to the

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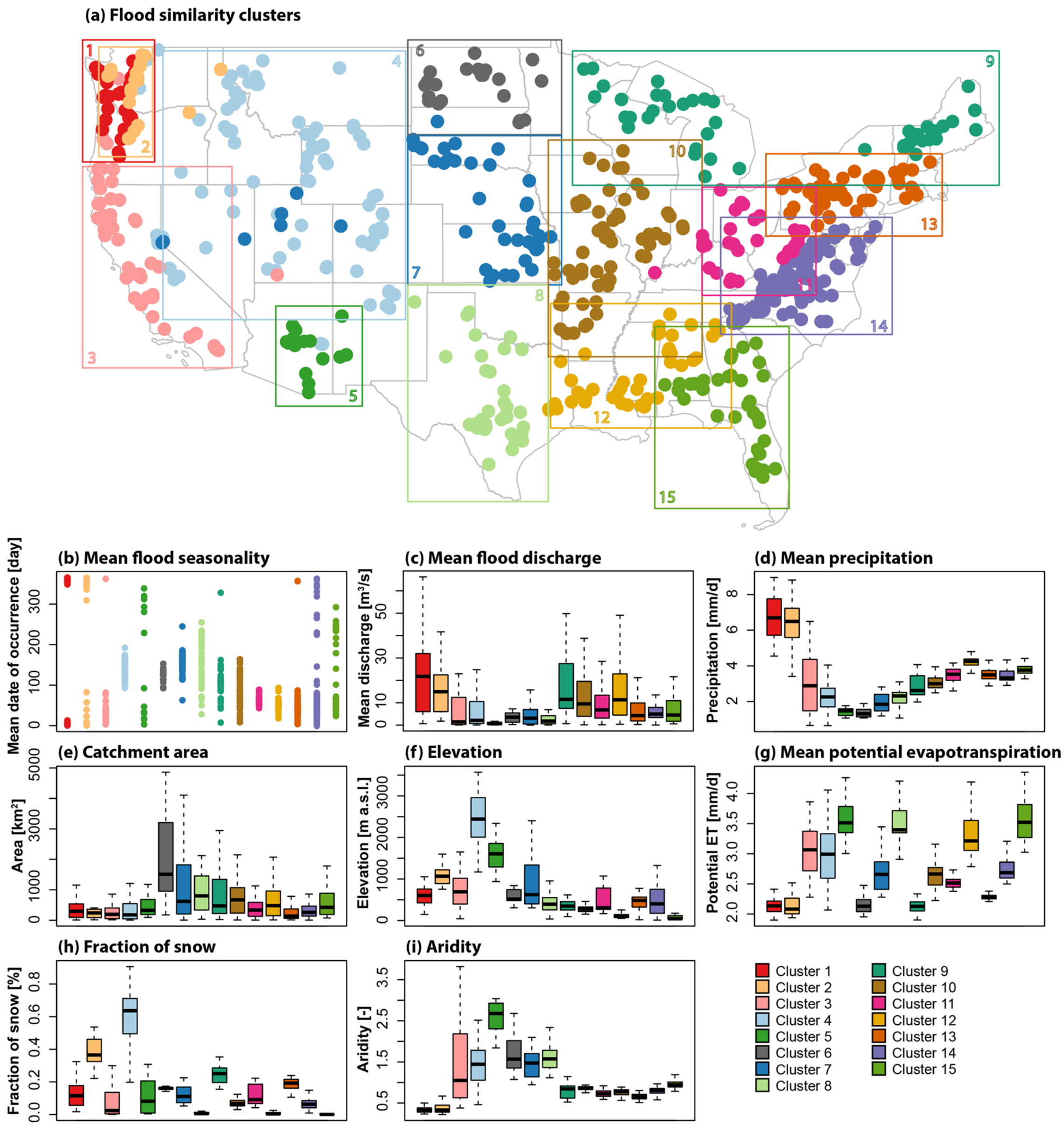

Figure 2. (a) 15 flood similarity clusters showing high spatial dependence in flood occurrence derived using the F-madogram as a distance measure and (b–i) their catchment characteristics.

seasonal connectedness of extreme precipitation events to identify seasons and regions where precipitation is insufficient to explain the spatial dependence of floods. This comparison allows for the identification of regions and seasons that show a higher dependence in floods than in extreme precipitation and vice versa; that is, it allows for the identification of regions where land-surface processes must presumably enhance or reduce spatial dependence, respectively.

