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Surface water storage influences streamflow signatures

Melanie K. Vanderhoof[1*], Peter Nieuwlandt[2], Heather E. Golden[3], Charles R. Lane[4], Jay R. Christensen[3], Will Keenan[1], Wayana Dolan[1]

[1]U.S. Geological Survey, Geosciences and Environmental Change Science Center, PO Box 25046, MS 980, Denver Federal Center, Denver Colorado 80225, USA
[2]Delaware Water Gap National Recreation Area, 1978 River Rd, Bushkill, PA 18324, USA
[3]Office of Research and Development, U.S. Environmental Protection Agency, 26 W. Martin Luther King Dr., Cincinnati, Ohio, 45268, USA
[4]Office of Research and Development, U.S. Environmental Protection Agency, 980 College Station Road, Athens, Georgia 30605, USA

Correspondence to: Melanie Vanderhoof (mvanderhoof@usgs.gov)

Abstract. Extreme flow conditions in river discharge have far-reaching environmental and economic consequences. The retention of surface water in lakes, wetlands, and floodplains can potentially moderate these extreme flows by modifying the timing, duration, and magnitude of flow generation. However, efforts to characterize the impact of surface water storage on river discharge have been limited in geographic extent. In this analysis, a suite of hydrologic signatures, quantifying components of watershed flow regimes, was calculated from daily discharge at 72 gaged watersheds across the conterminous United States. Random forest models were developed to explain variability in six hydrologic signatures related to flashiness and high and low flow conditions. In addition to traditionally considered variables such as climate, land cover, topography, and geology, a novel remote sensing (Sentinel-1 & 2) approach was used to study the contribution of surface water storage dynamics to each signature's variability. While climate variables explained much of the variability in the hydrologic signatures, models for five of the six signatures showed an improvement in explanatory power when landscape characteristics were added. Automated variable selection is part of the modeling process and can be indicative of the relative importance of certain variables over others. When all variables were considered, four of the six signature models selected remotely sensed inundation variables. The amount of semi-permanent and permanent floodplain inundation, for example, was both negatively correlated with, and showed the greatest variable importance for wet season flashiness. Further, increases in seasonal floodplain inundation were positively correlated with increases in peak flows. This suggests that the storage of surface water on floodplains is relevant to both flashiness and high flow signatures. In addition, spatial variability in the amount of semi-permanent and permanent non-floodplain water helped explain variability in the baseflow index. These findings suggest that watershed surface water storage dynamics explain a portion of streamflow signature variability. The results underscore the need for protection and restoration of surface water storage systems, such as wetlands, across watersheds.

Keywords: drought, floodplain, floods, hydrologic signatures, inundation, lakes, non-floodplain wetlands, stream discharge metrics, wetlands

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Short Summary

Streamflow signatures can help characterize a watershed's response to rainfall and snowmelt events. We explored if surface water storage-related variables, which are typically excluded from streamflow signature analyses, may help explain the variability in streamflow signatures. We found that remotely sensed surface water storage watershed location and hydroperiod were correlated with or explained a portion of the variability in hydrologic signatures across 72 streamflow gages.

1 Introduction

The response of streamflow to climate extremes has important environmental and economic implications. Drought events limit streamflow available for agriculture, drinking water, and wildlife (Stewart et al., 2020; Apurv and Cai, 2021), and have cost the United States $53 billion in just the past five years (2019-2023) (NOAA, 2024). Flood events, meanwhile, can endanger property, infrastructure, and human lives, and have caused global economic damages exceeding $1 trillion between 1980 and 2013 (Winsemius et al., 2016). Climate change is altering the frequency of these hydroclimatic extremes (Heidari et al., 2020) and may also alter how climate extremes propagate to impact runoff (Wu et al., 2022). In recent years, several studies have shown that surface water storage (e.g., wetlands, lakes, ponds), at least in some watersheds, can potentially increase baseflow and decrease peak flows (Rajib et al., 2020; Wu et al., 2020; Zeng et al., 2020), implying that consideration of surface water storage and storage dynamics in models could improve predictions of flood and drought impacts (Golden et al., 2021). However, surface water storage is typically excluded from both hydrological models (Golden et al., 2014; Jones et al., 2019) and analyses of river and stream hydrologic signatures (Addor et al., 2018; McMillan, 2019). Therefore, our understanding of when and where surface water storage influences river discharge is still very limited.

Hydrologic signatures are quantitative metrics, typically calculated from streamflow time series, that can describe the magnitude, timing, rate of change, duration, and frequency of flow conditions (Richter et al., 1996; Daigle et al., 2011; McMillan et al., 2019). Hydrologic signatures are often selected for a specific hydrological or ecological application or objective. For example, some studies have developed signatures that reflect wet conditions such as flashiness or seasonal flooding (Hannaford and March, 2008; Hendry et al., 2019), while others have focused on applying hydrologic signatures to characterize late-season, low flow regimes (Daigle et al., 2011; Kelly and White, 2016), or alternatively, the impact of hydrologic alterations, such as groundwater pumping, flow diversions, or land use conversion (Richter et al., 1996). The relationship between hydrologic signatures and watershed characteristics, such as climate and topography, has been characterized using statistical techniques such as correlation analyses (Berghuijs et al., 2016; Kuentz et al., 2017), random forest models (Trancoso et al., 2016; Addor et al., 2018; Oppel and Schumann, 2020) and regression functions (van Dijk, 2010; Beck et al., 2015; Kuentz et al., 2017), with studies finding variability in the model strength between different signatures (Beck et al., 2015; Addor et al., 2018).

Previous research has shown that drivers of hydrologic signatures can reflect specific aspects of flow. For example, signatures that reflect high flow events are often best predicted by climate, including precipitation (van Dijk, 2010; Kuentz et al., 2017), while signatures reflecting baseflow are often linked to geology (Kuentz et al., 2017), as well as potential evapotranspiration (van Dijk, 2010; Beck et al., 2013). Generally, hydrologic signatures are best

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explained by climate variables, such as aridity, precipitation, and snowfall (Beck et al., 2015; Addor et al., 2018). Land cover, such as proportion forest, often acts as a secondary controlling process (Kuentz et al., 2017; Trancoso et al., 2016; Addor et al., 2018). While Beck et al. (2013) found baseflow to be positively correlated with the average proportion of open water, and Beck et al. (2015) found slope, which can be indicative of potential water storage capacity, to be helpful in explaining multiple signatures, efforts to model drivers of hydrologic signatures have rarely included or considered surface water storage capacity, and have not, to our knowledge, considered surface water extent dynamics or hydroperiod.

Despite surface water storage being infrequently considered in the analysis of hydrologic signatures, it is widely accepted that wetlands and lakes have a significant influence on the hydrologic cycle (Bullock and Acreman, 2003). In watersheds lacking surface water storage (e.g., lakes, ponds, reservoirs, and wetlands) when precipitation falls, it is captured by vegetation, infiltrates the soils, or is transported downgradient as infiltration-excess or saturation-excess runoff (Eamus et al., 2006). Conversely, in watersheds where surface storage availability exists, precipitation, snow water equivalent and runoff can be stored and gradually released through time from both floodplain and non-floodplain storage - via groundwater baseflow, fill-spill surface runoff, or merging with streams via fill-and-spill mechanisms (Rains et al., 2016; Fritz et al., 2018; Lane et al., 2018; Stepchinski et al., 2023), creating a less "flashy" system (Shaw et al., 2012; Kuppel et al., 2015). Surface storage areas, both within and outside of the floodplain, can also contribute to streamflow when stream-connected water bodies rise, subsuming nearby, previously disconnected storage systems, e.g., upland wetlands (Vanderhoof et al., 2016). The influence of these disconnected systems, e.g., upland wetlands, can depend on the position of the wetlands relative to the stream network as well as watershed characteristics (Fritz et al., 2018; Lane et al., 2018; Wu et al., 2020). Although we know that lakes and wetlands can withhold and contribute water to river networks, it is less clear if surface water storage across multiple watersheds and regions has a measurable impact on river discharge dynamics.

Our limited understanding of how surface water storage dynamics impact river discharge is in part attributable to surface water storage being traditionally ignored by hydrologic models (Golden et al., 2014; Jones et al., 2019). In recent years, studies have shown that integrating wetlands, particularly non-floodplain wetlands, into hydrologic models can improve streamflow simulation accuracy (Rajib et al., 2020; Golden et al., 2021). While recent modeling studies have been limited in spatial extents, have simplified wetland volume estimates, and have relied, most commonly, on topographic estimates of potential water storage, each have demonstrated that surface water storage can potentially increase baseflow (McLaughlin et al., 2014; Zeng et al., 2020) as well as potentially reduce peak flow and flood duration (Evenson et al., 2018; Ameli and Creed, 2019; Wu et al., 2020).

Further research is needed to improve our understanding of when and where dynamic surface water storage influences river discharge across multiple diverse watersheds and regions. Here, we calculated a suite of hydrologic signatures to characterize variability in flow flashiness and high and low flow conditions across 72 diverse watersheds in the contiguous United States (CONUS). We developed two random forest models for each flow signature: one representing climate variables only and one representing climate, land cover, geology, topographic, and surface water storage input variables. This approach helped us to assess the relative ability of climate alone, compared to catchment characteristics that uniquely included novel remotely sensed surface water extent and hydroperiod, to explain the

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variability in hydrologic signatures. Specifically, our research questions were: (1) What are the dominant explanatory variables explaining the variability in flow flashiness and high and low flow condition-related hydrologic signatures across watersheds representing different climates, topography, and land covers? and (2) To what extent do surface water storage-related variables correlate with or help explain variability in these selected hydrologic signatures?

2. Materials and Methods

2.1 Watersheds

A total of 72 U.S. Geological Survey (USGS) stream gages and associated watersheds (Fig. 1) were selected across the conterminous U.S. (CONUS) from the GAGES-II dataset (Falcone 2011). Gaged watersheds, to the extent possible, were selected to be approximately co-located with regions used to train the Sentinel-1 and Sentinel-2 satellite-based surface water algorithms to maximize the accuracy of the algorithms (Vanderhoof et al., 2023). The algorithms were used to map surface water extent over time at each of the watersheds. Watersheds with tidal wetlands were excluded to focus on freshwater aquatic systems. Further, potential watersheds were reviewed to minimize the inclusion of major dams, defined as dams 15.2 meters or more in height (storage capacity of 6.17 million cubic meters) near watershed outlets (National Atlas of the United States, 2006). While most watersheds, 80%, were between 1500 km^2 and 5000 km^2, watersheds ranged in size from 292 km^2 to 9918 km^2.

Across the selected watersheds, stream density, as calculated from the National Hydrography Dataset (NHDplus) high resolution dataset (USGS, 2022), ranged from 259 m km^{-2} to 4182 m km^{-2} across the selected watersheds, with a median density of 1461 m km^{-2} (Table A1). The proportion of each watershed classified as wetland by the National Wetland Inventory (NWI) dataset (USFWS, 2019) ranged from 1.1% to 48.7% with a median wetland proportion of 5.6% (Table A1). Mean annual precipitation (2016-2023) ranged from 325 mm to 1659 mm, with a median annual average of 967 mm (GRIDMET; Abatzoglou, 2013). In addition, the dominant landcover class was cultivated crops or hay/pasture for 36 of the watersheds, with other dominant classes including forest (18 watersheds) and grassland-shrub/scrub (13 watersheds) (Homer et al., 2020; Table A1). The watersheds were grouped by U.S. region, including West, Southwest, North Central, Gulf Coast, Midwest, and East, to facilitate data interpretation (Fig. 1).

