Multisourced Flood Inventories over the Contiguous United States for Actual and Natural Conditions

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ABSTRACT: A reliable flood event inventory that reflects the occurrence and evolution of past floods is important for studies of flood hazards and risks, hydroclimatic extremes, and future flood projections. However, currently available flood inventories are based on single-sourced data and often neglect underreported or less impactful flood events. Furthermore, traditional archives store flood events only at sparse geographic points, which significantly limits their further applicability. Also, few publicly available archives contain all-inclusive records of potential natural flooded area over time. To tackle these challenges, we construct two types of multisourced flood event inventories (MFI) for all river basins across the contiguous United States covering the period 1998–2013 on daily and subcatchment scales, which is publicly available at <http://flood.umd.edu/download/CONUS/>. These archives integrate flood information from in situ observations, remote sensing observations, hydrological model simulations, and five high-quality precipitation products. The first inventory (MFI-Actual) includes all actual floods that occurred in the presence of flood protection infrastructures, while the second, “natural (undefended)” inventory (MFI-Natural) reconstructs the possible “historical” floods without flood protection, which could be more directly influenced by climate variation. In the proposed two inventories, 2,755 and 4,661 flood events were estimated, respectively. MFI-Natural reconstructed 1,597 floods in ungauged basins, and recovered 608 extreme streamflow events in gauged subcatchments where floods would have happened if there were no flood protection. There is an average of four upstream dams located in these flood-recovered subcatchments, which indicates that modern flood defenses efficiently prevent significant flooding from extreme precipitation in many catchments over the country.

KEYWORDS: Anthropogenic effects/forcing; Climate change; Climatology; Hydrometeorology; Databases; Flood events

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Floods are among the most prominent and catastrophic natural disasters in the world that account for a large portion of all geophysical hazards (Smith and Ward 1998; Wahlstrom and Guha-Sapir 2015; Alexander 2018). The frequency of flood hazards has been increasing during recent decades (Hirsch and Archfield 2015; Mallakpour and Villarini 2015; Wahlstrom and Guha-Sapir 2015), and more intense flood events are projected to increase in the future (Milly et al. 2002; Hirabayashi et al. 2013; Alfieri et al. 2017). Moreover, with the densification in population and expansion of built-up areas in the flood plains, the potential of floods that can cause huge economic losses has rapidly increased, in addition to the loss of life and cultural heritage (CRED 2019; UNDRR 2019).

Flood generation mechanisms have become more complex under the human-related changing land surface environment and a warming climate. Studies showed that intensive human activities have significantly increased their impacts on infiltration and groundwater holding capacities by altering the landscapes. The addition of dams and reservoirs further alters the timing, magnitude, and frequency of peak flood flows because of added storage capacity and flood regulation (Magilligan and Nislow 2005; Graf 2006; FitzHugh and Vogel 2011; Volpi et al. 2018). Apart from these human induced modifications, there is growing evidence that precipitation extremes show an increasing trend in many places over the past decades (Groisman et al. 2001, 2012; Alexander et al. 2006; Kunkel et al. 2013; Westra et al. 2013). Nevertheless, daily precipitation intensity changes, except at the very high end, generally have a relatively weak effect on floods (Yan et al. 2020a), and there is little evidence that flood magnitudes have increased in the past (Sharma et al. 2018). Only 36% of extreme precipitation events result in discharge extremes (Ivancic and Shaw 2015), and decreases in peak flow are typical for regulated basins over the contiguous United States (CONUS) (Hodgkins et al. 2019). Therefore, quantitatively assessing changes of flood frequency and intensity responding to the global environmental changes in landscape and/or climate requires appropriate benchmarks of historical flood inventories.

To address these challenges, a number of global and regional flood event datasets as well as flood estimation techniques have been proposed (Marchi, et al. 2010; Špitalar et al. 2014; Saharia et al. 2017a,b; Cohen et al. 2018; Yang et al. 2021). However, most of the existing flood event databases are developed based on single-sourced data and few focus on events under the assumption of no flood protection (He et al. 2020). Gauge-based databases (e.g., Gourley et al. 2013; Shen et al. 2017) enlist flood events that are restricted to the scattered stream gauges and limited by data availability. Report-/news-based flood databases, both global [e.g., the Dartmouth Flood Observatory (DFO), <http://floodobservatory.colorado.edu/>; the Emergency Disasters Database, www.emdat.be/;