We further explore spatiotemporal variations in the physical processes that modulate the hydrologic response to extreme precipitation by conducting a seasonally and regionally specific correlation analysis between flood connectedness and potential flood triggers (at the time of flood occurrence). In doing so, we select potential flood-relevant processes that might plausibly exhibit substantial changes in a warming climate, namely, (1) seasonal mean precipitation during flood events, (2) seasonal mean temperature during flood events, (3) seasonal mean SWE on the day of flood occurrence, and (4) mean soil moisture on the day of flood occurrence. We compute seasonal Kendall's rank correlation coefficients (Kendall, 1937) for these potential drivers and the catchments' flood connectedness for each of the flood similarity clusters established above (Figure 2a).

3. Results and Discussion

3.1. Spatial and Temporal Patterns in Flood Connectedness

We find that flood connectedness varies substantially in both space and time (Figure 1). Across all seasons, it is high along the entire Pacific coast and the Atlantic coast from the Mid-Atlantic northward to New England, where floods mainly occur in winter and spring, in the Rocky Mountains, where floods mainly occur in late spring and summer, and on the western slopes of the Appalachian Mountains, where floods mainly occur in winter and early spring (Figure 1a). However, flood dependence also exhibits strong seasonal variation. It is generally strongest in spring, when floods in Rocky Mountain catchments show a similar timing and catchments in the Mid-Atlantic/New England regions and west of the Appalachian Mountains co-experience floods. These latter regions also show a rather high spatial dependence in winter—a time of year when catchments at the West coast also show a high spatial dependence. In contrast, spatial dependence is broadly weak in summer and almost nonexistent in autumn. The only region showing high spatial dependence in summer is the Rocky Mountain region. In autumn, only Texas and Florida, as well as a small portion of the northern Appalachian watersheds, show some modest spatial dependence.

Following discussions in Touma et al. (2018) regarding extreme precipitation-related weather events, we discuss possible meteorological causes for the observed seasonal and regional variations in flood spatial dependence in the context of existing research. First, we note that the spatial dependence in winter and spring is particularly high in regions where rain-on-snow events—and/or snowmelt—are an important flood generating mechanism (Li et al., 2019). In winter, the high spatial dependence along the Pacific coast may largely be explained by atmospheric rivers and the broader synoptic-scale cyclones that drive them (e.g., Dettinger et al., 2011; Swain et al., 2015). The connection between coastal and inland catchments in this region is suggestive of inland-penetrating atmospheric rivers, which can lead to high flows both in coastal river systems and watersheds that drain higher elevation and drier regions to the east (Rutz et al., 2015).

The spatial dependence along the Eastern Seaboard is likely related to the propensity for oceanic cyclonic storm development in this region (Hirsch et al., 2001; Zielinski, 2002), while the zone of increased flood connectedness extending from the lower Mississippi basin to near the eastern Great Lakes may be the downstream result of cyclonic storm systems generated just east of the Rocky Mountains (Nieto Ferreira & Earl Hall, 2015).

The spatial dependence in spring in the Rocky Mountains can likely be explained by some combination of rain-on-snow and general snowmelt events (Li et al., 2019); across the Great Plains, snowmelt and/or intense precipitation from eastward-propagating mesoscale convective systems likely enhance dependence, mainly in spring (Ashley et al., 2003); and along the East coast, dependence can likely be explained by the occurrence of Gulf Stream-driven oceanic cyclogenesis that persists into spring (Nieto Ferreira & Earl Hall, 2015). The strong spatial dependence in summer in the Rocky Mountains is likely related to lingering snowmelt during the first half of the season, especially in June (Pederson et al., 2011). In autumn, spatial dependence in the coastal Pacific Northwest is likely once again explained by atmospheric rivers, which tend to shift southward along the Pacific coast later during the winter (Gonzales et al., 2019). The autumn dependence in Florida, and possibly southeast Texas, may be related to extreme precipitation events associated with land-falling tropical cyclones (Touma et al., 2019)—the frequency of which typically peaks in September (Kimball & Mulekar, 2004).