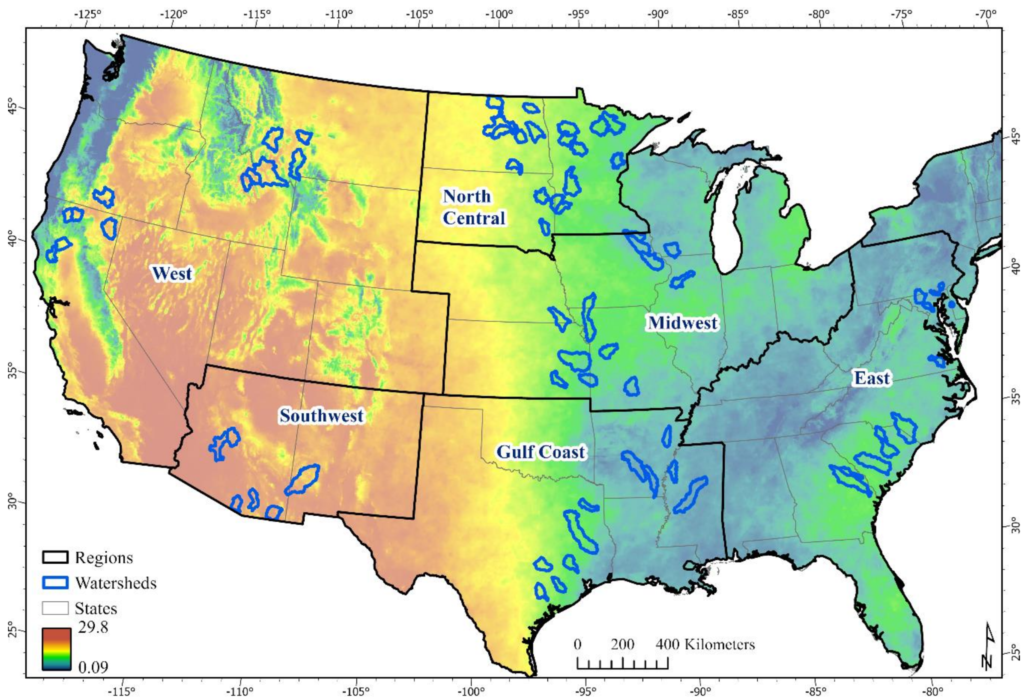

Figure 1. Selected U.S. Geological Survey (USGS) gaged watersheds in relation to aridity (2016-2023), defined as annual actual evapotranspiration divided by annual precipitation, where maroon/orange indicates arid conditions and blue indicates less arid conditions.

2.2 Hydrologic signatures: response variables

Hydrologic signatures were calculated from daily discharge at each gage and were used as the response variables in our statistical analyses (Table 1). Daily rate of stream discharge was acquired from the USGS National Water Information System for 2016-2023 (USGS, 2024). The period was limited by the temporal availability of Sentinel-2 imagery (Sentinel-2a and -2b launched in June 2015 and March 2017, respectively), required for the surface water algorithm. Signatures were selected from the literature to represent discharge extremes (high flow and low flow) as well as variability in discharge. Signatures related to characterizing high flow conditions included a (1) wet season flashiness index, where flashiness reflected daily variability in discharge within the wet season, defined as the three months in each year with the highest average discharge (Baker et al., 2004). (2) The maximum annual 30-day flow per drainage area (km^2) (MAX30/area) reflected seasonal peaks in discharge (Hannaford and Marsh, 2008); and (3) discharge exceeded 10% of the time, within a given year (Q10) minus discharge exceeded 95% of the time (Q95), within a given year ((Q10-Q95)/area) and averaged over multiple years, or the difference between high flows and the baseflow regime (National River Flow Archive, 2024). The (4) flashiness index, which reflected daily variability in discharge across seasons, was included as a metric on how rapidly a watershed responds to precipitation or snowmelt events (Baker et al., 2004). Low flow conditions were characterized using (5) a baseflow index (USFS, 2022), calculated as the ratio of the average annual baseflow volumes to the average annual flow volumes, and (6) the average driest month discharge per area (DryMonth/area, Daigle et al., 2011) (Table 1). Signatures were either calculated to be unitless or divided by the drainage area (km^2) so that they could be compared across watersheds (Daigle et al., 2011). The distribution of hydrologic signature values was evaluated using the Shapiro-Wilk test for normality. Variables with extreme outliers were normalized using log10 transform (Beck et al., 2015) and included the flashiness index and wet season flashiness index. To evaluate how the hydrologic signatures may depend on the analysis period selected, the signatures from the 8-year period (2016-2023), that corresponds with the time period of available imagery, were contrasted with signatures derived from daily discharge over a 24-year period (2000-2023), using Pearson correlation and relative bias.

2.3 Independent variables

2.3.1 Climate variables

Climate variables were averaged over the 2016-2023 period. Total annual, average precipitation and actual evapotranspiration (ET) were derived from the daily University of Idaho Gridded Surface Meteorological Dataset (GRIDMET, 4 km resolution; Abatzoglou, 2013; Table 2). An aridity index was calculated as annual total ET divided by annual total precipitation, where higher values represent arid watersheds and lower values represent less arid watersheds (Budyko, 1958), and water availability was evaluated as annual precipitation – annual ET. Maximum daily temperature was derived from DAYMET, which has been found to outperform GRIDMET for temperature (Mehdipoor et al., 2018), and variables included temperature seasonality, defined as the difference between average summer (June, July, August) maximum temperature and average winter (December, January, February) maximum temperature, as well as the maximum temperature coefficient of variation (CV). A precipitation CV and precipitation seasonality were also included, using DAYMET daily precipitation, since DAYMET includes daily estimates of snow-water equivalent (Table 2). DAYMET variables relied on 2016-2022 data, as 2023 was not yet available at the time of the analysis. To contextualize the climate conditions reflected in the 8-year period, (1) the GRIDMET 5-day Palmer Drought Severity Index values (PDSI; Abatzoglou, 2013) for the 2016-2023 period at each watershed were compared, using rank percentile, to the past 44 years (1980-2023).

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Table 1. Hydrological signatures included in the analysis. MAX: maximum

Signature	Targeted flow regime	Calculation	Units	Median	Min	Max	Source
Flashiness index	All flows	The sum of the absolute value of the changes in discharge from the day prior to the current day (discharge t_2 – discharge t_1) divided by the sum of the daily discharge values (log normalized).	Unitless	-0.81	-1.63	0.23	(Baker et al., 2004)
Flashiness index (wet season)	High flows	The sum of the absolute value of the changes in discharge from the day prior in the three wettest months (highest discharge) divided by the sum of daily discharge values in those months (log normalized).	Unitless	-0.84	-1.89	0.23	(Baker et al., 2004)
MAX30/ area	High flows	The flow rate for the 30 days per year with the highest flow rate, summed over the 30 days, and averaged per year, divided by the watershed area.	$m^3/sec/km^2$	0.94	0.01	3.48	(Hannaford and Marsh, 2008)
(Q10-Q95)/area	High flows	Discharge exceeded 10% of the time (Q10) minus discharge exceeded 95% of the time (Q95), divided by watershed area.	$m^3/sec/km^2$	0.016	0.000	0.056	(National River Flow Archive, 2024)
DryMonth/ area	Low flows	Average annual discharge in the driest month (excluding snow cover months) divided by watershed area.	$m^3/sec/km^2$	0.0019	0.0000	0.0112	(Daigle et al., 2011)
Baseflow index	Low flows	The ratio of the average daily flow during the lowest annual 7-day flow (excluding snow cover conditions) to the annual average daily flow.	Unitless	0.19	0.00	0.70	(USFS, 2022)

2.3.2 Land cover, soils, topography, and wetland variables

Vegetation was represented by the 2019 National Land Cover Database (NLCD), as the proportion of each watershed classified as (1) forest (evergreen, deciduous, or mixed), (2) developed, and (3) cultivated crops (Homer et al., 2020). Annual minimum depth to water table, average soil thickness, fraction clay and fraction sand were derived from the Soil Survey Geographic Database (SSURGO; Falcone, 2011). To represent topography, the percent slope and elevation range divided by average elevation were derived using the 10 m USGS Digital Elevation Model (DEM) (Table 2). The average watershed topographic diversity was also considered, calculated from the multi-scale Topographic Position Index (mTPI) and the Continuous Heat-Insolation Load Index (CHILI, 30 m; Theobald et al., 2015). Stream density was calculated using the total stream length, defined by the NHDplus high resolution dataset (USGS, 2022). The National Wetland Inventory dataset (USFWS, 2019) was used to calculate the proportion of each watershed mapped as wetlands. The floodplain variable was defined as the proportion of each watershed classified as within the 100-year floodplain (Woznicki et al., 2019). Lastly, the connectivity of wetlands to streams can influence the timing of water moving into the stream network, so the proportion of each watershed mapped as geographically isolated wetlands (GIWs; Leibowitz, 2015), or non-floodplain wetlands (NFW), that are surrounded by upland, as well as the proportion of total wetland area mapped as GIWs was considered (Lane and D'Amico, 2016).

2.3.3 Inundation variables

In addition to including non-temporal water variables, such as wetland area, remote sensing platforms allow us to include variables that characterize the hydroperiod of surface water stored within watersheds, including lakes, ponds, wetlands, and temporary inundation in flood prone areas. Although Landsat can provide a longer temporal record of surface water dynamics, observations are limited to periods free of clouds, snow, and ice, which can limit the accuracy of temporary and seasonal patterns of inundation. Alternatively, the more frequent Sentinel-2 revisit, and

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incorporation of a SAR satellite, like Sentinel-1, can help bypass these limitations. Sentinel-1 and Sentinel-2 based algorithms that map non-water, open water and vegetated water were previously developed using gradient boosted classifier algorithms for 12 sites across the conterminous U.S. (20 m resolution; Vanderhoof et al., 2023). Details on the surface water algorithms can be found in Vanderhoof et al., (2023). In this effort individual Sentinel-1 and Sentinel-2 images, collected between January 1, 2016, and December 31, 2023, overlapping each of the gaged watersheds (n=72) were classified into open water, vegetated water, and non-water. The classified Sentinel-1 and classified Sentinel-2 time series were consolidated at a 14-day time step where pixel values were assigned as the majority classification, water (defined as open water plus vegetated water), or non-water (Fig. 2). If, observations of water and non-water were equal, then open water was prioritized followed by non-water, and lastly vegetated water (Fig. 2), consistent with the higher accuracy of the open water class relative to the vegetated water class (Vanderhoof et al., 2023). Where no valid observations were present in the 14-day period, pixels were gap-filled using observations from the t-1 and t+1 timestep, as shown in Fig. 2.