the International Flood Network, www.internationalfloodnetwork.org; the ReliefWeb, www.reliefweb.int/ and regional (Diakakis et al. 2012; Du et al. 2015; Santos et al. 2017), usually tend to be biased toward well-reported areas (Wu et al. 2012, 2017). Survey-based databases (e.g., Gourley et al. 2010) highly depend on the subjective judgment of the respondents. There are also some databases that document flow time series without identifying the flood events (Lin et al. 2019). In general, single-sourced datasets tend to miss underreported or less impactful flood events, resulting in incomplete records in both time and space. Furthermore, the traditional flood event archives tend to store flood events only on a point-by-point basis with little attention to the spatial extension of floods (e.g., Gourley et al. 2013; Shen et al. 2017). Also, existing flood databases differ depending on the data sources, the definition of flood events, and processing algorithms, which have brought additional challenges to flood hazard studies.

In this study, we compile two multisourced, spatially distributed flood inventories to provide a comprehensive documentation of floods across the entire CONUS at subcatchment level for the period of 1998–2013. The multisourced flood inventories (MFI) are based on the integration of flood information from in situ observations, remote sensing measurements, and hydrological model simulations. Discharge simulations are derived from the Dominant River Tracing-Routing Integrated with VIC Environment (DRIVE) model (Wu et al. 2011, 2012, 2014) at 3-hourly and 0.125° temporal and spatial resolution driven by the phase 2 of the North American Land Data Assimilation System (NLDAS-2) precipitation product (Xia et al. 2012). The time period (1998–2013) chosen to be consistent with the TRMM era is mainly because most of our model calibration–validation, evaluation, and application efforts have been performed within that time period (e.g., Wu et al. 2012, 2014, 2017; Jiang et al. 2020; Yan et al. 2020a,b), which might allow us to provide a set of valuable flood inventories with higher confidence. The two types of flood inventory are supposed to be valuable in research studies across a variety of fields. The actual inventory (MFI-Actual) includes all flood events that actually occurred in the past with human-regulated landscape and flood protection infrastructures, which could be used to investigate the anthropogenic impacts on floods occurring under global environment changes. The “natural (undefended)” inventory (MFI-Natural) contains reconstructed “historical” flood events under the assumption of no flood protection, i.e., an estimate of events that would have happened under a “natural” system. Some basic statistics from both inventories are then explored and compared.

Data and methodology

Data. Point-based flood records are first derived using the observed daily discharge data from 1,611 USGS gauges, which are carefully selected from the entire USGS observation network (<http://waterwatch.usgs.gov>). The selection is based on the following criteria: 1) daily data of the gauge must be available during 1998–2013; 2) the gauge must be well located in the river network of the Strahler order system deployed in the DRIVE model, with difference in upstream drainage area between USGS dataset and flow accumulation map less than 10% (Wu et al. 2011, 2014); and 3) no more than 3 years of summers (i.e., June–August) that have more than 15 days of missing data. This selection procedure provides a high-quality in situ flood information dataset for the CONUS river basins, but still leaves significant gaps across the spatial domain.

The DFO provides a global active archive of large flood events, which is derived from news, governmental, instrumental, and remote sensing sources. The archive covers events from 1985 to the present and provides the locations (latitudes and longitudes) and the start and end dates of the reported floods. The 226 reported flood events with information on affected areas across the CONUS during the study period (1998–2013) represent the remote sensing–based events in this study.

The simulated flood events were derived from the retrospective hydrological model simulation results at 3-hourly temporal resolution and $1/8^\circ$ spatial resolution. The Global Flood Monitoring System (GFMS), built on the DRIVE model (Wu et al. 2014), has been used to steadily monitor and forecast the occurrence and evolution of flood events for more than a decade (Hou et al. 2014; Kirschbaum et al. 2017). Multiple-year efforts of model justification and validation have also been reported and discussed from various aspects in the previous studies (Wu et al. 2014, 2017, 2019; Yan et al. 2020a,b). The accuracy of DRIVE in global flood detection has been validated against streamflow observations from global river gauges and archived flood events from the DFO (Wu et al. 2014). Furthermore, the flood modeling results of DRIVE showed good concurrence and consistency with NASA Soil Moisture Active Passive (SMAP) fractional water cover retrievals in most of the global domain (Wu et al. 2019). Approximately 63.9% of the global domain showed good positive SMAP-GFMS correspondence ($r \geq 0.4$). In this study, the DRIVE model is driven by the precipitation information from the NLDAS-2 (Xia et al. 2012). Other atmospheric forcing data (i.e., air temperature and wind speed) were derived from the NASA Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) (Gelaro et al. 2017). The hydrography dataset (e.g., flow direction, flow accumulation, Strahler order) is derived using the hierarchical dominant river tracing (DRT) algorithm (Wu et al. 2011, 2012). A 5-yr model spinup run (1993–97) was performed preceding the retrospective run (1998–2013) to define initial conditions. Discharge is simulated for each grid cell over the CONUS at every 3-h time interval, where flood events for each $1/8^\circ$ grid cell were then derived.