3.2. Contiguous Regions of High Spatial Dependence in Floods

These previous results are summarized by the 15 F-madogram cluster regions with a similar annual and seasonal flood behavior (Figure 2a). Besides similar flood characteristics, these regions show a particular set of physiographical and climatological characteristics (Figure 2b–2i). We also discuss a number of plausible flood-triggering atmospheric phenomena previously identified by Schlef et al. (2019) and others.

3.2.1. Western United States

Catchments in the lower elevation coastal Pacific Northwest (region 1) are characterized by high mean annual precipitation and a strong discharge seasonality. They experience floods mainly in December and January, when the Pacific storm track is most active in this region (e.g., Gonzales et al., 2019). Catchments in the higher elevation Pacific Northwest (region 2), including much of the Cascades, are (similarly to region 1) characterized by high mean annual precipitation and strong discharge seasonality but with a higher fraction of snow. Flood seasonality is centered on winter but (unlike in lower elevation region 1) extends into later winter/early spring as well. Catchments along the lower Pacific coast (region 3) are characterized by primarily late winter flood seasonality and a low snow fraction, as well as high interannual variability of mean precipitation and aridity (e.g., Swain et al., 2018). High-elevation catchments in the Rocky Mountains (region 4) are characterized by a high fraction of snow. Here, floods mainly occur in spring and early summer and are strongly influenced by snowmelt. Arid catchments in Arizona and New Mexico (region 5) show a bimodal seasonal distribution of floods, with (a) summer/early autumn events associated with convective downpours during the North American Monsoon in July–August (Higgins et al., 1997) and the occasional remnants of east Pacific hurricanes during September–October and (b) late winter events associated with inland-penetrating Pacific storms (Rutz et al., 2015).

3.2.2. Central United States

Catchments in the northern Great Plains (region 6) have a relatively large catchment size and low mean discharge, and flood occurrence is strongly constrained to spring caused by a combination of spring storms (Ashley et al., 2003) and snowmelt. Catchments in the Central Great Plains (region 7) are characterized by low mean discharge and a low fraction of snow. Floods occur mainly in spring and early summer when extreme precipitation, resulting from warm-season convective storms, tends to peak. Catchments in Texas (region 8) show low mean discharge and flood occurrence in spring to fall caused by a combination of warm-season convective storms and tropical weather systems from the Gulf of Mexico (Touma et al., 2019).

3.2.3. Eastern United States

Catchments encompassing both the northern Great Lakes region and also northern New England (region 9) are characterized by a relatively high mean discharge and fraction of snow. Floods occur mainly in winter and spring and are caused by precipitation associated with cold season extratropical cyclones. Catchments in the Midwest (region 10) have flood occurrences mainly in winter and spring. Floods can be caused by the influence of warm-season convective precipitation (April to October) and the Gulf of Mexico meridional transport associated with cool-season extratropical cyclones (October to May) (Dirmeyer & Kinter, 2010). Catchments in the Ohio Valley along the western slopes of the Appalachian Mountains (region 11) have a modest fraction of snow. Floods occur almost exclusively in early spring, influenced by the Gulf of Mexico meridional transport. Catchments in the south (region 12) have very little snow. As with region 11, floods mainly occur from late winter into early spring, influenced by the Gulf of Mexico meridional transport. Catchments in the northeast (region 13), including southern New England, have relatively high mean precipitation and are influenced by snow. Floods occur in winter and spring and are influenced by the cold season extratropical cyclones. Catchments in the Mid-Atlantic coastal plain and central Appalachian Mountains (region 14) show flood occurrence for much of the year except early-mid summer and are influenced by cool-season coastal extratropical storms and warm-season tropical cyclones. Catchments in Florida (region 15) have no snow influence. Floods occur from spring to fall and are influenced by Atlantic/Gulf of Mexico tropical cyclones (Touma et al., 2019).

Among catchments in a given region, joint flooding is to be expected given the spatial contiguity of flood-driving weather patterns. Since geographically distant catchments are generally less likely to co-experience flooding, regions dynamically defined using intrinsic physical characteristics can therefore be valuable in a flood management context.