To limit commission error in the surface water time series, a water mask, defined as the maximum allowable surface water extent, was derived for each watershed, and applied across the time series. Pixels classified as water outside of the water mask were re-classified as non-water. To generate each water mask, the Sentinel-1 open water and vegetated water, and Sentinel-2 open water, and vegetated water percentile rasters were manually reviewed for each watershed (Fig. 2). Percentile thresholds were selected, below which the frequency of erroneously classified water pixels visually exceeded the frequency of correctly classified water pixels (Table A2). To help inform the threshold selection, ancillary data were used including the NWI dataset (USFWS, 2019), the 2019 NLCD (Homer et al., 2020), and base map imagery, delivered through ArcMap. The spatial extent where water pixels were retained was defined as pixels located within the 100-year floodplain (Woznicki et al., 2019), to account for short-term flood events, or pixels where the water percentile was greater than the selected threshold in any of the four 5-year percentile rasters (Table A2). The Sentinel-1 algorithm has a documented omission and commission error of 3.1% and 0.9% for open water, and a 28.4% and 16.0% commission error for vegetated water, respectively, while the Sentinel-2 algorithm has an omission and commission error of 3.1% and 0.5% for open water, and a 10.7% and 7.9% commission error for vegetated water, respectively, when validated against 36 high-resolution images (i.e., WorldView-2, WorldView-3, PlanetScope) (Vanderhoof et al., 2023). When consolidated at a monthly time-step to a S1-S2 water, non-water classification, errors of omission and commission for monthly surface water extent averaged 1.6% and 10.4%, respectively, when validated against 64 PlanetScope images (Vanderhoof et al., 2024). The use of a water mask was previously shown to reduce commission error, resulting in errors of omission and commission of 1.9% and 6.5%, respectively for the monthly surface water extent (Vanderhoof et al., 2024).

After gap-filling and applying the water masks, the time series for each watershed was then consolidated into an 8-year percentile. Categories of surface water, using the percent of watershed area, were defined in reference to the 100-year floodplain (Woznicki et al., 2019), and included, (1) temporarily flooded, defined as an average of $\geq$3 days but <1 month per year (Cowardin et al., 1979; Scott et al., 2019), (2) seasonally flooded, defined as inundated >1 month but <6 months per year, on average, and (3) semi-permanently and permanently inundated, defined as >6 months per year, on average (Cowardin et al., 1979; Donnelly et al., 2019) (Table 2). The total amount of inundation

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of any hydroperiod within the 100-year floodplain, and outside of the 100-year floodplain was also included (Table 2). The terms surface water extent and inundation are used interchangeably in this analysis.

Table 2. Independent variables considered modeling hydrological signatures. DEM: Digital elevation model, SRTM: Shuttle Radar Topography Mission, NLCD: National Land Cover Database, SSURGO: Soil Survey Geographic Database, NHD: National Hydrography Dataset

Variable Type	Variable	Units	Min	Max	Median	Source
Climate	Precipitation (P, annual)	mm	325.3	1659.1	967.4	GRIDMET (Abatzoglou, 2013)
	Evapotranspiration (ET, annual)	mm	714	1934.1	1181.1	GRIDMET (Abatzoglou, 2013)
	Aridity index (ET/P, annual)	unitless	0.84	5.88	1.27	GRIDMET (Abatzoglou, 2013)
	Water demand (P - ET, annual)	mm	-1586	265.6	-247.4	GRIDMET (Abatzoglou, 2013)
	Precipitation seasonality	mm	-396	276.6	105	DAYMET (Thornton et al., 2020)
	Precipitation coefficient of variation	mm	196.5	371.8	260.4	DAYMET (Thornton et al., 2020)
	Temperature seasonality	ºC	15.6	34.2	23	DAYMET (Thornton et al., 2020)
	Temperature coefficient of variation	ºC	26	151	57	DAYMET (Thornton et al., 2020)
Land cover	Forest (evergreen, deciduous, mixed)	% of area	0.059	56.1	17.5	NLCD (2019; Homer et al., 2020)
	Developed (low, medium, high intensity, open space)	% of area	0.323	35.7	4.69	NLCD (2019; Homer et al., 2020)
	Cultivated crops	% of area	0.0	84.7	17.9	NLCD (2019; Homer et al., 2020)
	Stream density	m km^2	259.2	4181.6	1460.9	NHDPlus High Resolution (USGS, 2022)
Sub-surface	Clay fraction	fraction	0.08	0.47	0.23	SSURGO (Falcone 2011)
	Sand fraction	fraction	0.07	0.74	0.33	SSURGO (Falcone 2011)
	Average soil thickness	cm	81.3	152.4	145.8	SSURGO (Falcone 2011)
	Annual minimum depth to water table	meters	0.49	1.83	1.40	SSURGO (Falcone 2011)
Topography	Slope	%	0.5	32.5	3.7	DEM (Gesch et al., 2002)
	(Elevation$_{max}$ - Elevation$_{min}$) / Elevation$_{average}$	unitless	0.2	4.9	1.0	DEM (Gesch et al., 2002)
	Global SRTM topographic diversity	unitless	0.03	0.7	0.1	(Theobald et al., 2015)
Inundation Dynamics	Temporarily flooded, floodplain (3 days - 1 month)	% of area	0.07	4.16	0.65	(Vanderhoof et al., 2023)
	Temporarily inundated, non-floodplain (3 days - 1 month)	% of area	0.03	5..85	1.29	(Vanderhoof et al., 2023)
	Seasonally inundated, floodplain (1 - 6 month)	% of area	0.04	8.58	1.77	(Vanderhoof et al., 2023)
	Seasonally inundated, non-floodplain (1 - 6 month)	% of area	0.01	45.81	4.07	(Vanderhoof et al., 2023)
	Semi-permanently and permanently inundated, floodplain (>6 month)	% of area	0	3.54	0.39	(Vanderhoof et al., 2023)
	Semi-permanently and permanently inundated, non-floodplain (>6 month)	% of area	0	5.55	0.44	(Vanderhoof et al., 2023)
	Total floodplain inundation	% of area	0.42	15.46	3.08	(Vanderhoof et al., 2023)
	Total non-floodplain inundation	% of area	0.04	52.59	6.06	(Vanderhoof et al., 2023)
Wetland	Geographically Isolated Wetlands (GIW)	% of area	0.0	9.4	0.6	(Lane and D'Amico 2016)
	Proportion of wetland area identified as GIW	% of area	0.6	80.9	11.4	(Lane and D'Amico 2016; USFWS 2019)
	Floodplain	% of area	1.2	36.8	7.7	(Woznicki, et al., 2019)
	National Wetland Inventory (NWI) wetlands	% of area	1.1	48.7	5.6	NWI (USFWS 2019)

2.4 Modeling analysis

The relationships between multiple predictor variables and hydrologic signatures were modeled with random forest regressions developing using the ‘sklearn’ python package (Pedregosa et al., 2011). For each hydrologic signature, random forest models were generated that (1) considered the inclusion of climate-related variables only ($M_{Climate}$), and (2) considered inclusion of all variables, including climate, topographic, land cover, and wetland and inundation related variables (M_{All}) (Table 2). The multi-model approach furthered our ability to quantify the relative contribution of different variable types to explain variability in the hydrologic signatures.

Random forest models use a bootstrapping approach to generate hundreds of regression trees and make no prior assumptions about cause-and-effect relationships or correlations among variables (Hastie et al., 2009). They have also been previously used in the analysis of hydrologic signatures (e.g., Trancoso et al., 2016; Addor et al., 2018; Oppel and Schumann, 2020). While random forest techniques are generally insensitive to multicollinearity, the inclusion of highly correlated variables can make it more challenging to identify the most predictive variables, deflate or bias variable importance values, and complicate model interpretation (Murphy et al., 2010; Gregorutti et al., 2016). Conversely, an automated variable selection can be indicative of the relative importance of certain variables over others (Murphy et al., 2010). A stepwise forward selection routine was implemented where the set of potential predictors were sequentially tested. The predictor that contributed most to reducing the RMSE was selected. During each step, the remaining predictors were removed if they had a correlation value of 0.8 or greater with any of the selected predictors. This process was iterated until the improvement in the model’s RMSE was <0.001 with any additional variables (Sherrouse and Hawbaker, 2023).

For each model the variable and hyperparameter selection process were concurrently run, where the potential models were compared using a nested cross-validation, KFold with 6 splits (Cawley and Talbot, 2010). The hyperparameters tested were n_estimators (the number of trees in the forest with tested values of 300, 500, 700, and 1000), max_depth (the maximum depth of a tree with tested values of 2, 3, and 4). For all models, max_features (the number of features to consider when looking for the best split) was set at the square root of the number of features, and max_samples (the proportion of samples selected to train each estimator) was set at 0.8. The model with the highest cross-validated adjusted R^2 was selected.

Random forest models do not consider the spatial pattern between samples, therefore any clustering of the watersheds included in the analysis could potentially bias model predictions (Hengl et al., 2018). The residuals of each selected model were tested for spatial autocorrelation using Moran’s I (Klute et al., 2002). Of the random forest model residuals, 5 out of 12 showed significant (p<0.01) spatial autocorrelation, therefore an autocovariate, or additional model term, representing the mean neighborhood (defined as within 500 km of the catchment center, reflecting catchment clusters) model residual value, was included in the subset of models to account for spatial dependency (Betts et al., 2006). Performance of final random forest models was evaluated using the leave-one-out cross validation to account for the limited sample size (n=72) (Vabalas et al., 2019), and the cross-validated model RMSE, R^2, adjusted R^2, to account for differences in the number of variables selected. Variable importance was calculated with Python Scikit-learn as the permutation importance. Single variable correlations between the hydrologic signatures and the

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predictor variables were also calculated using the non-parametric Spearman Rank Correlation Coefficient, as previously used by Berghuijs et al. (2016). Because of the number of comparisons, a Bonferroni correction was applied before significance was determined (Emerson, 2020).

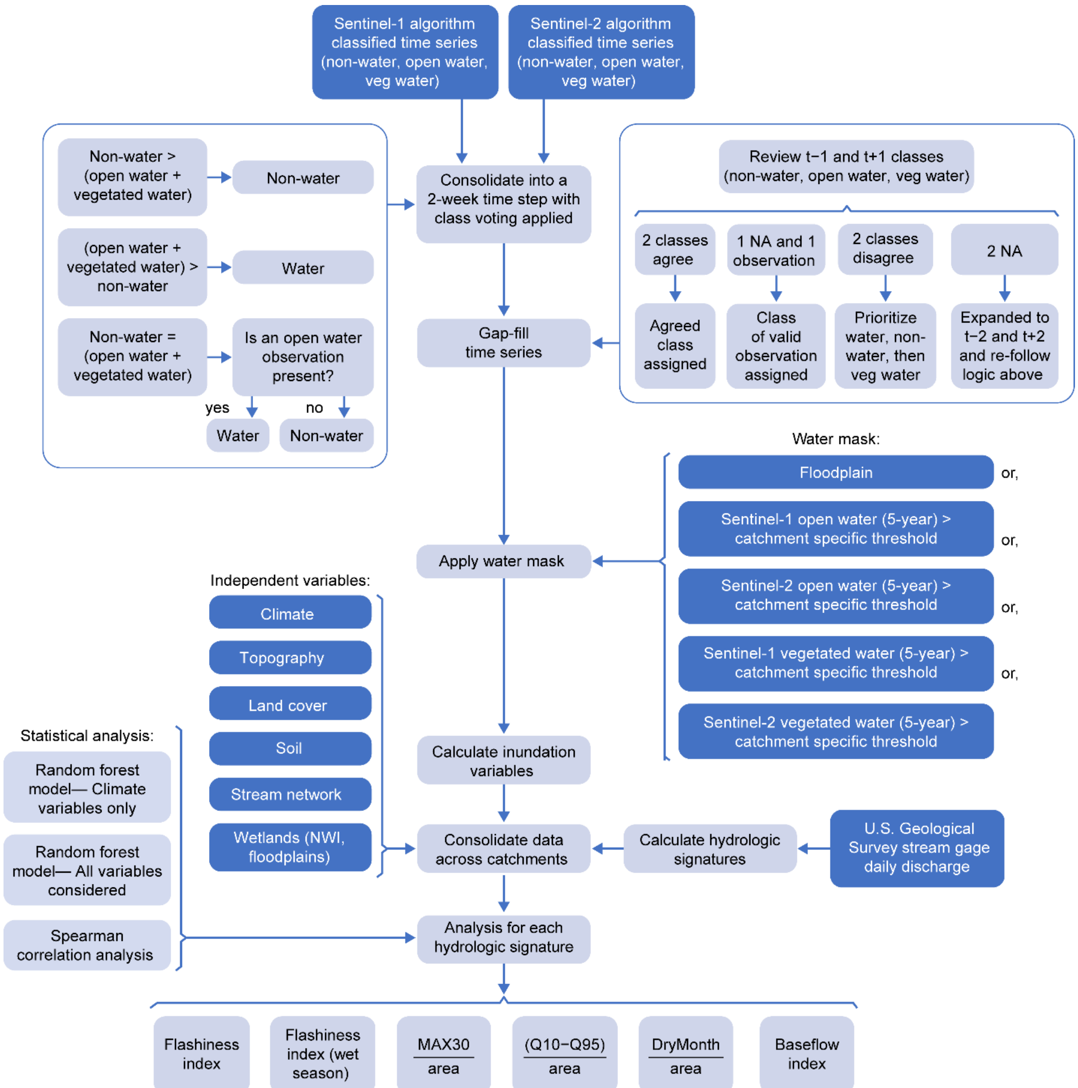

Figure 2. Flowchart of steps to generate the surface water variables and data analysis.