The hydrological model simulations, carefully considered in conjunction with high-quality precipitation information, should be able to provide information to supplement stream gauge information and help achieve a more comprehensive account of flood events, including in ungauged subcatchments. Given that precipitation has significant uncertainties in its measurement, five high-quality precipitation products based on different data sources are adopted in this study to provide additional verification for simulated flood events. The five precipitation datasets are the gauge-based CPC Unified (Xie et al. 2007; Chen et al. 2008); the gauge- and satellite-combined TMPA 3B42V7 (Huffman et al. 2007); the gauge- and radar-combined Stage IV (Lin and Mitchell 2005; Baldwin and Mitchell 1998); the satellite- and reanalysis-incorporated Multi-Source Weighted-Ensemble Precipitation (MSWEP) version 2.1 (Beck et al. 2017, 2019); and the gauge-, radar-, and satellite-combined NLDAS-2 (Xia et al. 2012). The time period used in this study for MSWEP and Stage IV is 2000–13 and 2002–13, respectively, while the other three products capture the entire period of interest, 1998–2013. To keep consistent with the model simulation and event validation process (shown below), the NLDAS-2 precipitation is converted to $1/8^\circ$ resolution and a 3-h time step, while the other four products are converted to $1/8^\circ$ resolution and a daily time step.

Methodology. This section describes the details on the proposed algorithm including steps of flood event identification, validation, and integration. A schematic view of the connections between each step is shown in Fig. 1, while detailed criteria are provided in Fig. ES1 in the online supplemental material.

FLOOD EVENT IDENTIFICATION. In this study, we focus on major flood events for better accuracy of the proposed flood inventories and used the magnitude of flow corresponding to a 20-yr average recurrence interval as the threshold to define flood events. This is because the uncertainties in small flood measurement and estimation tend to be larger, while the occurrence signals of larger flood events tend to be well captured in gauge observations even downstream of dams/reservoirs. Specifically, there are fewer river gauges in headwaters, particularly in mountainous areas, and remote sensing products tend to have strong signals with major

Fig. 1. Schematic view of the development of the multisourced flood inventories.

floods, while the DRIVE model tends to derive a higher false alarm rate when dam/reservoir prevent many minor-to-moderate floods for downstream areas (Wu et al. 2012, 2014).

To construct flood event databases at subcatchment scale, the DRT hydrographic dataset at $1/8^\circ$ resolution is used to discretize the land surface into a network of hierarchically connected subcatchments. All USGS gauges are located in the DRT river network representing corresponding subcatchments. For each gauge or grid cell, the 20-yr return period flood threshold of observed or simulated flow time series is calculated based on the log Pearson type III (LP3) distribution (IACWD 1982; Wu et al. 2012) and then used to perform the flood event identification. If the discharge crosses the threshold for several subsequent days or with a gap of no more than 3 days, we consider it to be a single flood event; if the discharge crosses the threshold for several days but with a gap beyond 3 days, this situation will be considered as two separate events, similar to Ward et al. (2016) and Yan et al. (2020a,b).

The DFO flood events are disaggregated into the DRT subcatchment network based on the area affected outlines provided in the archive. As the affected area represents an estimated extent of larger geographic regions affected by flooding rather than actual flooded areas, we use NLDAS-2 precipitation product to validate each subcatchment and remove those subcatchments that might not experience extreme flood events. The flood event in a segmented subcatchment will be retained if either of the corresponding 3-hourly precipitation and 7-day mean-basin precipitation accumulation reach the magnitude of 20-yr average recurrence interval for which we believe a significantly large flood event would happen (Yan et al. 2020a).

