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Water Resources Research

RESEARCH ARTICLE
10.1029/2025WR042131

Characterizing Watershed Responses and Reservoir Operational Flexibilities: Analyses to Support Forecast-Informed Reservoir Operations (FIRO) Planning and Assessments

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Key Points:

- A method for regional scale assessment of Forecast-Informed Reservoir Operations (FIRO) suitability and science needs based on watershed and reservoir characteristics is presented
- Precipitation and runoff are less coupled at sites with high runoff ratio variability and streamflow forecast skill assessments are needed
- The flood buffering capacity of reservoirs given available storage and release constraints varies across climatological gradients

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Albano, C. M., Shearer, E. J., Forbis, J. C., Yeates, E. M., Kalansky, J., Painter, C. A., et al. (2026). Characterizing watershed responses and reservoir operational flexibilities: Analyses to support forecast-informed reservoir operations (FIRO) planning and assessments. *Water Resources Research*, *62*, e2025WR042131. https://doi.org/10.1029/2025WR042131

Received 5 SEP 2025
Accepted 19 JUN 2026

Abstract Recent advances in weather forecast skill provide opportunities to manage reservoirs more flexibly using strategies like Forecast-Informed Reservoir Operations (FIRO). This is especially critical as changes in climate, population, and land use make balancing reservoir uses to minimize flood risks and maximize water availability more challenging. FIRO viability depends on the ability to forecast reservoir inflows with sufficient accuracy and lead time that storage and releases downstream can be maintained at safe levels. In this study, we develop a transferable approach for gaining early insights into potential challenges and opportunities for FIRO by (a) identifying how precipitation amount, phase, and soil moisture mediate runoff generation, and (b) characterizing how the timing and magnitude of reservoir inflows relate to the amount of space available for storage and the ability to safely release water without causing downstream flooding. The buffering capacity of the reservoir to accommodate inflows is quantified as an operational flexibility metric, which can help to inform streamflow forecast lead time requirements. Using historical hydrologic and meteorologic data and an automated baseflow separation routine, we assessed operational flexibility at 32 reservoirs in California and western Nevada. We demonstrate that operational flexibility varies regionally, with less flexibility in snow-dominated basins, where the amount of water that can be released from reservoirs is more limited relative to those in rain-dominated basins. A warming climate will further challenge this flexibility, indicating that FIRO efforts in snow-dominated basins will likely need to be coupled with other adaptation strategies.

Plain Language Summary Forecast-Informed Reservoir Operations (FIRO) is a water management strategy that uses advancements in weather and hydrologic forecasting to more flexibly manage water to mitigate flood risks, improve water availability, and meet multiple other societal needs. In this study, we develop a transferable approach for gaining early insights into potential challenges and opportunities for FIRO by identifying key factors that mediate how much streamflow is generated from precipitation and characterizing how the timing and magnitude of reservoir inflows relate to the amount of reservoir space available for storage and the ability to safely release water without causing downstream flooding. Based on our analysis of 32 reservoirs across California and Nevada, we find that the operational flexibility of reservoirs tends to be more constrained in snow-dominated basins relative to those where more precipitation falls as rain, thus combining FIRO with other water management strategies and infrastructure investments will likely need to be considered. Despite these challenges, expected transitions from snow to rain under a warming climate make added flexibility in water management operations in these regions especially critical.

1. Introduction

Increasing atmospheric and human demands for water due to warming climate, land use changes, and population growth are placing new stresses on water management infrastructure and policies that may extend beyond the limits these systems were designed to accommodate. In the last two decades California has experienced two of the driest 3-year periods on record and two of the wettest years on record (California Department of Water Resources, 2023b) and despite relatively stable water demand since the 1990's (Mount et al., 2023), groundwater levels have declined in nearly half of all wells across the state over the past 20 years (California Department of Water Resources, 2023a). These stresses have prompted important changes to California water management such as the 2014 Sustainable Groundwater Management Act (SGMA). While new groundwater management policies, such as SGMA, are being formed in the context of current conditions, reservoir infrastructure and operational rulesets for surface water management were established decades ago and were formulated based on historical precipitation regimes. Because climate warming is causing increases in interannual variability (Swain et al., 2018), reductions in snowfall and snowpack (Mankin et al., 2015), earlier snowmelt (Adam et al., 2009), and increasing the intensities of the more extreme atmospheric rivers (ARs; Gershunov et al., 2017; Payne et al., 2020) there is a need to update surface water management operations to adapt to changing conditions (Wilson et al., 2021).

Significant resources have been invested to advance weather forecast capabilities and better anticipate atmospheric river (AR)-driven storm events, as these are well-recognized key drivers of water supplies and flood risks in this region (Ralph et al., 2019). As a result of this, AR forecast capabilities have improved for up to 6-week lead times (e.g., Chapman et al., 2022; DeHaan et al., 2023; Lord et al., 2023; Zheng et al., 2021). In particular, forecast skill improvements in the short-to-medium-range (1–5 days) are enabling new management strategies such as forecast-informed reservoir operations (FIRO; American Meteorological Society, 2020). FIRO is a water management strategy that uses advancements in weather and hydrologic forecasting to more flexibly manage water to mitigate flood risks, sustain or improve water availability, and meet multiple other economic and ecological objectives. FIRO implementation is contingent on the ability to forecast weather and streamflow with suitable accuracy and at lead times that allow water to be safely stored and released.

Given advances in weather forecast skill of ARs, pilot implementations of FIRO have proven viable in a handful of basins of California (Lake Mendocino FIRO Steering Committee, 2020; Prado Dam Steering Committee, 2023; Talbot et al., 2023; Yuba-Feather FIRO Steering Committee, 2022) and have set the stage for assessing other locations where this strategy can be applied. Demand for large-scale implementation of the FIRO strategy has led the U.S. Army Corps of Engineers (USACE) to assess its national portfolio of nearly 600 reservoirs for FIRO potential. The FIRO screening process uses a multi-staged approach to identify sites where FIRO might be both possible and beneficial (Yeates et al., 2026). FIRO implementation at a site has historically involved years of rigorous study to assess viability, followed by a formal agency Water Control Plan update (Forbis & Ly, 2025). Screening and other higher-order analyses of site suitability can help to identify cases where significant investments in FIRO viability studies are likely to be worthwhile given benefits it can provide, as well as cases where a less rigorous approach is likely to be sufficient.

From a hydrologic perspective, FIRO suitability also requires an understanding of precipitation variability, how the watershed responds to precipitation, and in turn, how predictable these are (Forbis & Ly, 2025). This must all be considered in the context of operational constraints, including reservoir storage capacity, outlet release rates, downstream channel capacities, and travel times to downstream flood control points (Yeates et al., 2026). The central requirement for FIRO viability at a site is that forecasts reliably give reservoir operators sufficient time to release stored water ahead of incoming inflows. For reservoirs with required forecast lead times that exceed the availability of skillful forecasts, FIRO is likely not a viable strategy unless forecast skill is improved or project risk tolerance is increased (such as by adding off-channel flood storage).

The USACE FIRO screening process considers weather forecast skill at minimum lead times necessary for decision-making at a site, supplemented with site operators' assessment of the reliability of available inflow forecasts (Yeates et al., 2026). While the former metric provides a formal quantification of weather forecast skill, the latter is qualitative, and thus neglects to fully consider the reliability of lead time required to accommodate inflows. Inflow forecast reliability varies among reservoirs given differences in upstream watershed responses to precipitation and the physical and/or operational constraints of the reservoir, itself (Timberlake et al., 2025).

The primary objectives of this study are to develop a robust method to characterize watershed responses to precipitation, identify factors that influence variability in these responses, and characterize how response timing and magnitudes relate to the physical constraints of reservoirs (i.e., safe storage and release capacities), building on information describing reservoir operational policies and rules that were compiled as part of the FIRO screening process. To accomplish this, we applied an automated baseflow separation algorithm (Giani et al., 2021, 2022) to assess historical reservoir inflows at 32 sites using available data between 1950 and 2019. This automated approach was chosen to enable analysis of decades of streamflow and precipitation data at a large number of sites in a manner that is efficient, objective and replicable. Results from this study can address the need for higher order analyses of FIRO site suitability early in the evaluation process by (a) identifying watersheds where additional monitoring and research may be needed to improve predictability of hydrologic responses, and (b) provide insights into how and where reservoir storage and/or outflow constraints factor into the forecast lead times necessary for safe implementation of FIRO under current and anticipated future conditions. Implementation of FIRO involves creation of operational rulesets that enable greater flexibility to retain water in storage when conditions are forecasted to be dry and release water ahead of when conditions are forecasted to be wet. The potential for operational flexibility likely varies by site and is dependent on the reservoir's water storage and release rate capacities, which determine the forecast lead time that is required, as well as options available for supplemental storage either upstream or downstream.