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3. Results

3.1 Climate and flow signature temporal context

The minimum (i.e., driest), maximum (i.e., wettest) and median per watershed PDSI rank percentiles for 2016-2023, relative to 1980-2023, averaged 5%, 100%, and 62%, respectively, where 50% represents the median PDSI for the 1980-2023 period (Table A1). This indicated that the period was slightly wetter, on average, relative to the longer 44-year period, and that most watersheds exhibited a large range of PDSI conditions (maximum – minimum) over the 2016-2023 period.

While the period used was limited by the available Sentinel-1 and Sentinel-2 image record, signature uncertainty can increase when using shorter flow records (Kennard et al., 2010). Between-site variability in the hydrologic signatures derived from the 8-year period, was highly correlated with the between-site variability from a longer, 24- year period (2000-2023) (Table 3). The median value of hydrologic signatures showed some differences between the 8-year period (2016-2023) and the longer 24-year period (2000-2023). While both flashiness indices had a bias of <1%, the MAX30/area and (Q10-Q95)/area had a relative bias of 13.5% and 8.7%, respectively, indicating that average peak wetness conditions were wetter within the 8-year period, relative to the longer period. Additionally, the baseflow index and DryMonth/area showed a relative bias of -11.8% and -2.2%, indicating that these signatures reflected drier conditions, on average, within the 8-year period, relative to the longer period (Table 3). While the hydrologic signatures of the high and low flow conditions were amplified during the selected period, the signature values between the two periods were highly correlated, with Pearson *R* correlation values ranging from 0.94 to 0.99 (Table 3). This suggests that the relative variations in hydrologic signature values between the long-term flow records (24 years) compared to the study period (8 years) are tightly associated. We considered this a solid justification for using the 8-year Sentinel data availability period for our analyses.

Table 3. Pearson correlation values comparing the 2016-2023 hydrologic signatures with the same signatures derived from the 2000-2023 period. The relative bias compares the paired signature values from each watershed. All R values were significant at $p<0.01$. MAX: maximum

Metric	R (2016-2023 vs 2000-2023)	Median relative bias (%)
Flashiness index	0.99	0.9
Flashiness index (wet season)	0.99	0.2
MAX30/area	0.97	13.5
(Q10-Q95)/area	0.98	8.7
DryMonth/area	0.94	-2.2
Baseflow index	0.95	-11.8

3.2 Flashiness signatures

The flashiness and wet season flashiness signatures reflect how quickly discharge changes in response to episodic rainfall and snowmelt events, over the course of the year and within the wet season, respectively. Despite representing different portions of the year, the two signatures were highly correlated (R = 0.97, p<0.01). Flashiness and wet season flashiness were highest, on average, in the Southwest watersheds, and lowest in the West and North Central watersheds (Table A3, Fig. 3). Watershed flashiness and wet season flashiness were significantly correlated with very few of the independent variables considered. Most prominently, both significantly (p<0.01) decreased with an increase in areas mapped as semi-permanently and permanently inundated within the floodplain, and with increases in total area classified as wetland by the NWI dataset (Table 4). Correlations with climate variables were weaker relative to the other hydrologic signatures explored. The flashiness index and wet season flashiness index M_{All} models improved by 4.28% and 9.97%, respectively, in explanatory power and associated decreases in the RMSE, relative to $M_{Climate}$, or when landscape and water variables were added for consideration (Table 5). Variability in the flashiness signature was best explained by the temperature CV, annual minimum depth to the water table, slope, and amount of semi-permanent-permanent inundation within the floodplain. The wet season flashiness $M_{All,}$ model selected similar variables, but the amount of semi-permanent-permanent floodplain inundation had the greatest variable importance (Table 6; Fig. 4a). Improvement in model predictions, both across the year as well as in the wet season (Fig. 5a), were explained in part by more semi-permanently to permanently inundated water in the floodplain.

3.3 Peak flow signatures

Peak flow signature values, MAX30/area and (Q10-Q95)/area, were highest, on average, within the Gulf Coast watersheds, and lower, on average, within the Southwest, North Central, and West watersheds, although both signatures saw a higher degree of variability across the West region (Table A3, Fig. 3). The two signatures were positively correlated (R = 0.93, p<0.01). In relation to the independent variables considered, both signatures, MAX30/area and (Q10-Q95)/area, were most highly positively correlated with precipitation and water demand (P-ET), and negatively correlated with aridity (ET/P) (Table 4). The MAX30/area and (Q10-Q95)/area were also significantly correlated with 4 and 3 remotely sensed inundation variables, respectively. An example of the Spearman rank correlation of (Q10-Q95)/area in relation to seasonally inundated area in the floodplain (R=0.69, p<0.01) is shown in Fig. 4b. The high flow signatures had a positive, significant (p<0.01) correlation with the total amount of inundation within the floodplain, the amount of seasonal inundation in the floodplain, and the amount of temporary inundation outside of the floodplain (Table 4). These correlation values were equivalent to or exceeded correlation with existing water variables, specifically the 100-year floodplain (Table 4). The $M_{Climate}$ and M_{All} models for both signatures were best explained by annual precipitation, followed by the aridity index (ET/P) or water demand (P-ET) (Table 6). Despite the high explanatory power of climate variables for both high flow signatures, the M_{All} models improved by 2.73% and 6.31%, relative to the $M_{Climate}$ models, for MAX30/area and (Q10-Q95)/area, respectively. The (Q10-Q95)/area M_{All} model added only stream density, while the landscape-based variables for MAX30/area included forest, stream density, clay fraction, and the amount of temporarily flooded area within the floodplain (Table 6). Greater area

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temporarily flooded within the floodplain was also significantly positively correlated (p<0.01) with the MAX30/area (Table 4).

3.4 Low flow signatures

The DryMonth/area and baseflow index were highest within the East watersheds, on average, and lowest within the Southwest watersheds (Table A3, Fig. 3). Watersheds were also regionally variable. For example, DryMonth/area signature graded west (lower) to east (higher) within the North Central region (Fig. 3), concurrent with the aridity gradient within the region (Fig. 1). The two low flow signatures had a significant, but weaker correlation with one another (R = 071, p<0.01).

The DryMonth/area was significantly correlated with many more independent variables than the baseflow index. Like the peak flow signatures, DryMonth/area was positively correlated with greater annual precipitation and water demand (P-ET) and negatively correlated with greater aridity (ET/P). The DryMonth/area was also positively correlated with total inundation within the floodplain, seasonally inundated area within the floodplain, and temporarily inundated area outside of the floodplain. No significant correlations, in contrast, were found with topographic or wetland variables (Table 4). The DryMonth/area had the greatest model explanatory power, relative to the other hydrologic signature models (Table 5). However, despite significant (p<0.01) correlations with remotely sensed inundation dynamics, there was no model improvement as landscape variables were added between the $M_{Climate}$ and M_{All} models (Table 5). The DryMonth/area was best explained by watershed aridity and annual precipitation. Further, the $M_{Climate}$ model showed significant spatial autocorrelation within the residuals so that a residual autocovariate was included in the model and had a strong variable importance value (Table 6). This suggests that the DryMonth/area model would benefit from the addition of an independent variable, not yet identified in the analysis.

The baseflow index was negatively significantly (p<0.01) correlated with precipitation CV, evapotranspiration, and fraction of clay (Table 4). Adding landscape variables, unlike DryMonth/area, improved the baseflow index model by 5.43% (Table 5), and improved the relationship between the observed and predicted baseflow index values (Fig. 5b). While the precipitation CV was the most important variable in both the baseflow index M_{All} and $M_{Climate}$ models, the M_{All} model's improvement was entirely attributable to the inclusion of the amount of non-floodplain area classified as semi-permanent to permanent (i.e., large wetlands and lakes outside of the floodplain) (Table 6).

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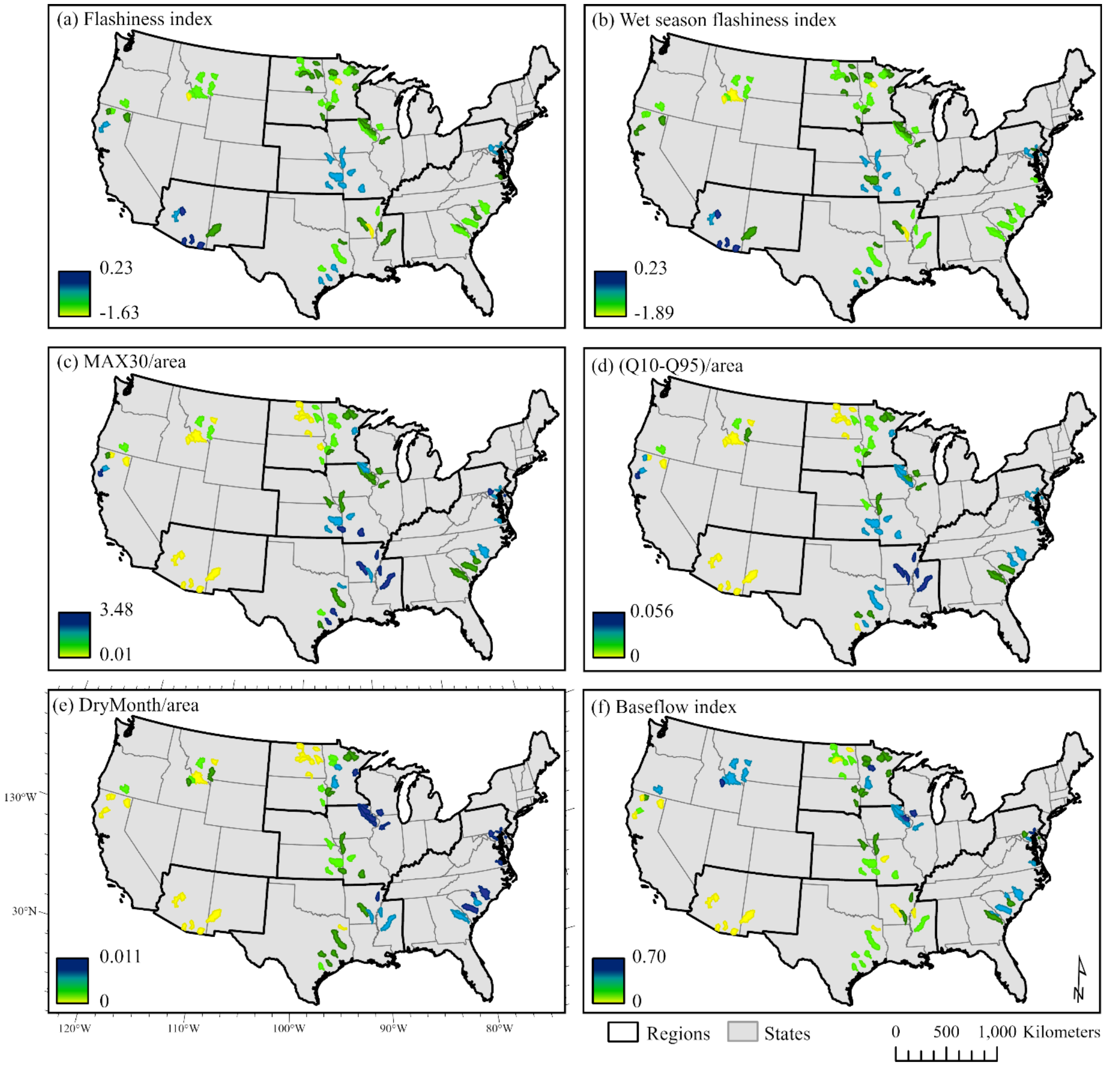