3.3. Flood Spatial Dependence is only Partially Governed by Extreme Precipitation Dependence

As with the spatial dependence of floods, we find that the spatial dependence of extreme precipitation (conditioned on dates of flood occurrence) also varies seasonally and regionally (Figure 3). It is strongest in winter and fall and very weak in summer. This result corresponds to findings by Touma et al. (2018), who found that extreme precipitation is often related even at distant locations in the winter months while it is only

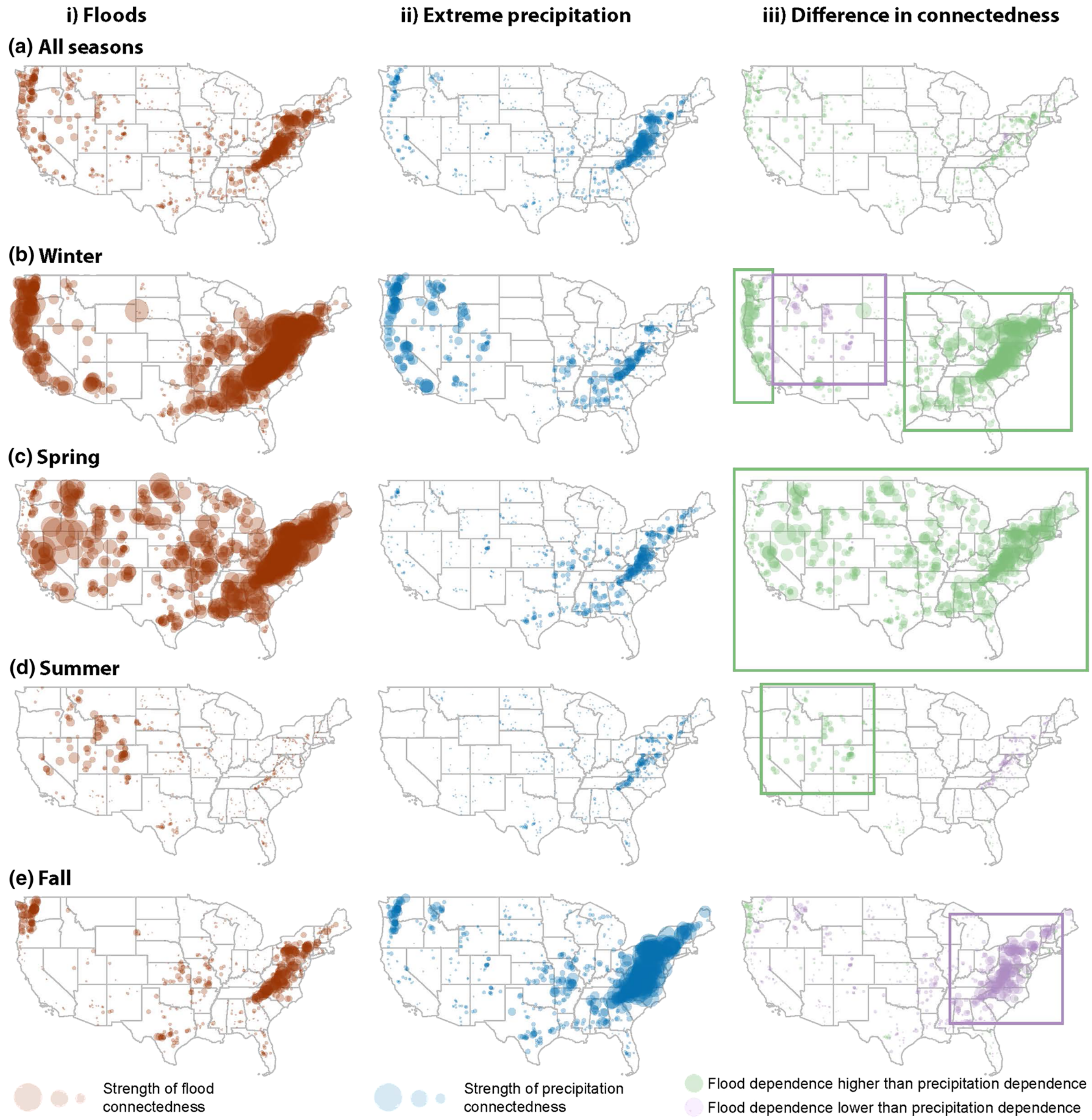

Figure 3. Connectedness of (i) floods and corresponding (ii) precipitation events over (a) all seasons and (b–e) per season. The larger the dot, the higher the connectedness. Differences between the connectedness of floods and extreme precipitation events are shown in panel iii.

related over short distances in summer when precipitation is more frequently associated with relatively localized convective storms.