FLOOD EVENT VALIDATION. Different validation steps are designed respectively for both actual and natural flood events. With regard to actual flood events, we remove insignificant (see below) observed events and identify events for ungauged basins. For the natural flood inventory, we verify the gauge-based events and recover additional natural events that are suppressed by flood defenses. Specifically, the validation is described as follows:

- 1) Remove insignificant events for MFI-Actual. It is known that flood events do not fit any specific statistical distribution, e.g., the widely used gamma distribution-based LP3 method has a tendency to estimate low upper bounds of the magnitudes (IACWD 1982; Wu et al. 2012). Flood events derived from USGS daily discharge time series that meet the following two criteria are considered to be insignificant events and are then removed: 1) the observed peak discharge of a given flood event is less than $1,000 \text{ m}^3 \text{ s}^{-1}$ if the drainage area of the gauge is over $100,000 \text{ km}^2$ and 2) the difference between the observed peak discharge and the mean of annual maximum daily discharge is less than 15%. For criterion 1, the magnitude of $1,000 \text{ m}^3 \text{ s}^{-1}$ for large river basins is determined based on the reference discharge data from Hydro-Climatic Data Network (Slack and Landwehr 1992), in order to exclude insignificant events in some large rivers that have been dammed, diverted and gradually shrinking. According to these two criteria, 25 events are excluded from the observed flood list, most of which are located in regions with a semiarid climate. An example of removed events at USGS gauge 09421500 is shown in Fig. 2a, which is located below the Hoover Dam and downstream of approximately 70 medium to larger dams. The two criteria help filter out those minor floods with insignificant peak magnitude in some river basins where seasonal and interannual streamflow show small variations.
- 2) Identify flood events in ungauged basins for MFI-Actual. The gauge-based flood events are regarded as “confirmed” events. For headwater subcatchments (upstream to Strahler order 2), a simulated flood event will be determined as a “confirmed” event, if it corresponds well to an immediate downstream confirmed flood event according to flood timing, because a downstream event is likely caused by its immediate upstream flood event (Wing et al. 2020). For higher-order subcatchments, a simulated flood will be recorded as a confirmed event, if it corresponds to a confirmed event in its immediate upstream/downstream subcatchment with the same Strahler order, or its lower-order subcatchment in the major upstream tributary. A similar process is followed hierarchically from headwater to most downstream subcatchments, until all subcatchments are assigned with observed or simulated flood events, if any.
- 3) Verify gauge-based events for MFI-Natural. As the hydrographs derived from gauges in highly regulated basins may not represent the natural flow conditions in some rare cases, all the gauge-based events are further verified by checking both 3-hourly and 7-day mean-basin precipitation accumulation derived from NLDAS-2 product. If one or both is greater than the 20-yr estimated recurrence interval, the gauge-based event would be preserved as a natural event.
- 4) Recover natural events for MFI-Natural. For those events that are only detected by model simulation, an additional flood event verification step is performed using the five precipitation products previously mentioned. We trace the flood-generating extreme precipitation within a 5-day temporal window before the flooding day, as lags larger than 5 days are most likely reflecting snowmelt, rather than rainfall from headwater catchments (Ivancic and Shaw 2015). If more than three precipitation products simultaneously show an extreme precipitation event, the flood event is considered as a natural event that would have happened under natural conditions. Apart from extreme precipitation, floods are also influenced by the wetness state of the catchment before the onset of flood. Therefore, we

(a) USGS 09421500 Colorado River below Hoover Dam, AZ-NV

(b) USGS 07010000 Mississippi River at St. Louis, MO

Fig. 2. Examples of (a) removed events and (b) recovered events. The USGS gauge 09421500 in (a) is located below the Hoover Dam and downstream of another 70 dams, showing a small magnitude and variation of flow relative to its basin area and no significant flood event existed. The magnitude of peak flow at USGS gauge 07010000, highly reduced by regulation or diversion, is recovered based on simulation and precipitation verification, as shown in the bottom panel of (b).

further introduce the antecedent precipitation index (API), which has been widely used in the hydrological community (e.g., Hong et al. 2007; Pui et al. 2011; Bennett et al. 2018; Ridolfi et al. 2020), as a secondary method to verify the remaining simulated events. The method proposed by Kohler and Linsley (1951) is used:

$$API_i = P_i + KP_{i-1} + K^2P_{i-2} + \dots + K^nP_{i-n},$$

where P is the daily precipitation sum, i is the day for which API is calculated, and K is the decay factor. The value of decay factor K is suggested to range from 0.8 to 0.98 (Viessman and Lewis 1996), and a midrange value of 0.9 is used in this study which is similar to Hong et al. (2007), assuming a decay rate of 10% day⁻¹ of water stored in a catchment. The 5-day API is calculated to compare with the climatological distribution of all APIs. The climatological sample is defined by a 2-month temporal window centered on the flood day from 1998 to 2013 (Froidevaux et al. 2015). If the 5-day API is higher than the 95th percentile of the climatological sample, the flood event is then considered to be reasonable and added to the natural inventory. An example of recovered events for the Mississippi River at St. Louis, Missouri, is shown in Fig. 2b. This river flooding event resulted from two upstream extreme rainfall events in Wisconsin and Iowa, which had produced peak-of-record streamflow at 77 USGS gauges in June 2008 (NWS 2009; Holmes et al. 2010). The peak discharge recorded at the USGS gauge 07010000, highly reduced by regulation or diversion (Holmes et al. 2010), resulted in failing to identify this as a major flood event. In this case, the precipitation-verified simulated hydrographs can generally capture the onset and evolution of the observed flood event, and reproduce the flow peak with a 5% annual exceedance probability that would have happened naturally. Similar cases would be further treated as recovered events.

FLOOD EVENT INTEGRATION. Flood events identified in the same subcatchment are integrated according to the following rules: 1) if only one single event or multiple separated events were derived in a given subcatchment, these events would be archived into corresponding inventory directly; 2) if there were overlapped events, the start date of the earliest flood event within a subcatchment is defined as the start date of the flood event for a given subcatchment, while the end date for the latest event is defined as the end date. The flood events in all subcatchments were compiled for MFI-Actual and MFI-Natural, respectively.

FLOOD MATCHING BETWEEN SIMULATED AND OBSERVED FLOOD EVENTS. To justify the reliability of supplementary simulated flood events, quantitative evaluation is further performed to ensure that the model results can capture the flood occurrence accurately and simulate the flood evolution reasonably. Three classic categorical verification metrics, including probability of detection [POD; $a/(a + c)$], false alarm rate [FAR; $b/(a + b)$], and critical success index [CSI; $a/(a + b + c)$], are calculated against observations based on a 2×2 contingency table (a = simulated yes, observed yes; b = simulated yes, observed no; c = simulated no, observed yes). A preset buffer time surrounding the observed flood duration is used for matching the observed and simulated flood events. A 15-day buffer is set for the flood events with drainage areas smaller than 100,000 km² while a 30-day buffer is set for the remaining 25 events that occurred in the larger rivers systems.

Results

Flood events according to USGS gauge data and DFO inventories. With the criteria listed in the “Data and methodology” section, a total of 1,611 USGS gauges and 1,654 DFO-based events at subcatchment scale are selected and used in this study to develop the MFI (see Fig. 3). These gauges are distributed in 927 subcatchments ranging from second to seventh order, appearing on a diminishing scale from east to west and covering 18.1% of all subcatchments in the CONUS. In total, 1,056 flood events that reached 20-yr average recurrence interval were extracted from 968 gauges. Around 90% of these gauges recorded one flood event during the

Fig. 3. Flood events observed by USGS gauges and DFO during 1998–2013. The colored polygons with borders represent subcatchments where DFO events happened. The green circles are locations of USGS gauges that observed flood events, while black circles are gauges with no floods. Gauges with removed flood events are presented as red cross.

16-yr period, and seven gauges observed the largest number of three events. Based on the aforementioned validation procedure, 25 events at 12 gauges are identified as insignificant events and removed from the database, most of which are located in the Colorado River and its tributaries with a semiarid climate. As for the DFO flood events, 1,654 events in 1,266 subcatchments were disaggregated from 226 original events based on the affected area and precipitation-based validation procedure, which shows a consistent distribution pattern with USGS gauges. According to Fig. 3, most of the observed flood events are captured along the Mississippi River and its tributaries, especially in the middle and eastern part of the Mississippi River basin. The proportion of the number of subcatchments with selected USGS gauges and DFO observed events to all subcatchments are 38.1%, 53.9%, 70.8%, 70.4%, 77.8%, and 100% for second- to seventh-order subcatchments, respectively. This distribution indicates that in situ and remote sensing-based observations notably miss flood events, particularly in lower-order catchments, due to either the absence of river gauges or the difficulties of remote sensing-based flood retrieval under various situations (Wu et al. 2019).