Figure 3. Hydrological signature values by watershed including (a) flashiness index, (b) wet season flashiness index, (c) MAX30/area (m^3/sec/km^2), (d) (Q10-Q95)/area (m^3/sec/km^2), (e) DryMonth/area (m^3/sec/km^2), and (f) baseflow index.

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382 **Table 4**. Spearman correlation values between hydrologic signatures and variables. Significance (*p*<0.01) correlations,
383 after Bonferroni correction was applied, is shown in shaded gray. CV: coefficient of variation, FP: floodplain, NFP:
384 non-floodplain, Prop: proportion, MAX: maximum, SP-P: semi-permanent and permanent

Variable Type	Variable	Flashiness Index	Flashiness (wet season)	MAX 30/area	(Q10-Q95)/area	DryMonth /area	Baseflow index
Climate	Precipitation (P)	0.06	0.01	0.86	0.87	0.68	0.16
	Evapotranspiration (ET)	0.43	0.32	0.18	0.14	-0.15	-0.47
	Aridity index (ET/P)	-0.03	-0.03	-0.84	-0.87	-0.84	-0.37
	Water demand (P - ET)	-0.03	-0.02	0.78	0.83	0.82	0.41
	Precipitation seasonality	0.17	0.26	0.01	-0.04	0.21	0.2
	Precipitation CV	0.34	0.33	-0.26	-0.38	-0.55	-0.62
	Temperature seasonality	-0.29	-0.18	-0.3	-0.28	-0.05	0.24
	Temperature CV	-0.4	-0.3	-0.31	-0.28	-0.06	0.3
Land cover	Forest	-0.14	-0.17	0.28	0.32	0.18	0.15
	Developed	0.22	0.18	0.62	0.6	0.62	0.18
	Cultivated crops	-0.16	-0.13	0.03	0.06	0.3	0.27
	Stream density	0.36	0.29	0.37	0.35	-0.06	-0.33
Sub-surface	Clay fraction	0.4	0.37	0.25	0.15	-0.12	-0.44
	Sand fraction	-0.23	-0.27	-0.32	-0.26	-0.07	0.16
	Average soil thickness	-0.29	-0.3	0.14	0.18	0.32	0.2
	Water table depth	0.12	0.13	-0.54	-0.55	-0.45	-0.09
Topography	Slope	0.13	0.13	-0.23	-0.22	-0.27	0
	Elevation range	0.12	0.03	0.24	0.24	0.14	-0.04
	Topographic diversity	0.11	0.11	-0.17	-0.15	-0.2	0.04
Inundation Dynamics	Temporarily flooded, FP	0.27	0.23	0.42	0.40	0.24	-0.05
	Temporarily inundated, NFP	-0.06	-0.03	0.49	0.51	0.58	0.30
	Seasonally inundated, FP	-0.12	-0.15	0.66	0.69	0.59	0.15
	Seasonally inundated, NFP	-0.21	-0.19	0.36	0.37	0.39	0.14
	SP-P inundated, FP	-0.44	-0.46	0.24	0.33	0.33	0.14
	SP-P, inundated, NFP	-0.34	-0.32	0.13	0.11	0.13	0.04
	Total inundation, FP	-0.12	-0.15	0.60	0.63	0.52	0.12
	Total inundation, NFP	-0.19	-0.17	0.37	0.37	0.41	0.17
Wetland	Geographically Isolated Wetlands (GIW)	-0.31	-0.29	0.07	0.08	0.13	0.04
	Prop. of wetland area identified as GIW	-0.08	-0.05	0.08	0.03	0.06	0.01
	Floodplain	-0.02	-0.07	0.49	0.51	0.39	0
	National Wetland Inventory wetlands	-0.44	-0.44	0.12	0.19	0.28	0.19

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Table 5. Model statistics for each hydrologic signature and version of the model including (1) climate variables only ($M_{Climate}$) and (2) all variables including wetland and surface water variables (M_{All}). LOOCV: leave-one-out cross validation, RMSE: root mean square error, AC: autocovariate, adj: adjusted, MAX: maximum

Signature	**Model**	**R^2 (LOOCV)**	**R^2 adj. (LOOCV)**	**RMSE LOOCV)**	**Change in adj. R^2 from $M_{Climate}$ to M_{All} (%)**	**Trees**	**Max. tree depth**	**Residual AC included**	**Variables selected**
Flashiness index	$M_{Climate}$	0.501	0.474	0.254		700	4		3
	M_{All}	0.545	0.494	0.242	**4.28**	500	4	x	6
Flashiness index (wet season)	$M_{Climate}$	0.435	0.394	0.283		700	4		4
	M_{All}	0.482	0.434	0.271	**9.97**	700	4	x	5
MAX30/area	$M_{Climate}$	0.666	0.648	0.463		700	4		2
	M_{All}	0.699	0.665	0.439	**2.73**	700	4		6
(Q10-Q95)/area	$M_{Climate}$	0.753	0.730	0.007		500	3	x	5
	M_{All}	0.795	0.777	0.006	**6.31**	1000	4		5
DryMonth/area	$M_{Climate}$	0.838	0.820	0.001		700	4	x	6
	M_{All}	0.838	0.820	0.001	**0.00**	700	4	x	6
Baseflow index	$M_{Climate}$	0.576	0.545	0.118		1000	4		4
	M_{All}	0.603	0.574	0.114	**5.43**	1000	4		4

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Table 6. Variable permutation importance of variables selected for $M_{Climate}$: model in which only climate variables were considered, and M_{All}: all variables were considered, CV: coefficient of variation, min.: minimum, FP: floodplain, NFP: non-floodplain, Q1, Q2, Q3, Q4: quartile, MAX: maximum, SP and P: semi-permanent and permanent

Variable Type	Variable	Flashiness index		Flashiness index (wet season)		MAX30/area		(Q10-Q95)/area		DryMonth/area		Baseflow index	
		$M_{Climate}$	M_{All}	$M_{Climate}$	M_{All}	$M_{Climate}$	M_{All}	$M_{Climate}$	M_{All}	$M_{Climate}$	M_{All}	$M_{Climate}$	M_{All}
Climate	Precipitation (P)			0.22		0.65	0.36	0.38	0.4	0.15	0.15	0.12	
	Evapo-transpiration (ET)	0.38		0.35		0.35				0.06	0.06	0.28	0.26
	Aridity index (ET/P)						0.32	0.31		0.28	0.28		
	Water demand (P - ET)	0.35		0.22					0.33				
	Precipitation seasonality	0.27		0.21				0.09	0.09	0.06	0.06	0.18	0.15
	Precipitation coefficient of variation									0.11	0.11	0.42	0.39
	Temperature coefficient of variation		0.27		0.27			0.06	0.08				
Landcover	Forest						0.08						
	Developed												
	Stream density						0.13		0.11				
Sub-surface	Clay fraction						0.06						
	Sand fraction		0.12										
	Annual minimum depth to water table		0.25		0.27								
Topography	Slope		0.12		0.16								
Inundation Dynamics	SP and P inundated, FP		0.24		0.3								
	SP and P inundated, NFP												0.2
	Temporarily flooded, FP						0.06						
Other	Residual autocovariate		0		0			0.16		0.33	0.33		

Color Legend: Q1 (0-25%), Q2 (26-50%), Q3 (51-75%), Q4 (76-100%)

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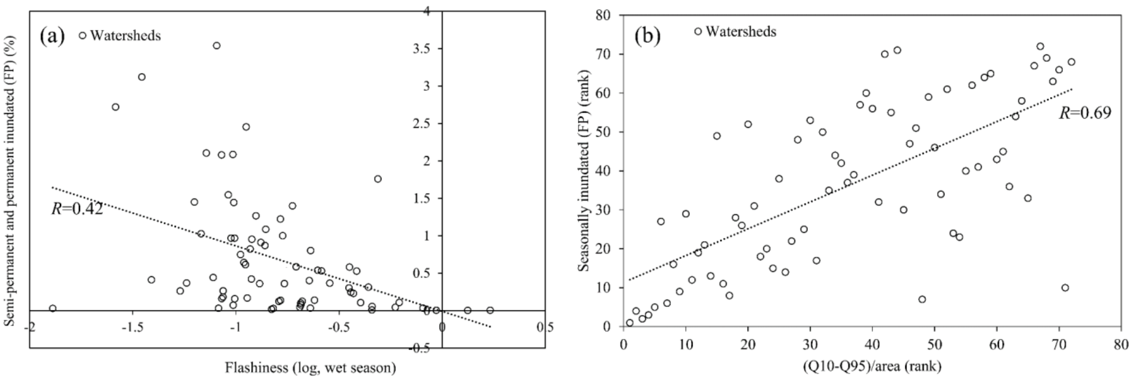

Figure 4. Scatter plot of (a) wet season flashiness versus the percent of semi-permanent and permanent floodplain (FP) inundation, which was included in the M_{All}, and (b) (Q10-Q95)/area in relation to the percent of seasonally inundated. To match the Spearman correlation analysis, both variables in panel b were converted to rank. FP: floodplain

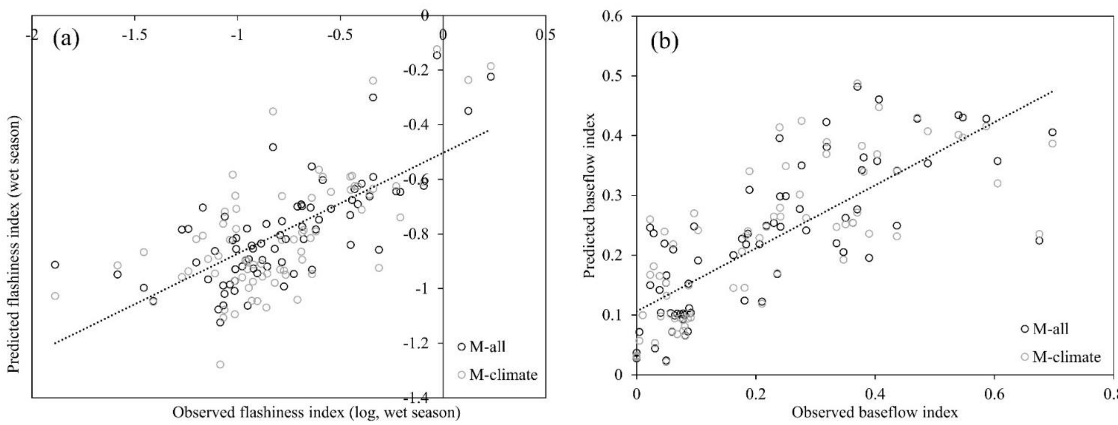

Figure 5. Scatter plots showing observed versus predicted with the $M_{climate}$ and M_{all} models for (a) flashiness (wet season, unitless) and (b) baseflow index (unitless).