2. Materials and Methods

2.1. Study Area and Site Selection

Our study includes 32 sites in California and Nevada (Figure 1, Table 1), where winter AR storms are the dominant driver of precipitation and where recent pilot studies of FIRO viability show promise (Talbot et al., 2023). The availability of long term records of daily reservoir inflow and storage data was the primary criterion for site selection, to enable the largest possible number of storm and flood events to be captured in the analysis. Sites were also selected to capture a diversity of watershed attributes (see Table S1 in Supporting Information S1), including area (102–16,766 km^2), slope (average 6°–25°), elevation (average 188–2514 m), climate (annual average precipitation 362–1654 mm, 1981–2020), aspect (e.g., leeward vs. windward sides of mountain ranges) and hydrologic response types (Albano et al., 2020). To achieve this, sites not currently under consideration for FIRO due to lack of regulation by USACE were included. According to the National Inventory of Dams (NID), eighteen sites have flood risk reduction listed as their primary purpose. Primary purposes at other sites are classified as hydroelectric (Trinity, Shasta, New Bullards Bar, Folsom, New Melones, Don Pedro, Exchequer Main), irrigation (Stampede, Indian Valley, Bradbury), and water supply (Prosser, Camanche, Bridgeport, Santa Felicia), albeit many of these dams are multi-purpose (U.S. Army Corps of Engineers, 2022).

2.2. Data

2.2.1. Hydrologic Data

Reservoir inflow, outflow, and storage data for 25 sites were obtained from the ResOps data set (Steyaert et al., 2022); which draws from the California Data Exchange Center (CDEC; https://cdec.water.ca.gov/). Of the seven remaining sites used in the study, data for four sites on the leeside of the Sierra Nevada were obtained from the Truckee River Federal Water Master. This data set had a longer historical record relative to data reported in ResOps and includes refined storage, inflow, and outflow estimates based on reservoir evaporation and operations not captured in the ResOps data set. Additional data for three USACE-regulated sites in the South Coast region were obtained from local contacts.It is important to note that inflow, outflow, and storage are not always directly observed at reservoirs, and thus these values are often inferred from water budget calculations based on the observations that do exist, which can be imprecise and introduce error (Song et al., 2022).

Watershed boundaries corresponding to USGS gages (Falcone, 2011) were used for all but five sites. For these sites, which lacked representative USGS gages, watersheds were generated using the Delineator.py Python tool on the MERIT-Hydro DEM (Heberger, 2021). Watershed delineation captured the drainage above the dam outlet and generated watershed sizes that were compared against reported drainage basin size in the National Inventory of Dams to ensure accuracy. Basin shapefiles do not account for upstream water management infrastructure that may influence downstream hydrology (i.e., dam shapefiles at the mouth of watershed will include the drainage basins of all dams in the watershed). Source information for hydrologic and watershed data are provided in Table S2 in Supporting Information S1.

2.2.2. Meteorological Data

Watershed average daily precipitation was calculated for each site over the 1950–2019 time period using the 4-km spatial resolution "extreme-preserving" data set (Pierce et al., 2021), which is a modified version of Livneh et al. (2015) that better captures extreme precipitation by omitting the time-adjustment that muted extreme

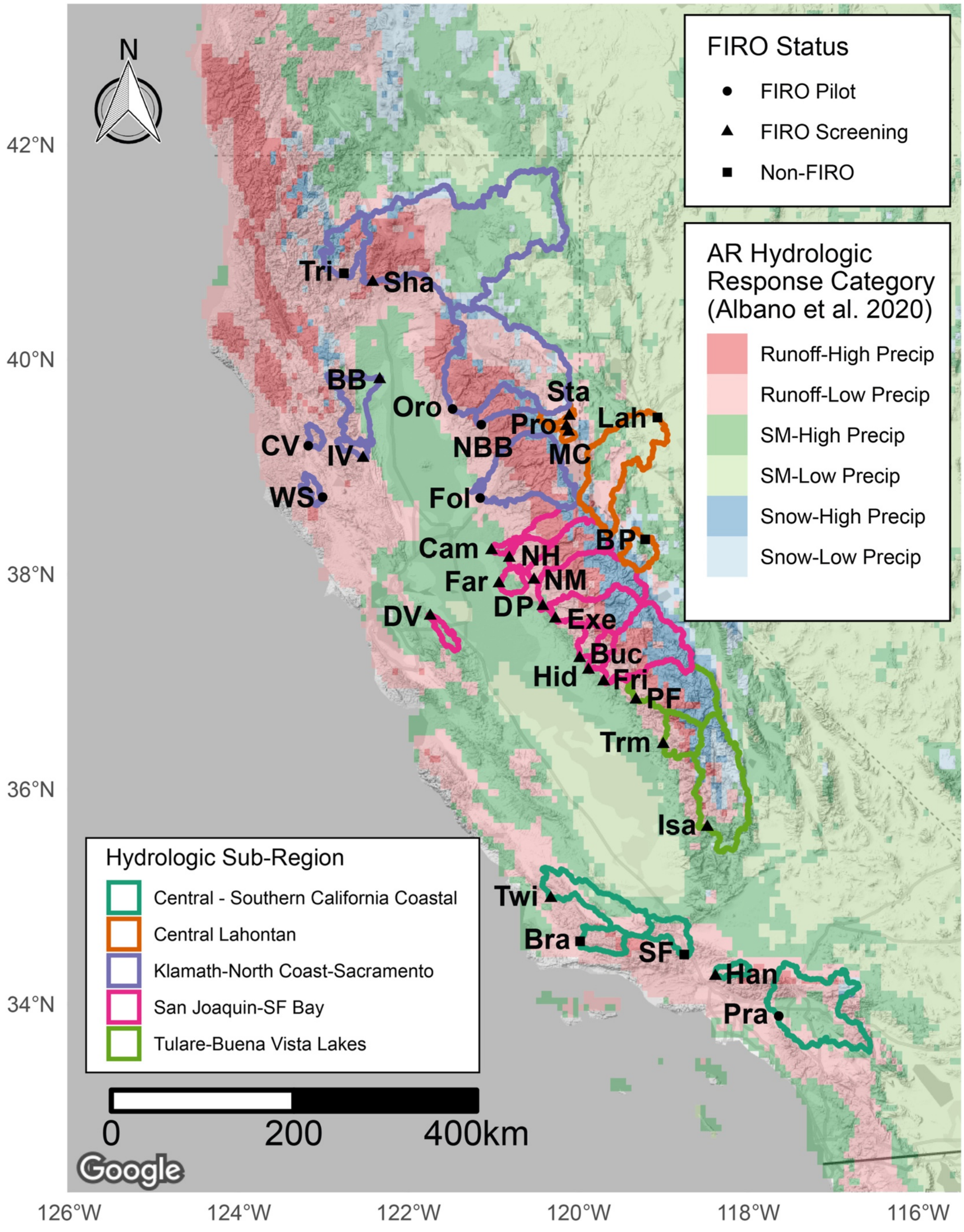

Figure 1. Reservoir sites included in the study and their contributing areas. See Table 1 for additional details on each site. Shading corresponds with atmospheric river hydrologic response categories defined in Albano et al. (2020).

precipitation in the latter data set. Although we recognize that precipitation data sets can vary substantially in complex terrain (Henn et al., 2018), the extreme preserving data set was selected given the widespread use of Livneh et al. (2015) for hydroclimatic studies in this region and our interest in accurately capturing the largest storm and flood events. Daily precipitation data were supplemented with daily estimates of antecedent soil moisture and snow-to-precipitation ratios based on the 1-km WLDAS (Erlingis et al., 2021) data set, which are available from 1979 to 2019, thus snow and soil moisture data from 1950 to 1978 were not included in the analysis. Correspondence between WLDAS and in situ soil moisture observations indicate reasonable representation of these conditions (Erlingis et al., 2021), however we are not aware of any assessment of how well this