Evaluation of simulated flood events. The DRIVE-simulated discharge shows a very good correlation with the observed daily discharge data from the USGS gauges (Fig. ES2), having 69.0% of all the gauges with daily correlation coefficient larger than 0.5 and a mean of 0.67, which indicates promising performance in flood event detection consistent with the validation in Wu et al. (2014). Based on the aforementioned flood event matching method, the DRIVE simulations detected 912 events (86.3%) out of total 1,056 observed events from USGS gauges. The model performance in flood detection is very stable across different Strahler levels of river, with PODs of 0.86, 0.87, 0.86, 0.87, and 0.89 for the second- to sixth-order subcatchment and FARs ranging from 0.13 to 0.16 (see Table 1). This is a much better performance than described in Wu et al. (2014), likely because we focus on larger flood events in this study in order to provide higher confidence of the results.

Additionally, we also compared streamflow modeling performances in river basins with different levels of flood protection, i.e., no dam, one to four dams, and more than four dams. The results (not shown) show a larger variation in model performance as the number of dams increases, indicating larger difference in flood event identification in the “natural floods” and

“actual floods” in river basins with more dams/reservoirs. A detailed study quantifying the dam/reservoir impacts on flood detection has been described in previous papers (e.g., Wu et al. 2014), in which about 30% more false alarms (floods which would likely occur naturally but are prevented by reservoir/dam operations) are reported in river basins with more dams. Examples of dam/reservoir impacts on flood detection are also shown in Figs. ES2d–f. Overall, good skill (high POD, low FAR, and high CSI scores in Table 1) validates the model reliability and efficiency on flood occurrence detection, providing a good justification of using the DRIVE model simulations to supplement observations.

The spatial distribution of flood events over CONUS. By integrating the results from USGS observations, DFO remotely sensed dataset, DRIVE simulations, and the verification based on five independent precipitation products, we archive a total of 2,755 and 4,661 flood events at subcatchment scale in MFI-Actual and MFI-Natural, respectively. The spatial distributions of flood events in MFI-Actual and MFI-Natural are depicted in Fig. 4. Overall, the spatial patterns of flood occurrence are roughly similar between actual and natural flood events. Floods occur more frequently in subcatchments in the Mississippi basin and states along the

Table 1. Flood detection verification against 1,611 USGS gauges.

	All	2nd	3rd	4th	5th	6th	7th
POD	0.86	0.86	0.87	0.86	0.87	0.89	—
FAR	0.15	0.15	0.16	0.16	0.16	0.13	0
CSI	0.71	0.70	0.72	0.72	0.78	0.47	—

Fig. 4. The distribution of flood event number from (a) actual and (b) natural flood inventories.

coastline (Fig. 4a). Spatial inconsistencies between upstream and downstream basins can be found in some rivers where no observations are available and/or where significant flood defenses are built, e.g., the absence of flooding in the confluence of upper Mississippi River and Missouri River (also shown in Fig. 2b). High frequency of natural flood is also found in subcatchments in the lower Mississippi and states along the coastline, with an even higher frequency in some south-central subcatchments (Fig. 4b). Through the validation procedure, MFI-Natural reconstructs 1,597 events in 1,398 ungauged basins, most of which are located in desert Southwest and northern basins (Fig. ES3d). Over 70% of these recovered natural events occurred in lower-order (upstream) catchments, in concert with the distribution of observational data. Apart from ungauged basins, flood events are also recovered as responses to intense precipitation in some gauged subcatchments, which are constrained by dams, levees, and other man-made structures (Fig. ES3d). In total, the natural flood inventory recovers 608 flood events in 523 subcatchments where flow might be affected and regulated by human activities. There is an average of four upstream dams located in these flood-recovered subcatchments, compared with a mean of two dams per subcatchment for the entire CONUS. This indicates that modern flood defenses (dams, levees, etc.) could alter the flood flows and efficiently prevent significant flooding from extreme precipitation (Poff et al. 2007; FitzHugh and Vogel 2011; Grill et al. 2015; Mei et al. 2017). Besides, the

better spatial homogeneity in the natural inventory along the watercourses compared with that in the actual version, provides a general view of flood distribution that affected by climate (natural) variations.