Over all seasons, we find that the spatial connectedness of floods is higher than the connectedness of extreme precipitation events, with the highest relative differences found in the Rocky Mountains (Figure 2a, cluster 4). This result corroborates results by Keef et al. (2009), who found that the spatial dependence of river flows was stronger than that of extreme precipitation because precipitation was more influenced by small-scale variability. The similarity in the general connectedness patterns of floods and extreme precipitation over all seasons, however, strongly suggests that the spatial dependencies of floods and extreme precipitation are indeed related. This positive relation between precipitation amount and flood connectedness in most seasons and regions is confirmed by our region-specific correlation analysis between flood connectedness and potential flood triggers (Figure 4i). These relations are in contrast to findings by Berghuijs et al. (2019), who showed that the distance between European catchments experiencing annual-maximum floods at the same time is not correlated with the distance between catchments simultaneously affected by

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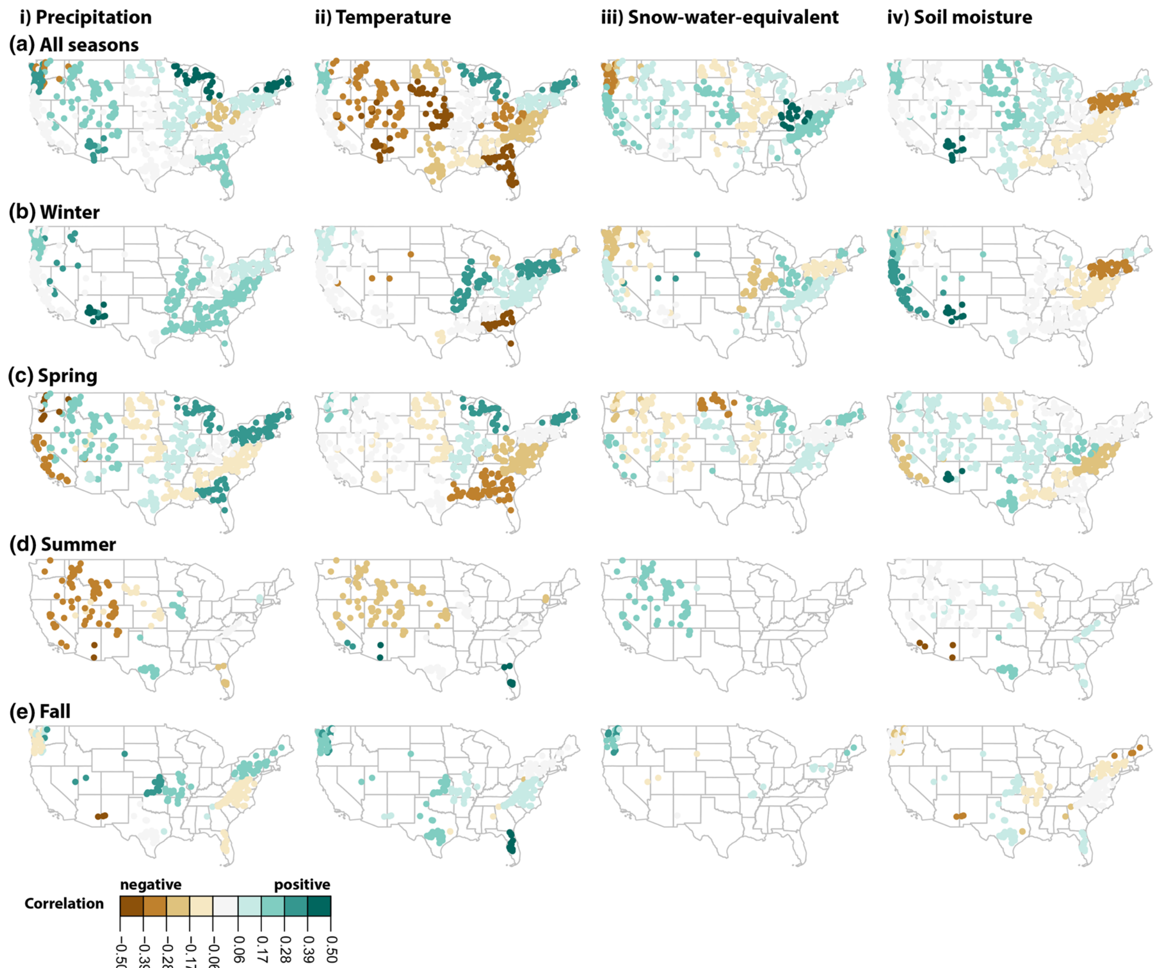