Table 1
Names and Abbreviations of Dams Included in This Study, Primary Purpose as Defined in the National Inventory of Dams, and Sample Size of Events Analyzed, Which Include the Largest 10% of Streamflow and Precipitation Events During the Historical Period of Record for Each Site (See Table S2 in Supporting Information S1)

Dam name and abbreviation		Primary purpose	Sample size (number of top 10% events analyzed)
Trinity[b]	Tri	Hydroelectric	61
Shasta	Sha	Hydroelectric	64
Black Butte Dam	BB	Flood Risk Reduction	25
Oroville[a]	Oro	Flood Risk Reduction	37
Stampede	Sta	Irrigation	42
New Bullards Bar[a]	NBB	Hydroelectric	19
Prosser Creek	Pro	Water Supply	47
Martis Creek Dam	MC	Flood Risk Reduction	43
Coyote Valley Dam[a]	CV	Flood Risk Reduction	30
Indian Valley	IV	Irrigation	22
Warm Springs Dam	WS	Flood Risk Reduction	31
Folsom[a]	Fol	Hydroelectric	75
Camanche	Cam	Water Supply	27
New Hogan Dam	NH	Flood Risk Reduction	30
New Melones	NM	Hydroelectric	34
Farmington Dam	Far	Flood Risk Reduction	16
Don Pedro	DP	Hydroelectric	49
Del Valle	DV	Flood Risk Reduction	57
Exchequer Main	Exe	Hydroelectric	26
Lahontan[b]	Lah	Flood Risk Reduction	21
Bridgeport[b]	BP	Water Supply	28
Buchanan Dam	Buc	Flood Risk Reduction	24
Hidden Dam	Hid	Flood Risk Reduction	25
Friant	Fri	Flood Risk Reduction	31
Pine Flat Dam	PF	Flood Risk Reduction	32
Terminus Dam	Trm	Flood Risk Reduction	26
Isabella Dam	Isa	Flood Risk Reduction	20
Bradbury[b]	Bra	Irrigation	9
Santa Felicia[b]	SF	Water Supply	17
Twitchell	Twi	Flood Risk Reduction	8
Hansen	Han	Flood Risk Reduction	37
Prado[b]	Pra	Flood Risk Reduction	42

[a]Indicates Forecast-Informed Reservoir Operations Pilot Sites, Where Viability Assessments Have Been Conducted or are Ongoing. [b]Indicates Sites That are Not Under USACE Jurisdiction, so Storage and Release Data Were Obtained From Alternate Sources (See Table S2 in Supporting Information S1).

data set characterizes precipitation phase and recognize that gridded data sets often fail to capture this well (Yu et al., 2024) and that this is an important limitation.

2.2.3. Reservoir Storage and Release Capacity Data

Reservoir storage and release capacity data (Figure 2; Table S2 in Supporting Information S1) were obtained from the USACE Water Control Manuals (27 sites that are regulated by USACE) and the National Inventory of Dams (NID; https://nid.sec.usace.army.mil, accessed in June 2022; 5 sites). Gross Storage represents the total volume

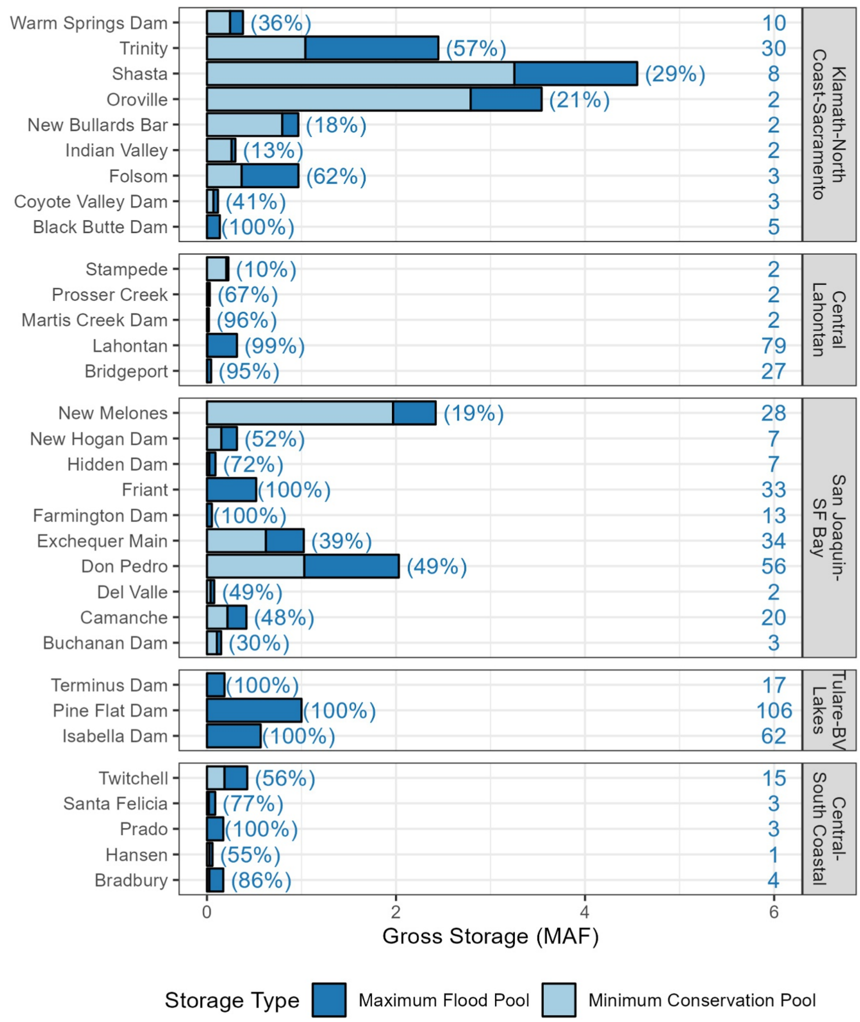

Figure 2. Gross storage volume available at each reservoir, with colors indicating the minimum conservation (light blue) and maximum flood (dark blue, number indicates % of Gross) pool volumes. The number of days required to empty the Maximum Flood Pool (dark blue) storage at the governing release rate (see Table S2 in Supporting Information S1) also is shown on the right side of the plot. For example, Warm Springs Dam has a gross storage capacity of 0.381 million acre feet, 36% of which is comprised of flood storage during the time of year when flood storage is at a maximum, as designated by the Water Control Manual. Based on the governing release rate and assuming an outlet position and operational rules that would enable all water to be released consistently at this rate, it would take 10 days for the full volume of maximum flood storage water to be released. See Table 2 for definitions of storage and release terms.

when the reservoir is considered 100% full, which, for a gated spillway, is typically associated with the storage volume that is at or near the crest of the spillway (Institute for Water Resources, 2016). Maximum Flood Storage at the 27 USACE sites is the difference between Gross Storage and the volume of the minimum Conservation Pool, which is water stored for non-flood control authorized purposes. Although the conservation pool and flood storage volumes can vary seasonally and/or are conditional on antecedent snowpack and rainfall conditions at many of the sites, we use a static value of the maximum flood storage across seasons in a year to simplify comparisons among reservoirs and to target how inflows relate to the maximum amount of space that could potentially be reserved for floodwaters. This value is also inclusive of conditional spaces within the conservation pool that are reserved for anticipated snowmelt. For example, 100% of gross storage is available for flood storage at Pine Flat, Isabella, and Terminus when the snowpack is large (California Department of Water Resources, 2022). Governing release constraints are represented by either the maximum flow limit at a downstream control point or the objective release specified in the Water Control Manual. We also note that storage and release

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capacities used in this study represent current documented conditions, recognizing that these may not reflect previous operational rules and/or infrastructure capacities, if they have changed over the course of the study period.