The CONUS study area was divided into 17 major river basins according to the Watershed Boundary Dataset (USGS 2013) to further explore the characteristics of actual and natural flood events (see Fig. 5). Among most river basins, the number of natural flood events presented a similar but not identical pattern to that of the actual events. The natural flood events had a higher number, indicating higher flood frequency or larger flooding area compared to the actual events. Flood events under the real-world scenario are mainly contributed by observations from the USGS gauges and the DFO archive (Fig. 5a), whereas the natural flood events are primarily based on simulation results (Fig. 5b). It is important to note that the regional disparity in the number of recovered flood events is largely affected by basin area and subcatchment number. For example, the marked difference between the number of actual and natural flood events in the Missouri River is greatly attributed to its basin area, which is the largest among all the major basins with the most subcatchments. Taking the subcatchment number into account, flood-prone areas are generally located in the southern United States, while areas with fewer floods tend to be along the Rocky Mountains, regardless of scenarios. The largest difference between actual and natural flood events appears in the Tennessee, Arkansas–White–Red, Texas–Gulf, lower Mississippi, and lower Colorado basins, with differences larger than 0.5 event per subcatchment (see Fig. 5c). This might be related to the high precipitation amount in those regions, which increases the risk of flooding as indicated by the number of flood events on average (1.5 events) for each subcatchment. In the New England, Mid-Atlantic, and California regions, observed events comprise a substantial portion of the whole, which could be attributed to the high percentage of subcatchments with observations and might be an explanation for the small differences between the two inventories.

Fig. 5. Distribution of flood events in 17 major river basins under (a) regulated and (b) natural scenarios, and (c) events per subcatchment of both scenarios.

Temporal characteristics of flood events in CONUS. Variations in the mean monthly count of flood events originating from each data source and each inventory are depicted in Figs. 6a and 6b. All single-sourced or observation–model combined inventories show consistent monthly and seasonal distributions over the entire domain. A majority of flood events are concentrated in May, June, and September, which comprise around 50% of the total flood events. The higher number of flood events in May and June can be explained by prevailing convective thunderstorms throughout the central and eastern half of the United States (Ashley and Ashley 2008). For some northern basins (e.g., Columbia River, upper Missouri River), springtime snowmelt and rain-on-snow events are the primary driver of floods in May. The peak flood frequency in September is largely attributed to tropical storms and hurricanes making landfall in the Southeast. The largest difference between MFI-Actual and MFI-Natural also appears in May, June, and September. Interestingly, a clear drop of the flood frequencies is shown in July. Although the average precipitation in July is comparable to that of the other warm season months, the number of July extreme precipitation events (e.g., 20-yr events) is significantly lower; 31% and 68% fewer than that in June and September, respectively. The more frequent outbreaks of flooding in June and September are also consistent with the study

Fig. 6. The variations of flood events originated from each data source and inventory: (a) mean monthly count for each data source, (b) mean monthly count for each inventory, (c) mean yearly count for each inventory, and (d) monthly number of flood events in South Atlantic–Gulf and Texas–Gulf Basin against Niño-3.4 index.

of Yan et al. (2020a) who found that flood frequencies tend to be more related to mid- to high-end precipitation frequencies and less related to the mean value of precipitation.

There are on average 177 and 297 events per year according to actual and natural repositories, respectively, while significant interannual variations consistently show in all the observations and the modeled results (Fig. 6c). Most of the significant floods happened in the periods of 2004–08 and 2010–11. Pearson correlation coefficients between monthly flood number and Niño-3.4 anomalies (www.cpc.ncep.noaa.gov/data/indices/) were calculated. The annual flood variation is seen to correspond to ENSO phase changes in a number of river basins particularly in South Atlantic–Gulf ($r = 0.18$, p value = 0.01) and Texas–Gulf basins ($r = 0.12$, p value = 0.09; Fig. 6d), which is consistent with the findings in Yan et al. (2020a,b). The 2011 Missouri–Mississippi River floods are among the largest, most widespread, and most damaging ones recorded along the U.S. waterway in the past century and recent decades (Lovett 2011). The flooding was triggered by record snowfall in the Rocky Mountains of Montana and Wyoming, which is most likely linked to the La Niña event that started in 2010. The snowmelt along with near-record spring rainfall and associated tornado outbreaks turned the Missouri–Mississippi Rivers into a torrent, contributing to a significant part of the 2011 archive. Hurricane Irene in 2011 also caused significant floods in Mid-Atlantic catchments during the above-average Atlantic hurricane season (Avila and Stewart 2013; Suro et al. 2015). It is worth mentioning that a large flood event in the lower Colorado River is reconstructed for this same year, which can be attributed to a persistent storm track in the upstream basin. Few events happened in the year of 2000 and 2012, probably associated with the well below-average annual precipitation. The drought of 2012 was the worst drought in more than half a century, given the combined effect of antecedent drought conditions triggered by La Niña and a record-high average temperature (NOAA 2013; Rippey 2015).