Figure 4. Regional correlations of flood connectedness with (i) mean precipitation during flood events, (ii) mean temperature during flood events, (iii) mean SWE on the day of flood occurrence, and (iv) mean soil moisture on the day of flood occurrence over (a) all seasons and (b–e) per season computed per flood similarity cluster (number of catchments 16–94; Figure 2). Turquoise and brown colors indicate positive and negative correlations, respectively. Catchments showing seasonal connectedness values smaller than five and catchments where seasonal mean event SWE is lower than 0.01 mm are not displayed.

annual-maximum daily precipitation. Our results suggest that such an annual perspective does not provide a complete answer to the question of how spatial precipitation and flood dependence are linked.

3.4. Land-Surface Processes Influence Spatial Dependence of Floods

We find that differences between the spatial dependence of floods and extreme precipitation vary both seasonally and regionally (Figure 3iii), and that the spatial dependence of floods is not always higher than that of extreme precipitation. In winter, flood connectedness is higher than extreme precipitation connectedness along both the east and west coasts but lower in the Rocky Mountains (Figure 3b). The increase in spatial connectedness for floods relative to precipitation is likely related to the observation that SWE enhances flood connectedness across much of the northeastern United States during this season (Figure 4iii) because it allows for rain-on-snow floods (Li et al., 2019). In contrast, the decrease of flood connectedness relative to the connectedness of extreme precipitation in the Rocky Mountains appears to be caused by snow accumulation, which weakens the spatial dependence seen in extreme precipitation due to its predominately solid phase and subsequently delayed runoff.

In spring, the connectedness of floods is broadly higher than that of extreme precipitation (Figure 3c). This behavior is likely related to high soil moisture availability at this time of year (Coopersmith et al., 2012), which leads to the occurrence of many floods in this season and synchronizes the timing of flood events across catchments (Figure 4iv). In summer, precipitation connectedness is generally very low (Figure 3d) likely because of the occurrence of relatively localized convective events with low spatial dependence (Touma et al., 2018). In the Rocky Mountains, however, floods are still spatially connected because snowmelt leads to an increase in spatial dependence as compared to extreme precipitation (Figure 4iii). In fall, the connectedness of extreme precipitation across much of the Eastern Seaboard is higher than that of floods (Figure 3e). This loss of dependence for floods relative to precipitation is likely caused by the relatively dry soils, which do not necessarily lead to an immediate flood reaction and therefore lead to low flood connectedness (Figure 4iv). While it is commonly understood that antecedent soil moisture, snowmelt, and extreme precipitation play an important role in flood generation, these findings quantify the way in which such processes and inputs also govern the spatial dependence (coherence) of floods. Collectively, our results show that the importance of individual drivers in governing the strength of spatial dependence varies substantially in space and time and that previous studies employing broad spatiotemporal smoothing likely miss these critical variations.