4. Discussion

4.1 Role of climate

Climate variables often provide the highest predictive power for many hydrologic signatures (Beck et al., 2015; McMillan et al., 2021). Similarly, in our analysis, climate variables showed the greatest variable importance within most of the models, especially in the high flow and low flow hydrologic signature models. The climate variables selected in the random forest models were generally consistent with variables in other studies exploring processes underlying hydrological signatures. Processes generating high discharge and flooding are variable across the United States (Berghujs et al., 2016), but rainfall and snowmelt (Jiang et al., 2022), as well as aridity (Sauqet et al., 2021), have been found to account for most peaks in discharge. Similarly, in our effort, annual precipitation, followed by aridity or water demand, had the greatest variable importance in predicting both seasonal peaks in discharge (i.e, MAX30/area) as well as the difference between baseflow and high flow conditions (i.e., (Q10-Q95)/area). For the low flow signatures, annual evapotranspiration was selected for both DryMonth/area and the baseflow index, and the baseflow index was negatively significantly correlated with annual evapotranspiration, a finding consistent with Beck et al. (2013) and van Dijk (2010). Several studies have also related low flow metrics to precipitation (e.g., Small, 2006, Kelly and White, 2016). Consistent with this finding, for both the $M_{Climate}$ and M_{All} baseflow index models, precipitation variability was an important variable.

4.2 Role of surface water inundation

There are still opportunities to incorporate new watershed descriptors that may improve the characterization of flow signatures (Gnann et al., 2020). Specifically, McMillan et al. (2021) argued that novel relationships may be discovered where hydrology is more important than climate. For example, flood signatures have been predicted using watershed drainage patterns (Oppel & Schumann, 2020), and surface waterbodies have been found to help predict baseflow signatures (Beck et al., 2013). More generally, the influence of a watershed's landscape, including vegetation type (Trancoso et al., 2016; Addor et al., 2018), topography (Beck et al., 2015, and geology (Kuentz et al., 2017), on discharge has been well established. Therefore, it was unsurprising that in our analysis most of the hydrologic signatures, five of the six, showed an improvement in the model explanatory power, relative to using climate variables alone. However, novel to this study was that model improvement for four of the six hydrologic signatures–flashiness, wet season flashiness, MAX30/area, and the baseflow index–was attributable, at least in part, to the inclusion of a remotely sensed inundation dynamic variable. Model selection of remotely sensed inundation dynamic variables over existing wetland and floodplain dataset variables suggests that consideration of surface water hydroperiod, alongside landscape position, was more helpful in explaining these hydrologic signatures then static datasets representing the spatial extent of wetlands (e.g., NWI, GIW) and floodplains (e.g., 100-year floodplain). Additionally, five of the six hydrologic signatures were significantly correlated with one or more of the remotely sensed inundation dynamic variables. Although we acknowledge that the results could be influenced by watershed selection, watershed size, and hydrologic signatures included in the analysis (McMillan et al., 2021), an improved understanding of the potential influence of surface water storage, such as wetlands, on stream behavior can help support watershed management and guide surface water storage restoration efforts across landscapes (Walters and Babbar-Sebens, 2016).

While it is evident that lakes and wetlands can store and contribute water to river networks (Fritz et al., 2018; Lane et al., 2018), it is less clear if surface water storage across multiple watersheds and regions has a measurable impact on river discharge dynamics. In our analysis, we found that although baseflow was significantly correlated with very few independent variables, the improvement in the baseflow index model from $M_{Climate}$ to M_{All} was entirely attributable to the addition of the semi-permanent to permanent non-floodplain inundation variable. This finding suggests that baseflow may be influenced by wetlands and lakes that persist during dry seasons and years and are external to the floodplain. Similarly, previous research within select watersheds has found that wetlands stabilize low flow conditions (McLaughlin et al., 2014; Ameli and Creed, 2017; Blanchette et al., 2019). Geographically isolated wetlands, specifically, can contribute to baseflow (Evenson et al., 2015) and contribute water to as well as from shallow groundwater, like a sponge (McLaughlin et al., 2014; Yeo et al., 2019).

Surface water inundation variables also helped explain the flashiness signatures. Flashiness signatures represent streamflow response to high rainfall and snowmelt events, where streams that rise and fall quickly are considered flashier than those that maintain a steadier flow (Hannaford and March, 2008). Both flashiness signatures were inversely and significantly related to semi-permanent to permanent inundation within the floodplain, i.e., the locations of large wetlands and lakes continuous with, adjacent to, or near the stream network. Semi-permanent to permanent inundation within the floodplain was also selected by both M_{All} models and had the greatest variable importance of all selected variables for the wet season flashiness M_{All} model. While non-floodplain wetlands decrease streamflow variability (Yeo et al., 2019) and reduce flashiness (McLaughlin et al., 2014) in select watersheds, our analysis suggests that floodplains may also provide inundation storage important to stabilizing flow, a finding that confirms an abundance of prior research (Fritz et al., 2018; Wohl, 2022), and supports resilience against watershed-scale hydrological disturbances (Lane et al., 2023). The importance of variables that tend to be correlated with patterns of inundation has been previously documented, such as topography which has been found to control flashiness in streams across Europe (Kuentz et al., 2017), and soil moisture, which has been found to be helpful in explaining flood generation (Berghuijs et al., 2016) and the runoff coefficient (Trancoso et al., 2016). Yet, our flashiness findings were novel as most high flow signatures have not yet explicitly tested inundation- related, observation-based variables.

4.3 Challenges and limitations

Even when incorporating novel, remotely sensed inundation data, characterizing the potential influence of surface water storage on river discharge is challenging (Golden et al., 2021). In our analyses, river discharge and surface water extent were significantly related to climate variables, including like precipitation (+), evapotranspiration (-), and aridity (-) (Song et al., 2018; Tulbure and Broich, 2019; Xia et al., 2019). Therefore, a correlation between surface water extent and river discharge may not necessarily be indicative of an interaction or influence and may simply suggest they are driven by the same climate forcing functions. For instance, in our analysis, watersheds with large seasonal peaks in discharge, MAX30/area and (Q10-Q95)/area, also tended to co-occur, or be significantly correlated with, watersheds that contained more floodplain and greater temporary and seasonal inundation. Yet, it is still unclear if the seasonal flooding acts to reduce or otherwise impact the peak discharge amount. Process-based hydrologic models can therefore potentially be used to complement statistical analyses and to help distinguish between correlation and causality. For example, large wetlands have been shown to reduce storm-induced discharge peaks using a semi-distributed process-based watershed model (SWAT; Evenson et al., 2018). Further, discharge simulations for 96 watersheds across the globe demonstrated that surface water storage in wetlands reduced peak flows (Stacke and Hagemann, 2012). However, process-based hydrologic models are typically developed for a single or series of nested watersheds (Jones et al., 2019), limiting our ability to compare geographically disparate watersheds. Hydrological signatures, conversely, can facilitate the rapid comparison of many different, diverse watersheds.

A related challenge is deciphering the relative importance of environmental variables when they are highly correlated with another. Temporal variability in surface water extent, for instance, is a function of climate inputs, topography, and sub-surface characteristics (Heimhuber al., 2016; Hayashi et al., 2016; Vanderhoof et al., 2018), making it difficult to clearly identify the influence of wetland and surface water inundation variables from other landscape variables. For example, in our study, slope was highly correlated (Spearman R>0.7) with seasonal, semi-permanent to permanent and total non-floodplain inundation variables, and the amount of temporary and seasonal non-floodplain inundation variables were significantly correlated with watershed aridity and water demand (Table A4). Therefore, while a forward selection process, guided by reduction in the RMSE, was used to select model variables, there could be some uncertainty in the model selection of one variable over another. In other cases, correlations between the inundation dynamic variables and previously available datasets can provide insights on the potential value-add of new independent variables. For example, while the NWI wetland dataset had a high correlation with semi-permanent and permanent inundation (R=0.86 and R=0.81, for floodplain and non-floodplain, respectively), weaker correlations were observed with temporary and seasonal patterns of inundation (Table A4). Additionally, while surface water extent was used to represent surface water storage, the two are distinct measurements, and in the future, conversion of surface water (2D) to storage (3D) will facilitate improved modeling of total water distribution.

4.4 Management implications

Hydrologic signatures have been used to support watershed management. For example, signatures related to flow magnitude, high flow frequency and flow variability have applications for flood management (Mogollon et al., 2016), wildlife habitat condition (Lowe et al., 2019), and riparian vegetation (Richter et al., 1996). Further, changes in hydrologic signatures over time have been used to examine the impacts of management actions or to assess a watershed's vulnerability or resilience to change (Hannaford and Marsh, 2008; Mogollon et al., 2016; McMillan et al., 2021; Lane et al., 2023).

Applying results linking different watershed characteristics (e.g., climate, land use, geology) to hydrologic signature variability can therefore help inform future watershed management actions. However, a challenge is how to synthesize this information in a useful way (Gnann et al., 2020). One approach would be to focus on managing watershed characteristics that are highly correlated with a pre-determined flow signature target (e.g., those associated with flood risks). For example, in our analyses, the association of greater semi-permanent and permanent floodplain inundation with less flashiness suggests that protection and restoration of floodplains may be particularly important in watersheds with flashy discharge. On the other hand, we found that non-floodplain surface water inundation helped explain the variability in the baseflow index, which describes the proportion of flow coming from groundwater, and

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by inference the relative potential vulnerabilities for drought and extreme low flow conditions. Results from our analyses–and other future analyses leveraging large satellite-based data sets against streamflow records–can therefore advance our ability to support improved watershed management, e.g., in the face of future floods and drought (Winsemius et al., 2016; Stewart et al., 2020).

5. Conclusion

Here we demonstrate that in addition to the insights hydrologic signatures provide about process-based streamflow dynamics (Addor et al., 2018; McMillian, 2019), they can also be used to assess the potential influence of surface water inundation dynamics on river discharge. While climate variables represented the dominant explanatory variables, additional variables, in particular the novel, remotely sensed inundation dynamics, also contributed to explaining variability in many of the hydrologic signatures. Five of the six flow signatures, or all except the baseflow index, were significantly correlated with surface water inundation dynamic variables, and four of the six signature models that included all variables included surface water inundation dynamics as significant variables. Our models suggest that increased floodplain inundation co-occurs with decreased streamflow flashiness and higher peak flows. These results highlight the importance of protecting and restoring surface water storage capacities within floodplains. Additionally, our model results suggest that protection and restoration of non-floodplain wetlands could potentially benefit baseflow conditions–and thereby minimize or moderate drought and low flow extremes. The study further underscores that managing risks and watershed resilience associated with high and low flow river conditions may require consideration of watershed-wide surface water storage dynamics.