To further explore the temporal distribution of flood events, months with the highest flood frequency at every subcatchment are identified and are depicted in Fig. 7. Both MFI-Actual and MFI-Natural manifest similar fragmented spatial patterns of flood peak months, generally corresponding to respective hydroclimatic conditions of different regions. The peak month of floods described at subcatchment scale in this study (Fig. 7) clearly shows much more detailed heterogeneity in flood climatology compared to Yan et al. (2020b). For example, May is usually known as the peak month of flooding in the Mississippi River basin (Yan et al. 2020b), while the peak month varies significantly between January and December across different subcatchments of the entire river basin (Fig. 7). The footprint of tropical cyclones can also be seen in subcatchments with a peak between August and November in South Atlantic states and along the Gulf Coast. Attributed to the significant moisture from the Gulf of Mexico, subcatchments along the Gulf Coast, particularly on both sides of the Mississippi River, are prone to flooding in the winter season, while the mainstem of the lower Mississippi River tends to have its flood peak in late spring. More details for other regions can be explored. For instance, subcatchments within northern river basins and the Colorado Plateau are dominated by late spring floods, largely due to snowmelt and heavy rain. Winter floods are prominent along the Pacific Coast and some interior areas in the Great Basin region, likely associated with the landfalling atmospheric rivers which cause most of the largest rainstorms in California (Dettinger et al. 2011). Generally, the flood-prone months of reconstructed events correspond well in time with actual events in adjacent subcatchments. However, in the desert Southwest, some of the reconstructed events are more evident during the summer in association with the monsoon rather than during the cool season (Fig. 7b).

Conclusions

This study provides a detailed documentation of significant flood events (with annual exceedance probability of the peak less than 5%, or for a 20-yr average recurrence

Fig. 7. Peak months of flood frequency at subcatchment scale based on (a) actual and (b) natural inventories.

interval) for each Strahler-order subcatchment over the CONUS domain during the period of 1998–2013.

Two multisourced, spatially distributed flood inventories are compiled by integrating flood information from in situ observations, remote sensing retrievals, and hydrological model simulations, which is now available to the community at <http://flood.umd.edu/download/CONUS/>. The actual inventory (MFI-Actual) records the flood events that happened in reality according to in situ or remote sensing–based observations with supplemental information from a hydrological model, while its counterpart, the “natural (undefended)” inventory (MFI-Natural) includes all floods that would have happened if there were no flood defenses, based on a carefully conducted procedure using multiple independent precipitation products and a hydrological model. With the integration of various flood information to compensate for the limitations of single sources, a total of 2,755 and 4,661 flood events were embodied in the MFI-Actual and MFI-Natural, respectively. Compared with the actual one, the natural flood inventory not only reconstructs 1,597 events in 1,398 ungauged basins, but also recovers 608 flood events in 523 gauged subcatchments where flow might have been affected and regulated by human activities. These recovered events indicate that existing flood defenses (dams, levees, etc.) efficiently prevent significant flooding from extreme precipitation and also demonstrate the importance of documenting actual and natural flood events separately.

The largest difference between the actual and natural flood events appears in Tennessee, Arkansas–White–Red, Texas–Gulf, lower Mississippi, and lower Colorado basins, probably associated with high precipitation amount and/or dam volume. It is also noted that most of the significant floods happened in the periods of 2004–08 and 2010–11. Months with the greatest difference between MFI-Actual and MFI-Natural are also the time period with the most floods (i.e., May, June, and September). Regional disparity is notable in both flood frequency and temporal distribution. For example, the Tennessee Basin has the highest flood frequency, dominated by late spring floods, while flood events in Pacific Coast mainly occur in winter.

This study is a first attempt to establish a set of flood inventories that can help facilitate further understanding of hydroclimate extremes under a changing global environment and climatic conditions, which is highly limited by the lack of reliable benchmark datasets. Therefore, these types of databases may be developed further by extending to earlier years and to global coverage, which would require more reliable discharge and precipitation data. Furthermore, incorporating multimodel hydrological simulations and remote sensing–based flood information should be also included in future work.

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Data availability statement. The inventories and documentations are now available for public access at <http://flood.umd.edu/download/CONUS/>. The daily discharge data used in the study were downloaded via the USGS National Water Information System (<https://waterdata.usgs.gov/nwis>), while the flood events from the DFO were downloaded via <https://floodobservatory.colorado.edu/>.

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