For the five sites that lack USACE regulation, Normal Storage from NID was used to represent Gross Storage. Maximum Flood Storage and governing release capacities are represented by conservation storage and release objectives identified from alternate sources at these sites (see Table S2 in Supporting Information S1). Although these five reservoirs were not originally designed for flood risk management purposes, flood space is still an important consideration given that downstream communities and infrastructure have potential to be affected by flooding. Because many of the 32 sites included in the study have upstream water management infrastructure that alters natural rainfall-runoff patterns, the sum of Normal Storage across all upstream reservoirs in NID that are contained within the site's watershed boundary was calculated to characterize this (see Table S2 in Supporting Information S1).

2.3. Analytical Approach

2.3.1. Rainfall-Runoff Event Separation

Given the long-term data records spanning 14–69 years (Table 1) and large number of sites, we used an automated event separation algorithm to delineate streamflow events and discretize the amount of streamflow derived from the precipitation event (quickflow) from that contributed by baseflow so that characteristics such as runoff ratios, lag times, and event-specific flow volumes could be quantified. We used the Detrending Moving-average Cross-correlation Analysis Event Separation Routine (DMCA-ESR; Giani et al., 2021, 2022) to achieve this, implemented in MATLAB. DMCA-ESR estimates catchment response times by identifying the timescale at which the precipitation and streamflow centers of mass are most highly correlated and delineates events based on bivariate fluctuations in both precipitation and streamflow. Because of this, streamflow events are not detected in the absence of preceding precipitation (Fischer et al., 2021), which offers an advantage over other methods in systems such as those included in this study, where upstream flow management and releases could result in event detections that are independent of precipitation. The DMCA-ESR method requires two parameters—the minimum daily precipitation rate that constitutes an event (here we use 1.75 mm/day; equivalent to the rate of light rainfall), and the maximum number of days (here we use 7) across which to search to determine catchment response time. We performed a sensitivity analysis to determine the optimal value of these parameters (See Text S1, Figures S1 and S2 in Supporting Information S1). Given changes in reservoir operations and flows over the course of the year and to limit our analysis to the time period when the largest precipitation and streamflow events occur, we restricted our analysis to the months of October -April.

2.3.2. Metrics

To focus our analysis on the largest storms and floods, which are the most consequential and of greatest interest in the context of determining site suitability for FIRO, we filtered results to include only events with the largest 10% precipitation or quickflow volumes for the period of record at each site. Using just these top 10% events, we calculated a suite of metrics (Table 2) to characterize (a) variability in watershed responses to precipitation events (watershed hydrologic response metrics), and (b) how event-scale reservoir inflows relate to reservoir storage and release capacities (physical constraint metrics; Figure 3).

Watershed metrics were selected to characterize the magnitude, variability, timing, and predictability of reservoir inflows in relation to precipitation. The runoff ratio, calculated as the ratio of event quickflow to precipitation volume, indicates the magnitude and variability of streamflow responses to precipitation. Variability in runoff ratios among watersheds and storm events can be driven by differences in antecedent soil moisture or snowpack, precipitation duration or intensity, whether precipitation is falling as rain or snow (Berghuijs et al., 2016), or by upstream water management. In cases of high runoff ratio variability, precipitation amount may not necessarily be predictive of runoff and thus more information on upstream conditions and precipitation phase are required for accurate prediction. The lag time between peak daily precipitation and peak reservoir inflow provides information on how much additional decisional lead time might be available to release water beyond the lead time enabled by a weather forecast, which is an important consideration for FIRO.

Table 2
Variable Definitions and Metrics Calculated for Each of the Top 10% Events at Each Site

Metric	Interpretation
Variable Definitions	
Gross Storage	The total volume when the reservoir is considered 100% full. If a reservoir has a gated spillway, that would mean the storage volume that is at or near the crest of the spillway (Institute for Water Resources (2016))
Normal Storage	The total storage space in a reservoir below the normal retention level, including dead and inactive storage and excluding any flood control or surcharge storage. (U.S. Army Corps of Engineers (2021))
Maximum Flood Storage	Maximum space available for flood storage; this volume tends to be held vacant with the goal of attenuating floodwaters downstream (Institute for Water Resources (2016)
Minimum Conservation Pool	Minimum space available for non-flood control authorized purposes (Institute for Water Resources (2016))
Governing Release	Either the objective release (the maximum allowable flows at locations downstream of reservoirs operated for flood damage reduction; Institute for Water Resources (2016) or the downstream channel capacity
Occupied Storage	Volume of gross storage occupied by water on a given day
Watershed Response Metrics	
Runoff Ratio	Ratio of event quickflow to precipitation volumes. Larger values indicate larger flow magnitudes for a given precipitation amount. Precipitation volume is calculated as the sum of spatially averaged daily precipitation depths during the precipitation event, multiplied by the watershed area.
Lag Time	Difference (in days) between the occurrence of daily precipitation and streamflow event peaks. Larger values indicate more lead time to accommodate event inflows.
Physical Constraint Metrics	
Governing release constraint	Ratio of event inflow and the governing release volumes. Values >1 indicate inflows are greater than the volume that could be released during the same number of days, given current governing release constraints. This metric was used to calculate the additional number of days required to release water to avoid storage accumulation for each event. Larger values indicate greater governing release constraints.
Flood Storage constraint	Ratio of event inflow to maximum flood storage. Values between 0 and 1 indicate the amount by which inflow was greater than the maximum flood storage. Larger values indicate greater flood storage constraints.
Occupied Storage Constraint	Ratio of occupied storage one day prior to the start of the flow event to gross reservoir storage. Larger values indicate less available storage prior to the event and larger occupied storage constraints.
Operational Flexibility	Ratio of post-event available storage as a proportion of gross storage. Post-event available storage is calculated by subtracting the sum of pre-event occupied storage and event net flow (inflow-governing release over same number of days) from gross storage. Values greater than or equal to 1 indicate 100% of gross storage could be available post-event because more water can be released over the duration of the event than combined event inflow and pre-event occupied storage. Values closer to 1 indicate greater flexibility to release water at shorter lead times without significant encroachment into flood and/or overall gross pool storage. Values closer to 0 indicate tighter margins and thus less flexibility due to a combination of less available storage pre-event and constrained release capacity relative to the inflow volume.

Note. Storage and release constraints for each site are listed in Table S2 in Supporting Information S1 and visual depictions of the physical constraint metrics are in Figure 3.

The four physical constraint metrics normalize historical reservoir inflow event volumes to the physical constraints of the dam and reservoir (Figure 3). The constraints analyzed are based on (a) the governing release capacity, which is either the objective release or the downstream channel capacity, (b) flood storage capacity, which is the space available for use as flood storage, (c) the occupied storage, which is the proportion of the reservoir's gross storage capacity that is occupied one day prior to the inflow event, and (d) the operational