3.5. Implications for Changes in Spatial Flood Dependence in Warming Climate

The important role of both meteorological and land-surface processes in shaping spatial flood dependence suggests the potential for substantial change in the spatial dependence (and even overall occurrence) of floods in a warming climate. Kemter et al. (2020) have shown in a recent study that spatial flood extents are already undergoing changes because of changes in the importance of different flood generating mechanisms. In future, the spatial dependence of floods may evolve in a spatially and temporally nonuniform manner due to changes in snowmelt contributions to runoff (Li et al., 2017), the frequency of rain-on-snow events (Li et al., 2019), the spatial extent of convective storms (Chang et al., 2016; Wasko et al., 2016), widespread projected soil moisture aridification (Cook et al., 2015), and shifting regional seasonality of precipitation (Swain et al., 2018). Our results suggest that the projected precipitation increase in the northern and northeastern United States in winter and spring has the potential to increase flood connectedness in these seasons, while flood connectedness might decrease across the southern tier of the United States due to projected increases in temperature and decreases in precipitation (Easterling et al., 2017). Moreover, the large projected further decreases in snowmelt contributions associated with higher temperatures (Easterling et al., 2017) will lead to a decrease in spatial flood dependencies in the Rocky Mountains in summer and perhaps to an increase in coherence earlier in the year in association with projected earlier snowmelt timing.

Precisely how these future changes may influence the spatial dependence of floods remains to be investigated given the complex interplay between atmospheric, biospheric, and land-surface processes in a warming world. Still, the expected changes in climate and associated land-surface processes clearly have strong potential to amplify or mitigate spatial dependence and therefore influence the risk of widespread flooding. An increase in spatial dependence would imply an increase in the probability of joint flooding and subsequent areal damages, while a decrease in dependence would imply more independent events and subsequently reduced areal damages.

3.6. Implications for Modeling Spatial Floods

The finding that spatial flood dependencies vary considerably in space and time highlights the importance of taking into account seasonal variations in the development and application of spatial flood modeling approaches used for flood hazard and risk assessments. These considerations particularly apply to statistical models, which must make assumptions regarding the type and strength of spatial dependence. As a consequence, statistical model development should focus on approaches that allow for seasonal variations—not just limited to marginal distributions—and also extending to dependence structures. This goal can be achieved by moving away from fitting models on annual maxima series (e.g., through the use of max-stable processes; Ribatet & Sedki, 2013) toward the development of models based on partial duration series (e.g., through the use of Pareto processes; Tawn et al., 2018) or continuous flow series (e.g., Brunner & Gilleland, 2020).

The finding that spatial flood dependencies are governed by both spatial precipitation dependencies and land-surface processes highlights the importance that these processes must be realistically represented in physical/hydrological models and are present in the initial and boundary conditions used to drive these models. Such models implicitly make assumptions regarding underlying drivers via model parameterizations for processes not explicitly simulated. Thus, it is critical that different land-surface and flood generation processes, including soil moisture storage and snow-related processes, are realistically represented. In addition, precipitation data sets must adequately represent spatial dependencies in extreme precipitation—a consideration that is especially important in the case of gridded data sets, for which spatial interpolation schemes may change the nature of spatial dependencies (Newman et al., 2015; Wong & Skamarock, 2016).

4. Conclusions

This work introduces a flood connectedness measure enabling the mapping of spatial flood dependence. Our results for the United States reveal that the spatial dependence of floods varies strongly on a regional and seasonal basis. It is generally strongest in winter and in spring and is almost universally low in summer and autumn except in the Rocky Mountains. We further find that the spatial dependence of floods substantially differs from the spatial dependence of extreme precipitation in a manner that varies between regions and seasons—with flood dependence generally exceeding precipitation dependence in winter/spring. We therefore conclude that land-surface processes such as snowmelt or soil moisture anomalies not only influence the magnitude of floods but also strongly shape the spatial dependence of floods by modulating the role of the driving atmospheric (precipitation) forcing. It is demonstrated that this filtering of the spatial dependence of floods by land-surface processes also varies in space and time. While spatial flood dependence is mostly related to precipitation in winter, it is more related to soil moisture in spring and to snowmelt in summer in the Rocky Mountains. We emphasize that regional and seasonal nuances are critical in understanding both underlying processes and actual flood risk and that failure to include these spatiotemporal aspects when simulating spatial flood events in flood hazard and risk assessments may under (or over-) estimate risk.

Data Availability Statement

The daily discharge time series used in this study are available via the USGS website: https://waterdata.usgs.gov/nwis, and the CAMELS catchment attributes can be downloaded via https://ral.ucar.edu/solutions/products/camels.

Conflict Of Interest

The authors do not have any conflict of interests.

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