Data Availability

Data archiving is currently underway, and the surface water data produced for this analysis will be available for download in the U.S. Geological Survey ScienceBase Data Catalog concurrent with the manuscript publication.

Author Contribution

MV, PN, HG, CL and JC contributed to the work’s conception. PN, WK, and MV contributed to data processing and analysis. MV, PW, HE, CL, JC, WK and WD contributed to the interpretation of the results as well as the writing and editing.

Competing Interests

The authors declare that they have no conflicts of interest.

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Appendix

Table A1. The 72 U.S. Geological survey gages and watersheds included in the analysis. The 2016-2023 period is shown relative to the Palmer Drought Severity Index (PDSI, 1980-2021). NHD: National hydrographic dataset, NWI: National Wetland Inventory. CC: cultivated crops, DF: deciduous forest, D: developed, HP: hay/pasture, EF: evergreen forest, WW: woody wetlands, MF: mixed forest, SS: shrub/scrub, H: herbaceous

Gage ID	Site ID	U.S. State(s)	Area (km^2)	NHD Density (m km^2)	NWI (% area)	PDSI (min, %)	PDSI (max, %)	PDSI (median, %)	Primary land cover
01491000	MD1	MD, DE	292	2030.7	28.6	32.6	100.0	66.5	CC (47%)
01578475	MD2	MD, PA	458	1069.2	2.6	6.1	100.0	72.4	CC (43%)
01580520	MD3	MD, PA	425	1130.1	2.1	8.9	100.0	67.4	DF (30%)
01594440	MD4	MD	907	1571.9	6.4	16.7	100.0	64.4	D (36%)
01643000	MD5	MD, PA	2112	1394.3	3.0	4.2	100.0	57.5	HP (27%)
02049500	VA1	VA	1583	1497.8	15.7	33.0	100.0	79.3	EF (29%)
02131500	SC1	SC, NC	1720	1451.6	10.3	18.3	100.0	53.7	EF (26%)
02135000	SC2	SC, NC	7256	1628.6	27.2	8.5	100.0	78.0	WW (31%), CC (31%)
02136000	SC3	SC	3211	1738.0	27.0	17.6	100.0	75.2	CC (32%), WW (31%)
02175000	SC4	SC	7077	1163.0	17.3	27.1	98.0	75.5	EF (25%), WW (24%)
02198000	GA1	GA	1676	1365.2	12.0	19.4	96.6	61.1	EF (26%)
02202500	GA2	GA	6887	1249.8	16.8	21.1	97.7	60.2	EF (26%)
05056000	ND1	ND	4862	283.9	10.6	1.2	100.0	56.3	CC (52%)
05057200	ND2	ND	1897	259.2	11.6	0.0	100.0	65.0	CC (67%)
05062500	MN1	MN	2407	745.9	23.9	3.4	100.0	58.6	CC (39%)
05066500	ND3	ND	3218	774.1	6.9	0.3	100.0	63.4	CC (81%)
05078500	MN2	MN	3518	862.3	23.5	1.2	100.0	54.5	CC (48%)
05090000	ND4	ND	1742	1068.9	3.7	1.5	100.0	51.0	CC (73%)
05123400	ND5	ND	3206	515.6	12.2	1.0	97.8	48.8	CC (48%)
05131500	MN3	MN	4384	608.9	42.4	4.5	100.0	84.4	WW (49%)
05132000	MN4	MN	3895	537.3	48.7	5.6	100.0	71.1	WW (49%)
05244000	MN5	MN	2683	471.2	23.8	0.9	100.0	52.3	DF (27%)
05300000	MN6	MN, SD	2468	1286.4	11.5	11.6	100.0	66.6	CC (68%)
05304500	MN7	MN	4899	733.6	17.0	4.8	100.0	62.5	CC (66%)
05313500	MN8	MN, SD	1801	1129.0	8.8	8.5	100.0	58.8	CC (80%)
05336700	MN9	MN	2252	676.5	34.1	17.0	100.0	87.8	WW (34%)
05388250	IA1	IA, MN	2010	1548.4	2.7	9.2	100.0	76.1	CC (61%)
05412500	IA2	IA	3858	1414.9	2.4	6.9	100.0	81.6	CC (66%)
05418500	IA3	IA	4019	1452.5	2.1	6.3	100.0	70.8	CC (69%)
05422000	IA4	IA, MN	6049	1248.5	4.6	5.9	99.7	70.2	CC (79%)
05434500	WI1	WI, IL	2677	1618.6	3.0	5.1	100.0	71.9	CC (44%)
05447500	IL1	IL	2576	1115.6	1.9	20.7	100.0	74.9	CC (85%)
06018500	MT1	MT	9373	1628.9	3.9	0.3	89.3	50.9	SS (47%)
06052500	MT2	MT, WY	4634	1376.2	2.9	1.2	97.4	61.8	EF (47%)
06076690	MT3	MT	2189	1695.3	4.3	1.4	98.1	62.7	H (35%)
06468170	ND6	ND	2809	302.6	7.4	1.0	100.0	66.3	CC (67%)
06471200	ND7	ND, SD	1869	627.2	11.2	1.2	100.0	70.8	CC (62%)
06479525	SD1	SD	2467	947.8	9.8	19.3	100.0	67.4	CC (59%)
06481500	SD2	SD	1604	1102.0	8.7	8.8	100.0	62.0	CC (72%)
06815000	NE1	NE, KS	3473	1688.2	1.8	4.1	99.2	52.8	CC (54%)
06821190	MO1	MO, IA	6179	1925.6	4.8	11.3	99.0	56.6	CC (50%)
06908000	MO2	MO	2895	1737.9	4.2	3.5	90.4	51.9	HP (38%)
06916600	KS2	KS, MO	8387	1685.9	3.8	12.3	100.0	57.5	HP (37%)
06918060	MO3	MO, KS	2773	1669.2	5.4	4.7	100.0	57.0	HP (56%)

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Gage ID	Site ID	U.S. State(s)	Area (km^2)	NHD Density (m km^2)	NWI (% area)	PDSI (min, %)	PDSI (max, %)	PDSI (median, %)	Primary land cover
06928000	MO4	MO	3275	1538.7	1.8	12.8	100.0	79.9	DF (45%), HP (43%)
07047950	AR1	AR	1985	1864.2	12.5	20.2	100.0	82.5	CC (73%)
07169500	KS3	KS	2098	1781.3	2.9	4.9	100.0	62.0	H (595)
07288500	MS1	MS	2009	1809.9	9.8	7.1	97.9	55.9	CCs (82%)
07290000	MS2	MS	7124	2565.5	10.0	13.3	100.0	74.8	EF (19%), MF (19%)
07346070	TX1	TX	1809	2010.3	9.3	6.5	100.0	70.4	HP (27%)
07363500	AR2	AR	5429	1762.5	3.0	28.8	99.1	83.0	EF (40%)
07364200	LA1	AR, LA	3138	1507.9	14.6	22.8	100.0	79.5	CC (31%)
08033500	TX2	TX	9406	1712.0	8.0	3.2	99.9	64.9	EF (29%)
08068090	TX4	TX	2539	1695.0	9.9	10.9	100.0	71.4	EF (32%)
08110000	TX5	TX	2616	1630.0	4.8	8.9	100.0	73.8	HP (55%)
08117500	TX6	TX	1869	1085.4	5.6	6.4	98.6	64.8	HP (43%)
08164000	TX7	TX	2124	1435.4	2.1	8.8	94.1	52.3	HP (59%)
09439000	AZ1	AZ, NM	9279	1679.3	1.2	1.2	98.1	40.2	SS (45%)
09485700	AZ2	AZ	2238	2347.0	2.1	0.0	95.4	48.3	SS (64%)
09487000	AZ3	AZ	2028	3229.6	2.3	0.0	87.7	42.4	SS (79%)
09512800	AZ4	AZ	2876	1639.6	1.3	0.1	88.1	47.1	SS (68%)
09517000	AZ5	AZ	3967	1664.7	1.7	0.2	90.8	50.6	SS (81%)
09537500	AZ6	AZ	2912	1392.5	1.1	0.0	96.6	46.0	SS (67%)
11348500	CA1	CA	3884	1469.4	8.0	0.0	84.1	55.6	SS (50%)
11376000	CA2	CA	2313	2450.2	1.9	0.0	89.1	29.9	SS (56%)
11473900	CA3	CA	1925	4181.6	1.2	0.0	88.2	35.5	EF (45%)
11501000	OR1	OR	4121	1028.4	8.2	0.0	83.3	43.4	EF (55%)
11517500	CA4	CA	2047	1495.8	5.6	0.0	94.6	17.6	EF (37%)
11519500	CA5	CA	1714	2381.7	3.8	0.0	97.6	26.3	EF (46%)
12324680	MT4	MT	4590	1287.2	3.5	1.4	97.7	46.4	EF (45%)
13302005	ID1	ID	2143	1615.5	1.2	0.5	97.8	51.2	SS (76%)
13305000	ID2	ID	2412	1443.0	1.3	0.5	93.6	48.6	SS (59%)
All (median)	~	~	**2647**	**1461.0**	**5.6**	**5.0**	**100.0**	**62.0**	~

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Table A2. Thresholds selected from 5-year Sentinel-1 (S1) and Sentinel-2 (S2) based surface water percentiles to account for variable accuracy between sites, sensors, and classes (open water (OW) compared to vegetated water (VW). ~ indicates that this output was excluded from the allowable water mask.

Site ID	S1 OW (%)	S1 VW (%)	S2 OW (%)	S2 VW (%)	Site ID	S1 OW (%)	S1 VW (%)	S2 OW (%)	S2 VW (%)
AR1	15	30	15	30	MN7	10	35	5	25
AR2	5	20	10	25	MN8	10	25	5	15
AZ1	10	5	15	10	MN9	5	25	5	25
AZ2	5	15	10	15	MO1	10	20	10	20
AZ3	5	10	10	15	MO2	5	15	15	25
AZ4	5	20	15	20	MO3	5	30	10	30
AZ5	5	20	20	15	MO4	10	15	10	35
AZ6	10	15	10	~	MS1	10	30	10	35
CA1	5	15	10	20	MS2	5	10	5	30
CA2	10	10	15	15	MT1	25	~	10	30
CA3	10	~	15	15	MT2	25	~	15	40
CA4	10	15	20	20	MT3	30	~	10	40
CA5	10	10	20	15	MT4	30	~	10	30
GA1	5	5	5	20	ND1	15	20	5	10
GA2	5	10	10	15	ND2	20	20	10	20
IA1	~	15	10	15	ND3	15	~	5	20
IA2	~	10	10	20	ND4	15	35	5	30
IA3	10	10	10	20	ND5	20	30	5	25
IA4	10	20	10	20	ND6	15	30	5	25
ID1	30	~	15	35	ND7	20	30	5	20
ID2	30	~	20	35	NE1	15	15	10	20
IL1	10	30	10	15	OR1	10	20	25	25
KS2	10	20	10	30	SC1	5	20	10	35
KS3	~	15	10	20	SC2	5	25	5	25
LA1	10	25	15	35	SC3	5	30	5	30
MD1	5	~	10	20	SC4	5	30	10	35
MD2	5	15	10	20	SD1	10	25	5	25
MD3	5	10	10	15	SD2	15	25	5	25
MD4	5	10	10	15	TX1	5	10	10	30
MD5	10	30	15	~	TX2	5	30	10	35
MN1	15	20	5	20	TX4	5	30	10	35
MN2	10	20	5	30	TX5	5	20	10	~
MN3	10	30	10	30	TX6	10	~	10	35
MN4	5	30	5	30	TX7	5	35	10	30
MN5	10	30	5	25	VA1	5	30	10	45
MN6	15	25	5	20	WI1	~	15	10	20

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779 **Table A3**. Hydrologic signatures by watershed. The blue to red shading reflects the high to low values for each
780 signature. The bold values indicate the average values for the watersheds within each region.