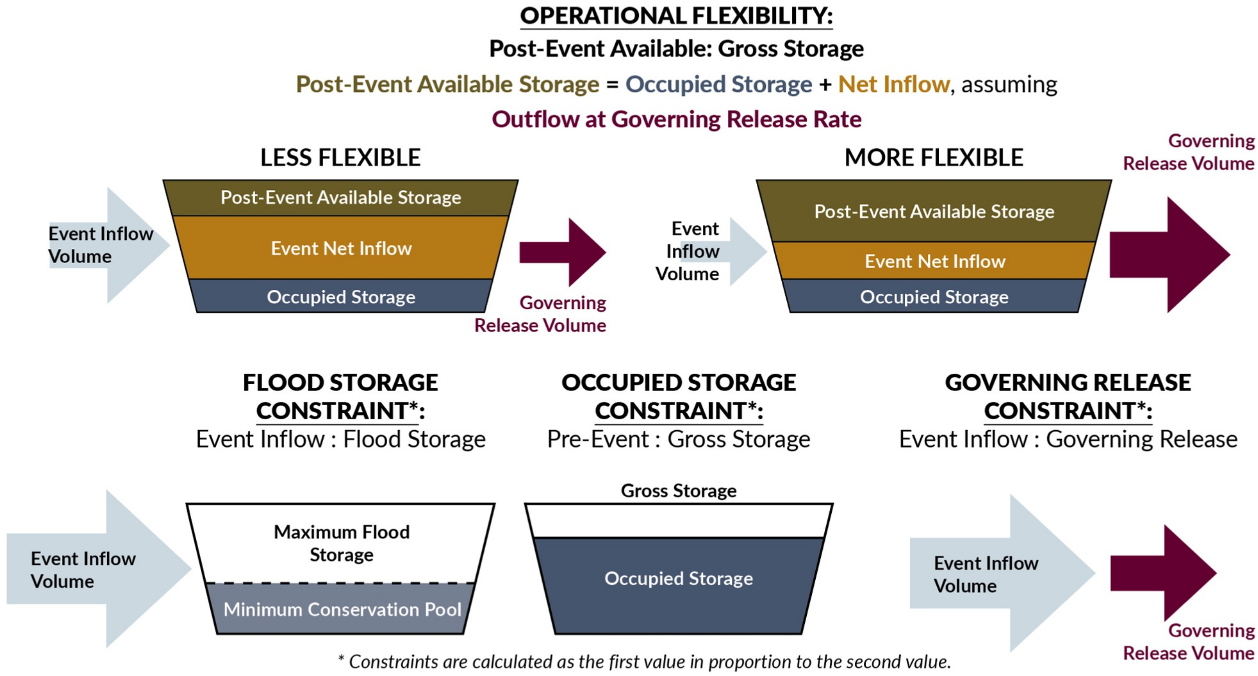

Figure 3. Illustration of physical constraint metrics (see Table 2 for definitions) and their relations to operational flexibility. In the examples shown in the top row, the reservoir on the right has greater operational flexibility relative to that on the left because the governing release volume is larger than the average inflow, resulting in less water accumulation in the reservoir (net inflow) and thus more available post-event available storage. Although occupied and gross storage are both held constant in this example, these also influence operational flexibility. For example, a larger pre-event occupied storage volume would result in smaller post-event available storage and thus, less operational flexibility.

flexibility, which is the remaining volume available for storage immediately following the inflow event, assuming water is released at the governing release rate over the duration of the inflow event. This final metric is intended to represent the overall flexibility and buffering capacity the reservoir has in order to accommodate large volumes of water --given inflows, available storage, and release constraints --over the historical period of record. While many other factors (e.g., ecological needs, water rights) may determine the timing, magnitude, rate of change, and durations of outlet flows, the constraints considered here represent the physical limitations of safe storage and release under typical conditions.

We note here that several simplifying assumptions are embedded in the metrics described above that collectively result in the most conservative (i.e., best case) scenario in terms of the reservoirs ability to accommodate the largest historical inflow volumes. These include: (a) use of maximum flood storage despite there being less available flood storage during some parts of the year, and (b) the ability to instantaneously release water at the governing release rate without consideration of ramping rates, other flows that may also need to be considered at the downstream control point, or the ability to release the full volume due to variations in reservoir outlet elevations. Although no simplifying assumptions related to storage are embedded in the operational flexibility metric given that it incorporates historical observations of occupied storage, the release constraint assumption remains a limitation that would require a more complicated reservoir operations model to fully represent. Thus, the results presented here provide a first-order estimation of operational flexibility.

Sites were further characterized according to basin wetness and the proportion of precipitation falling as rain versus snow, given that reservoir design and operations are conditioned on historical climate and streamflow patterns (Williams, 1997). The physical constraint metrics are presented at the event scale and are summarized as the average across the top 10% events at each site. Summarized values were analyzed using Principal Components Analysis (PCA) to quantify and visualize how metrics relate to each other and to historical climate.

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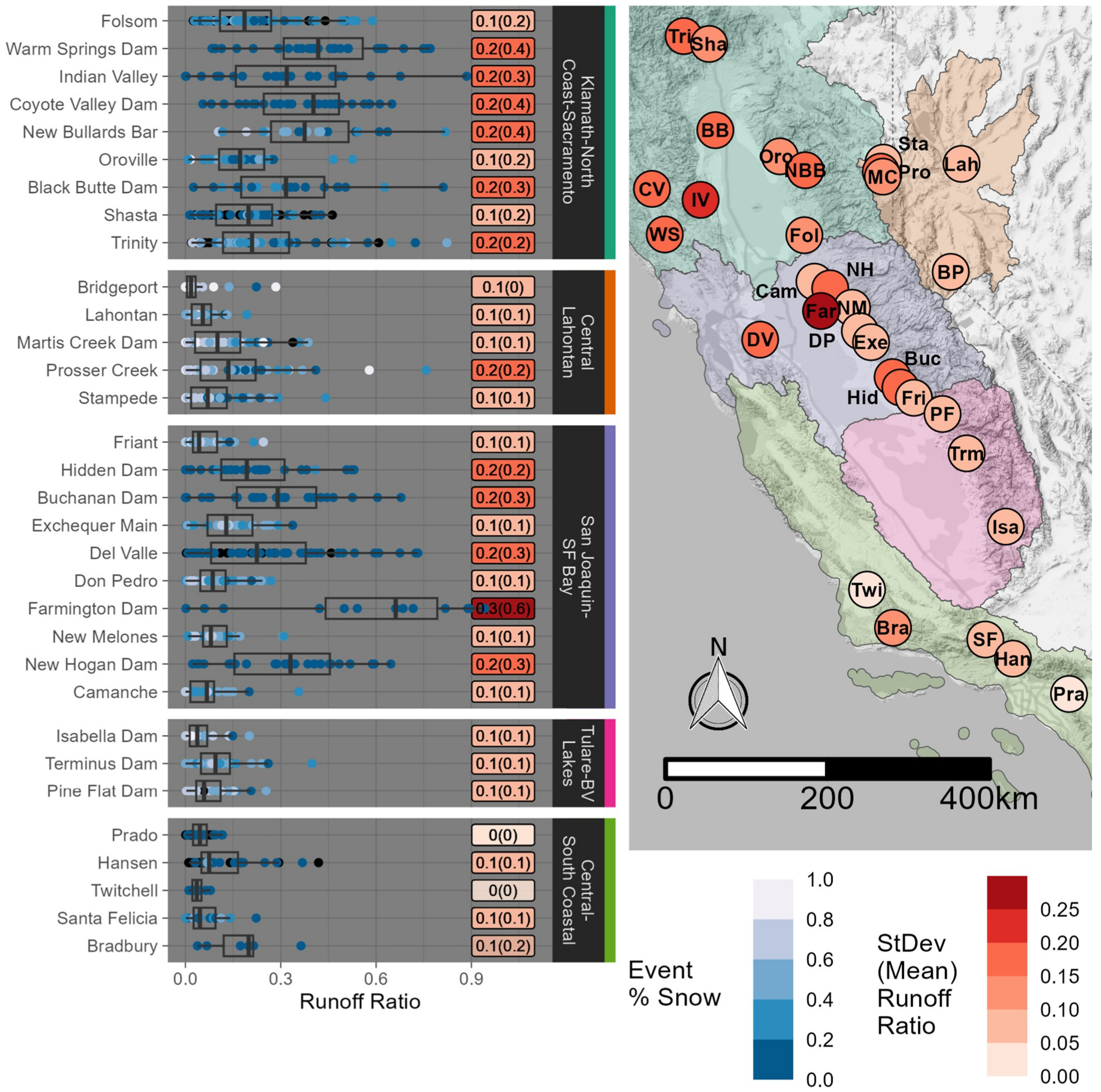

Figure 4. Range, standard deviation, and average values of runoff ratios for the top 10% events at each site (left). Each point represents the event runoff ratio and is colored according the % of precipitation occurring as snow. Events occurring prior to 1980 are shown in black, as WLDAS data used to calculate event percent snow are not available prior to 1980. The numbers to the right indicate the standard deviation of all top 10% event runoff ratios. The average runoff ratio is in parentheses. Events with larger snow proportions tend to have smaller average and less variable runoff ratios. The map shows site locations, colored by standard deviation of the runoff ratio. See Table 1 for site abbreviations.

3. Results

3.1. Watershed Response Metrics

The two watershed response metrics: Runoff Ratio and Lag Time (Table 2) characterize the magnitude, variability, timing, and predictability of reservoir inflows for the purpose of identifying watersheds where additional monitoring and research may be needed to better anticipate hydrologic responses at the event scale. Results are presented for the top 10% of precipitation or reservoir inflow events during the period of record for each site (Table 1).

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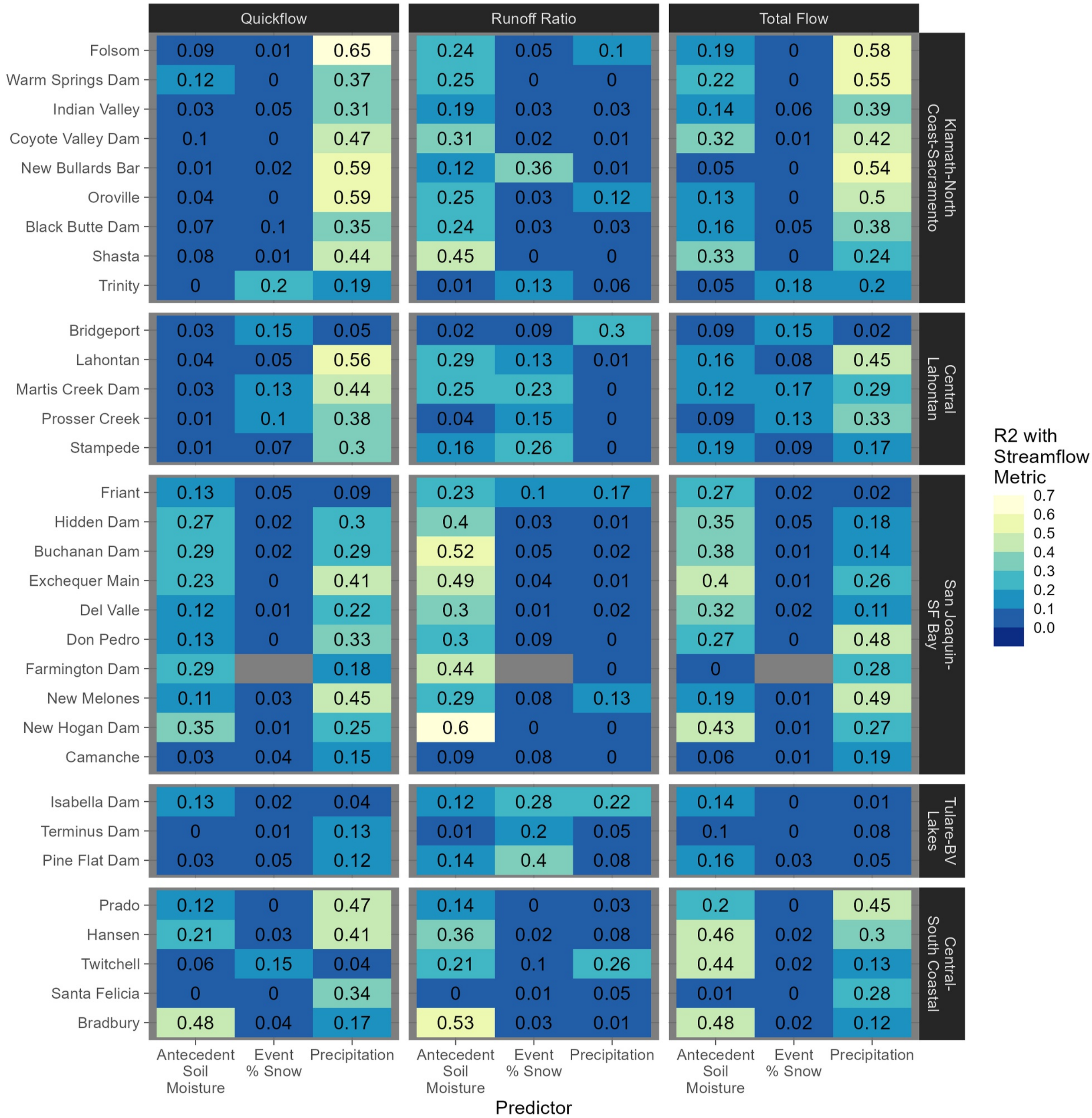

Figure 5. Variance explained (R^2) between event precipitation volume, antecedent soil moisture, and percentage of precipitation falling as snow (predictors) and streamflow metrics (quickflow, total flow, and runoff ratio) across the top 10% events at each site. See Table 1 for site abbreviations and Figures S3a and S3b in Supporting Information S1 for associated scatterplots and regression equations.

3.1.1. Runoff Ratio

The magnitude and temporal variability of runoff ratios (event quickflow: precipitation) is largest in the wetter Klamath-Sacramento and San Joaquin-SF Bay regions, and where events are more rain-than snow-dominated (Figure 4). Linear regression analyses of event runoff ratio, quickflow, and total flow responses to precipitation volume, phase, and antecedent soil moisture predictors demonstrate key drivers of this variability across sites. All sites in the South Coast, San Joaquin SF-Bay, and Klamath-Sacramento regions (except Trinity and New Bullards Bar) have runoff ratios that relate to antecedent soil moisture (Figure 5), while sites in the Central Lahontan and Tulare-Buena Vista Lakes as well as Trinity and New Bullards Bar have runoff ratios that are more strongly controlled by precipitation phase (Figures 4 and 5; associated scatterplots and regression equations are shown in

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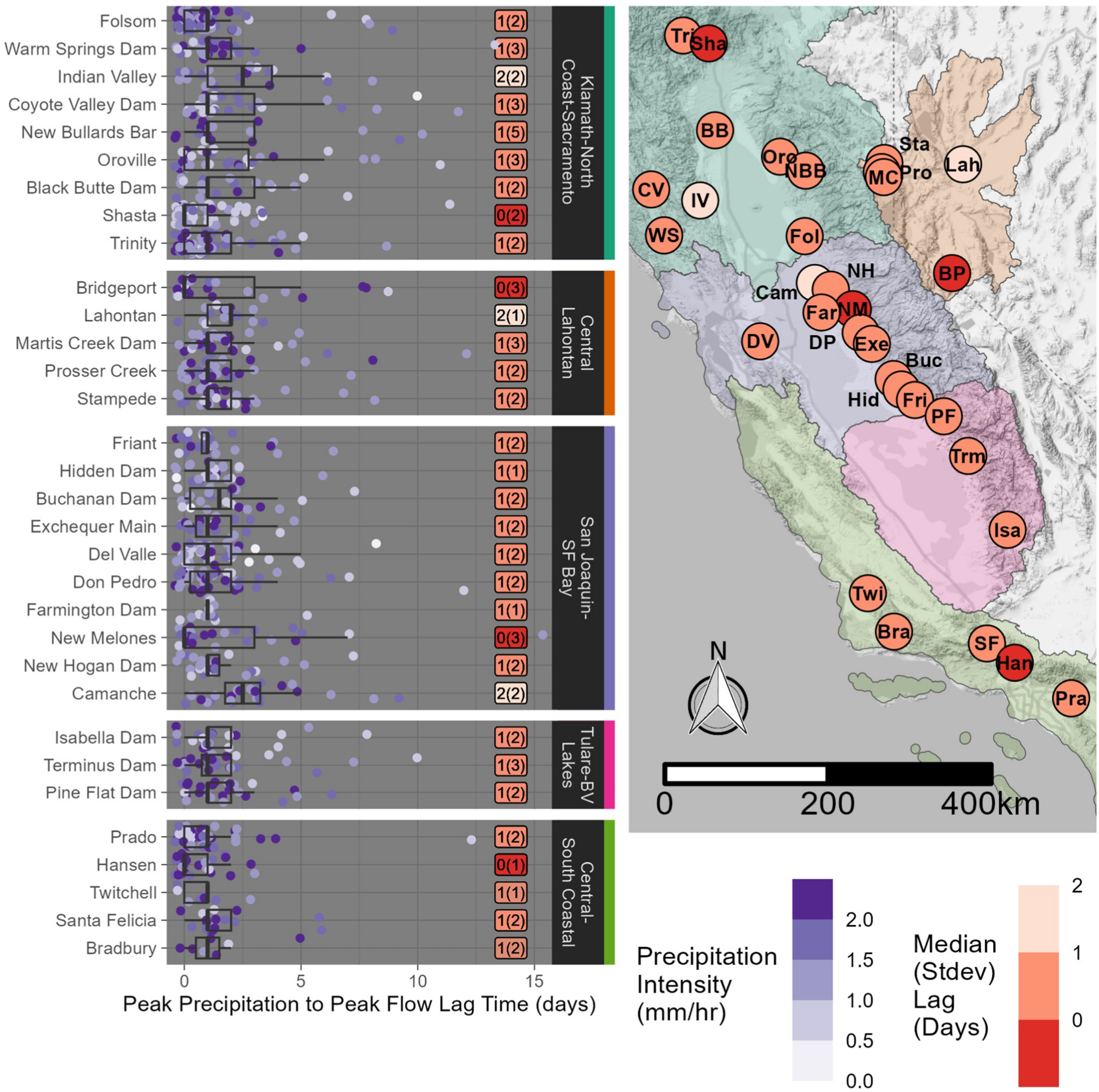