Region	ID	Gage	Flashiness Index	Flashiness index (wet season)	MAX30 /area	(Q10-Q95)/area	Dry Month /area	Baseflow index
	East		**-0.74**	**-0.78**	**1.37**	**0.023**	**0.0065**	**0.38**
East	MD1	01491000	-0.48	-0.45	2.16	0.034	0.0072	0.28
	MD2	01578475	-0.44	-0.43	1.52	0.024	0.0105	0.55
	MD3	01580520	-0.52	-0.64	1.45	0.024	0.0112	0.54
	MD4	01594440	-0.43	-0.42	1.38	0.021	0.0089	0.49
	MD5	01643000	-0.35	-0.40	1.98	0.028	0.0058	0.24
	VA1	02049500	-0.87	-1.01	1.27	0.028	0.0060	0.36
	SC1	02131500	-0.66	-0.64	1.29	0.022	0.0059	0.39
	SC2	02135000	-1.05	-1.07	1.55	0.025	0.0055	0.35
	SC3	02136000	-0.91	-1.04	1.22	0.023	0.0039	0.28
	SC4	02175000	-1.13	-1.20	0.89	0.017	0.0055	0.44
	GA1	02198000	-0.90	-0.95	0.86	0.016	0.0043	0.37
	GA2	02202500	-1.09	-1.17	0.92	0.017	0.0030	0.24
	Gulf Coast		**-0.79**	**-0.83**	**1.88**	**0.032**	**0.0026**	**0.09**
Gulf Coast	AR1	07047950	-0.99	-1.01	3.48	0.050	0.0057	0.18
	MS1	07288500	-0.79	-0.90	2.23	0.056	0.0035	0.04
	MS2	07290000	-0.85	-0.93	2.22	0.046	0.0030	0.10
	TX1	07346070	-0.74	-0.71	1.64	0.025	0.0006	0.02
	AR2	07363500	-0.82	-0.86	2.46	0.050	0.0024	0.05
	LA1	07364200	-1.45	-1.58	1.37	0.044	0.0030	0.16
	TX2	08033500	-0.94	-1.01	1.19	0.024	0.0027	0.08
	TX4	08068090	-0.35	-0.31	2.30	0.016	0.0022	0.09
	TX5	08110000	-1.00	-1.02	0.54	0.020	0.0024	0.08
	TX6	08117500	-0.51	-0.59	2.10	0.021	0.0019	0.08
	TX7	08164000	-0.21	-0.23	1.13	0.003	0.0010	0.07
	Midwest		**-0.62**	**-0.60**	**1.43**	**0.021**	**0.0042**	**0.28**
Midwest	IA1	05388250	-0.78	-0.68	1.51	0.025	0.0083	0.47
	IA2	05412500	-0.73	-0.62	1.53	0.024	0.0066	0.37
	IA3	05418500	-0.80	-0.69	1.11	0.016	0.0077	0.59
	IA4	05422000	-0.99	-1.06	1.14	0.023	0.0060	0.41
	WI1	05434500	-1.12	-1.01	0.96	0.014	0.0094	0.70
	IL1	05447500	-0.79	-0.78	1.03	0.018	0.0055	0.38
	NE1	06815000	-0.25	-0.21	0.96	0.007	0.0013	0.24
	MO1	06821190	-0.52	-0.55	1.14	0.016	0.0018	0.19
	MO2	06908000	-0.40	-0.44	1.61	0.022	0.0010	0.05
	KS2	06916600	-0.55	-0.60	1.48	0.023	0.0013	0.09
	MO3	06918060	-0.39	-0.45	2.13	0.030	0.0020	0.06
	MO4	06928000	-0.38	-0.34	2.24	0.026	0.0024	0.10
	KS3	07169500	-0.42	-0.36	1.69	0.032	0.0015	0.06
	North-Central		**-0.93**	**-0.93**	**0.52**	**0.008**	**0.0016**	**0.19**
North-Central	ND1	05056000	-1.04	-0.98	0.11	0.002	0.0005	0.08
	ND2	05057200	-0.83	-0.88	0.21	0.004	0.0004	0.07
	MN1	05062500	-0.94	-0.92	0.48	0.007	0.0014	0.24
	ND3	05066500	-0.76	-0.79	0.54	0.006	0.0007	0.09
	MN2	05078500	-0.81	-0.77	0.54	0.006	0.0011	0.23
	ND4	05090000	-0.78	-0.82	0.34	0.004	0.0004	0.05
	ND5	05123400	-1.09	-1.11	0.10	0.002	0.0001	0.06

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Region	ID	Gage	Flashiness Index	Flashiness index (wet season)	MAX30 /area	(Q10-Q95)/area	Dry Month /area	Baseflow index
	MN3	05131500	-0.90	-0.86	1.15	0.018	0.0028	0.19
	MN4	05132000	-1.01	-0.95	0.77	0.013	0.0020	0.27
	MN5	05244000	-1.45	-1.46	0.31	0.006	0.0038	0.68
	MN6	05300000	-0.99	-0.96	0.65	0.011	0.0019	0.21
	MN7	05304500	-1.16	-1.14	0.46	0.010	0.0029	0.34
	MN8	05313500	-0.90	-0.89	0.83	0.015	0.0025	0.18
	MN9	05336700	-0.77	-0.78	1.69	0.027	0.0055	0.25
	ND6	06468170	-0.93	-0.93	0.18	0.003	0.0001	0.04
	ND7	06471200	-0.68	-0.64	0.24	0.002	0.0002	0.09
	SD1	06479525	-1.00	-1.09	0.23	0.005	0.0010	0.22
	SD2	06481500	-0.73	-0.73	0.48	0.009	0.0016	0.18
	Southwest		**-0.12**	**-0.16**	**0.06**	**<0.001**	**<0.0001**	**0.01**
	AZ1	09439000	-0.61	-0.83	0.09	0.001	0.0000	0.03
	AZ2	09485700	0.07	0.12	0.08	0.000	0.0000	0.00
Southwest	AZ3	09487000	0.23	0.23	0.01	0.000	0.0000	0.00
	AZ4	09512800	-0.08	-0.09	0.16	0.001	0.0000	0.00
	AZ5	09517000	-0.30	-0.34	0.02	0.000	0.0001	0.05
	AZ6	09537500	-0.02	-0.03	0.01	0.000	0.0000	0.00
	West		**-1.03**	**-1.09**	**0.67**	**0.012**	**0.0009**	**0.26**
	MT1	06018500	-1.23	-1.41	0.04	0.001	0.0004	0.44
	MT2	06052500	-1.18	-1.06	0.69	0.013	0.0022	0.32
	MT3	06076690	-1.04	-1.01	0.18	0.004	0.0007	0.32
	CA1	11348500	-0.70	-0.77	0.22	0.004	0.0001	0.02
	CA2	11376000	-0.51	-0.69	1.62	0.023	0.0006	0.06
West	CA3	11473900	-0.51	-0.69	3.31	0.051	0.0003	0.01
	OR1	11501000	-1.25	-1.24	0.31	0.005	0.0011	0.35
	CA4	11517500	-1.13	-1.27	0.14	0.003	0.0005	0.21
	CA5	11519500	-0.82	-0.95	0.92	0.023	0.0003	0.03
	MT4	12324680	-1.16	-1.07	0.33	0.006	0.0015	0.38
	ID1	13302005	-1.63	-1.89	0.12	0.002	0.0019	0.61
	ID2	13305000	-1.22	-1.08	0.20	0.003	0.0012	0.40

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Table A4. Spearman correlation values between remotely sensed surface water variables and other independent variables. Significant (p<0.01) correlations, after Bonferroni correction has been applied, are shown shaded in gray. CV: coefficient of variation, FP: floodplain, NFP: non-floodplain, temp: temporarily, inun: inundation, Geographically Isolated Wetlands: GIW

Variable Type	Variable	Temp. flooded, FP	Temp. inun., NFP	Seasonally inun., FP	Seasonally inun., NFP	SP-P inun., FP	SP-P inun., NFP	Total inun., FP	Total inun., NFP
Climate	Precipitation (P)	0.39	0.52	0.75	0.44	0.41	0.21	0.69	0.45
	Evapo-transpiration (ET)	0.4	-0.12	0.19	-0.22	-0.1	-0.27	0.19	-0.23
	Aridity index (ET/P)	-0.3	-0.62	-0.66	-0.45	-0.34	-0.14	-0.58	-0.49
	Water demand (P - ET)	0.22	0.61	0.61	0.46	0.34	0.16	0.53	0.5
	Precipitation seasonality	0.03	0.19	0.06	0.29	0.03	0.09	0.11	0.26
	Precipitation CV	-0.02	-0.28	-0.18	-0.03	-0.08	0.06	-0.11	-0.07
	Temperature seasonality	-0.37	0.02	-0.25	0.19	0.06	0.23	-0.21	0.19
	Temperature CV	-0.44	0.02	-0.29	0.17	0.08	0.26	-0.26	0.18
Land cover	Forest	0	0.3	0.1	-0.02	0.06	0	0.04	0.04
	Developed	0.39	0.37	0.63	0.28	0.28	0.04	0.58	0.28
	Cultivated crops	0.07	0.05	0.21	0.28	0.17	0.16	0.23	0.25
	Stream density	0.43	-0.11	0.13	-0.32	-0.24	-0.48	0.13	-0.32
Sub-surface	Clay fraction	0.39	-0.01	0.27	0	0	-0.1	0.27	-0.06
	Sand fraction	-0.35	0.05	-0.17	0.08	0.1	0.22	-0.18	0.09
	Average soil thickness	-0.12	0.33	0.49	0.71	0.66	0.69	0.51	0.68
	Water table depth	-0.18	-0.51	-0.68	-0.78	-0.67	-0.64	-0.72	-0.73
Topography	Slope	0.02	-0.3	-0.55	-0.77	-0.63	-0.76	-0.56	-0.71
	Elevation range	0.21	0.02	0.12	-0.22	-0.13	-0.23	0.04	-0.18
	Topographic diversity	0.02	-0.22	-0.5	-0.71	-0.57	-0.7	-0.51	-0.65
Wetland	GIW	-0.27	0.32	0.37	0.8	0.73	0.89	0.4	0.76
	Proportion of wetland area identified as GIW	-0.09	0.14	0.26	0.55	0.38	0.62	0.29	0.5
	Floodplain	0.64	0.28	0.84	0.36	0.55	0.19	0.92	0.3
	National Wetland Inventory wetlands	-0.27	0.48	0.45	0.81	0.86	0.85	0.46	0.8