Figure 6. Range, median, and standard deviation of lag times between daily peak precipitation and daily peak flow for the top 10% events at each site. Each point represents the event lag time and is colored according to precipitation intensity. Median lag time (shown on the right side of the plot) is 1 day for most sites (ranging from 0 to 2) and lag times tend to be shorter for events with high precipitation intensity, which correspond with shorter duration events. The map shows site locations, colored by median lag time. See Table 1 for site abbreviations and Figure S4 in Supporting Information S1 for site-specific relations between lag time, precipitation intensity, and duration.

Figures S3a and S3b in Supporting Information S1). Variability in event quickflow volumes is best explained by precipitation volume at most sites, with R^2 values generally ranging from 0.2 to 0.65. Exceptions to this include sites where quickflow volumes are better explained by precipitation phase (Trinity, Bridgeport, and Twitchell) or antecedent soil moisture (Friant, Farmington, New Hogan, and Bradbury; Figure 5). In the case of total inflow (quickflow + baseflow), precipitation volumes exhibit the strongest influence at most sites in the Klamath-Sacramento and Central Lahontan, but the influence of antecedent soil moisture is stronger than that of precipitation at many sites in the three southernmost regions, indicating seasonal influences of water storage in the watershed on both quickflow and baseflow volumes.

3.1.2. Lag Time

Median watershed response times for the top 10% events are 0–2 days across all sites. The longest lag times tend to occur during events with lower precipitation intensities (Figure 6), which correspond with longer duration precipitation and streamflow events (Figure S4 in Supporting Information S1). The sites with the longest median lag times include Lahontan, Camanche, Indian Valley, and Black Butte. Considerable upstream regulation may explain longer lag times in the cases of the former two (Table S2 in Supporting Information S1), while sedimentary geology could explain this in the case of the latter two (California Department of Conservation, 2010). We note that because our analyses are based on daily streamflow and meteorological data, we were unable to characterize lags occurring at sub-daily timescales and thus, we consider these estimates to be coarse-level first approximations.

3.2. Physical Constraint Metrics

The four physical constraint metrics: Governing Release Constraint, Flood Storage Constraint, Occupied Storage Constraint, and Operational Flexibility (Table 2, Figure 3) are intended to provide insights into how and where reservoir storage and/or outflow constraints factor into operational flexibility, and in turn, the forecast lead times necessary for safe implementation of FIRO under the current physical site configurations.

3.2.1. Governing Release Constraint

Governing release constraints are greatest in the higher-elevation, snow-dominated basins in the San Joaquin, Lahontan, and Tulare-Buena Vista Lakes regions (Figure 7). Inflows during the top 10% events at Don Pedro, and Pine Flat are consistently larger than the governing release, requiring an average of 2–4 additional days of water released at that rate to avoid water storage accumulation. Events in 1986, 1995, 1997, 2005, and 2017 tended to have the largest ratios at multiple sites (Figure S5 in Supporting Information S1).

3.2.2. Flood Storage Constraint

The Flood Storage Constraint metric characterizes event inflow volumes relative to maximum flood storage (Figure 8). Values are consistently high in the Klamath-North Coast-Sacramento region but are more variable in other regions. Top 10% event inflows are consistently larger than flood storage at New Bullards Bar and Black Butte. Top 10% event inflows are consistently larger than 50% of flood storage at another seven sites and exceeded maximum flood storage at least once at 18 sites (Figure 8). We characterized the flood storage constraint as a simple ratio of event inflow volume to maximum flood storage to assess this constraint in isolation from other reservoir attributes. That said, how consequential this constraint is also depends on the governing release capacity. To assess this, we calculated the ratio of net inflow to maximum flood storage (Figure S7 in Supporting Information S1). This calculation provides additional nuance by combining information on both the release and flood storage constraints. For example, although New Bullards Bar and Black Butte have event inflows that regularly exceed maximum flood storage, the potential for larger volumes of water to be released make this less consequential as compared to Friant (Figure S7 in Supporting Information S1), which is limited by both flood storage and release capacities. Combining these metrics also reveals that although event inflows at Pine Flat and Don Pedro never exceed maximum flood storage, there can still be a net accumulation of water in flood storage (Figure S7 in Supporting Information S1) due to the limited release constraints at these sites (Figure 7).

3.2.3. Occupied Storage Constraint

The Occupied Storage Constraint metric indicates that occupied storage prior to the top 10% events averaged greater than 50% of gross storage at most sites. Prado, Hansen, Twitchell, Farmington, Martis Creek, and Terminus had the smallest proportions of pre-event storage (Figure 9) and are all primarily used for flood risk reduction. The only sites with pre-event occupied storage amounts that were always less than the minimum conservation pool are Indian Valley, Hansen, Twitchell, and Del Valle. Storage volumes greater than the minimum conservation pool tend to occur more frequently in the spring months, when conservation pools are larger than the minimum value used for this analysis (Figure 9). This is not exclusively the case because occupied storage may include water from recent events that has not yet been fully released either due to release constraints or reservoir operational rulesets that are conditioned on recent precipitation, runoff, or snowpack storage.

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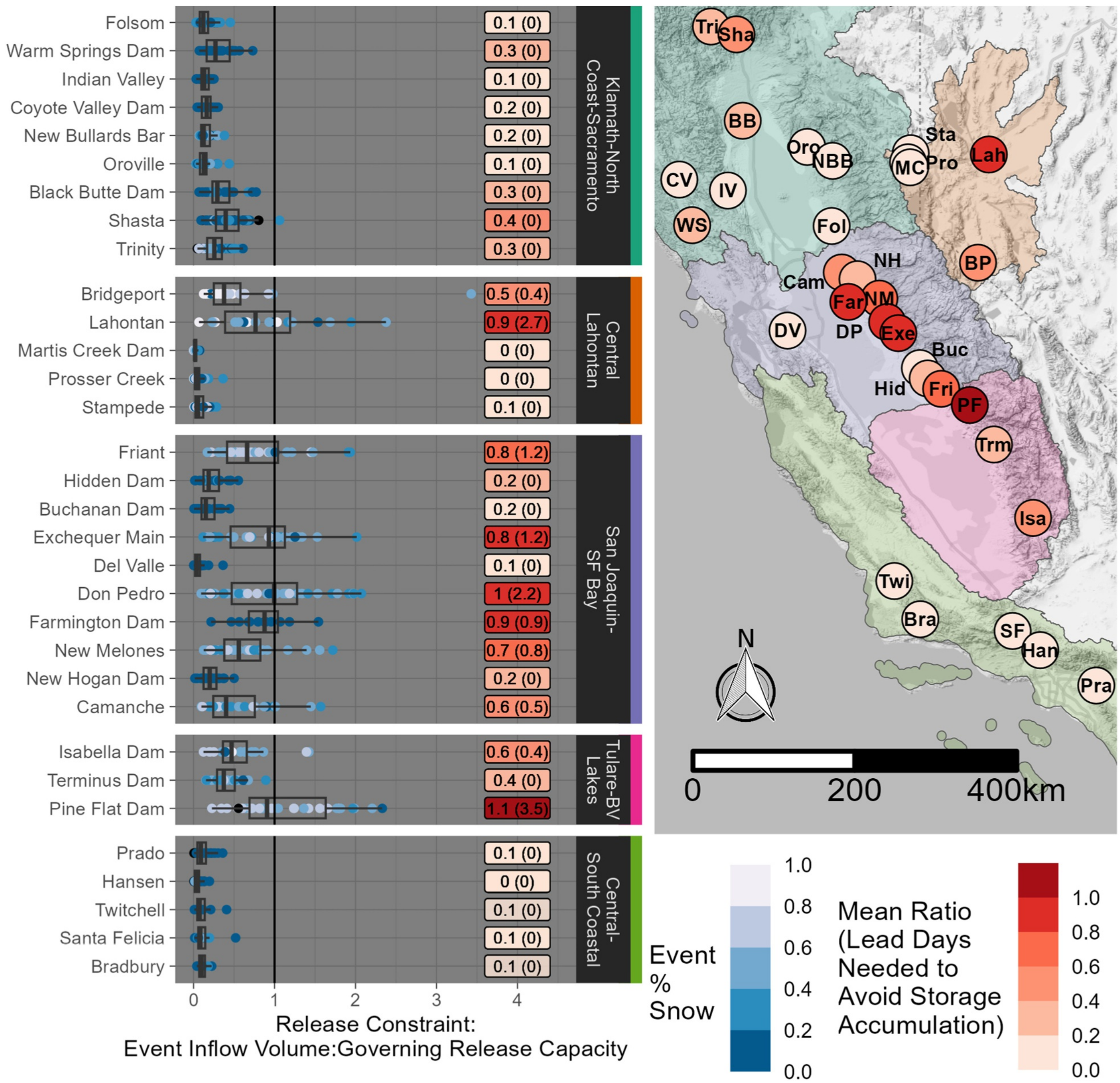

Figure 7. Governing release constraint values calculated for the top 10% of events as the ratio of event inflow and outflow volumes over the same period of time, assuming outflows are at the governing release rate. Values greater than 1 indicate that inflow is greater than outflow. The mean value across all top 10% events is shown to the right. Numbers in parentheses represent the average number of additional days water would have needed to be released to avoid storage accumulation. The map shows site locations, colored by the mean ratio. See Table 1 for site abbreviations and Figure S5 in Supporting Information S1 to view relationships between the governing release constraint and precipitation volume at each site.

3.2.4. Operational Flexibility

The Operational Flexibility metric (Figure 10) brings the other physical constraint metrics together to represent how readily the reservoir can accommodate large inflows based on events in the historical record. Operational Flexibility is measured as the relative amount of gross storage available following an event (more post-event available storage = greater flexibility), assuming water is consistently released at the governing release rate for the duration of the inflow event. For example, if two reservoirs have the same gross storage capacity and inflow volumes but the first can release more water (smaller release constraint) or has less pre-event occupied storage (smaller occupied storage constraint) than the second, the first reservoir has greater flexibility; see Figure 3).

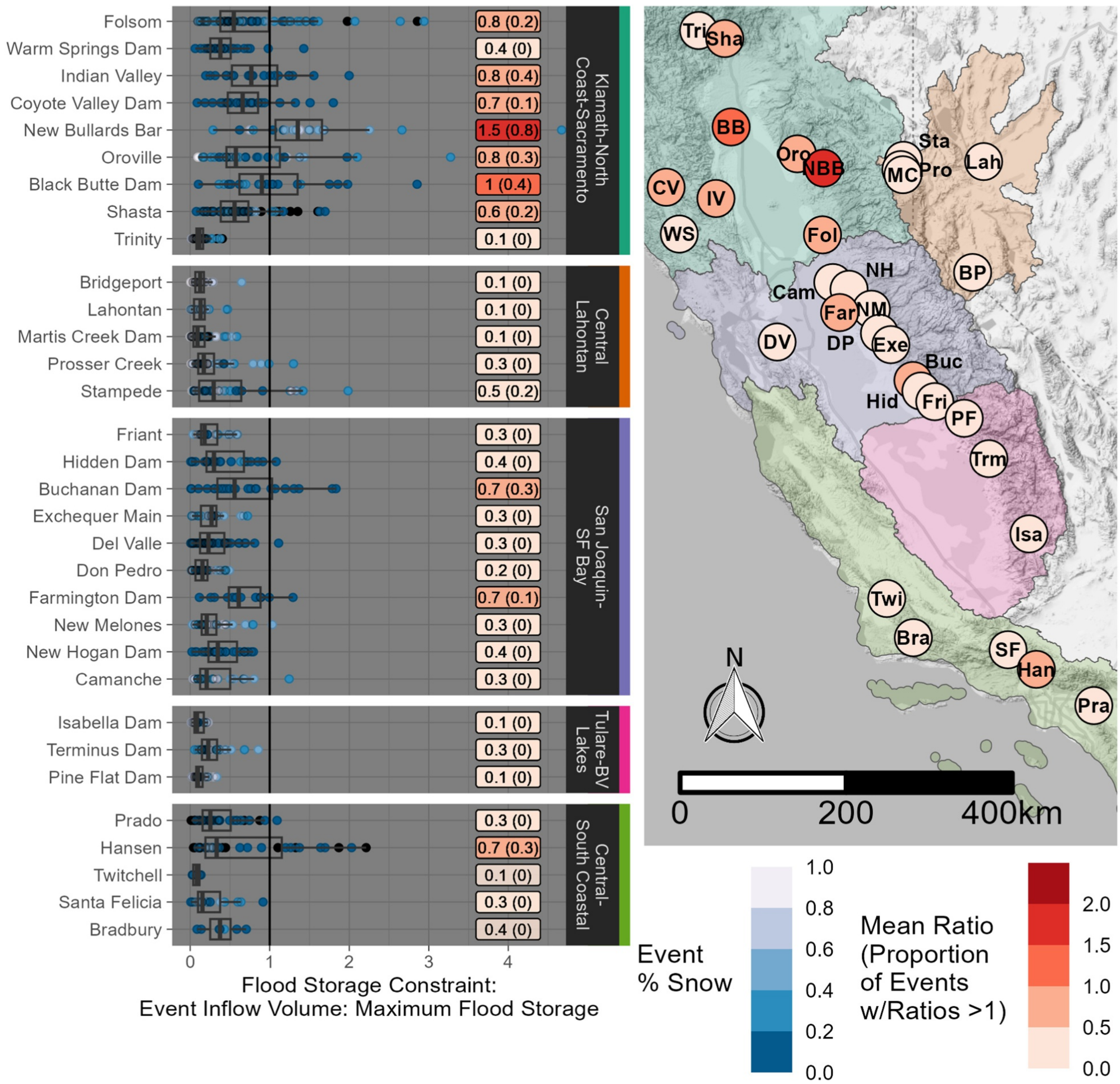

Figure 8. Flood storage constraint calculated as the top 10% event ratios of event inflow to maximum flood storage. The mean value across all top 10% events is shown to the right. Numbers in parentheses indicate the proportion of events when event inflow volume is greater than flood storage (ratio = 1). The map shows site locations, colored by the mean ratio. See Table 1 for site abbreviations and Figure S6 in Supporting Information S1 for site-specific relationships between the flood storage and precipitation volume.

Snow-dominated watersheds in the Central Lahontan, Tulare, and San Joaquin tend to have less storage available post-event (i.e., less operational flexibility), especially at sites with greater release constraints (Figure 7). Reservoirs with the least flexibility had occurrences where available storage was less than 10% at the end of the event, and storage capacity would have been exceeded at two sites (Bridgeport and Friant; Figure 10). The lead time required to release water at the governing release rate to avoid exceeding 90% gross storage ranges from 1 to 14 days, with the longest required lead times and most frequent potential exceedances at Don Pedro. Using an exceedance threshold of 99%, the lead time needed during the largest events examined (2017 in Don Pedro, 1997 in Friant and Bridgeport) is 3–6 days (Figure S8 in Supporting Information S1). At most reservoirs, the operational flexibility is driven more strongly by antecedent storage than by event inflows (see Figures S9a and S9b in Supporting Information S1), but relations between event inflow volumes and operational flexibility are evident at sites like Pine Flat, Friant, Exchequer, and Don Pedro, which have greater release constraints than all other sites

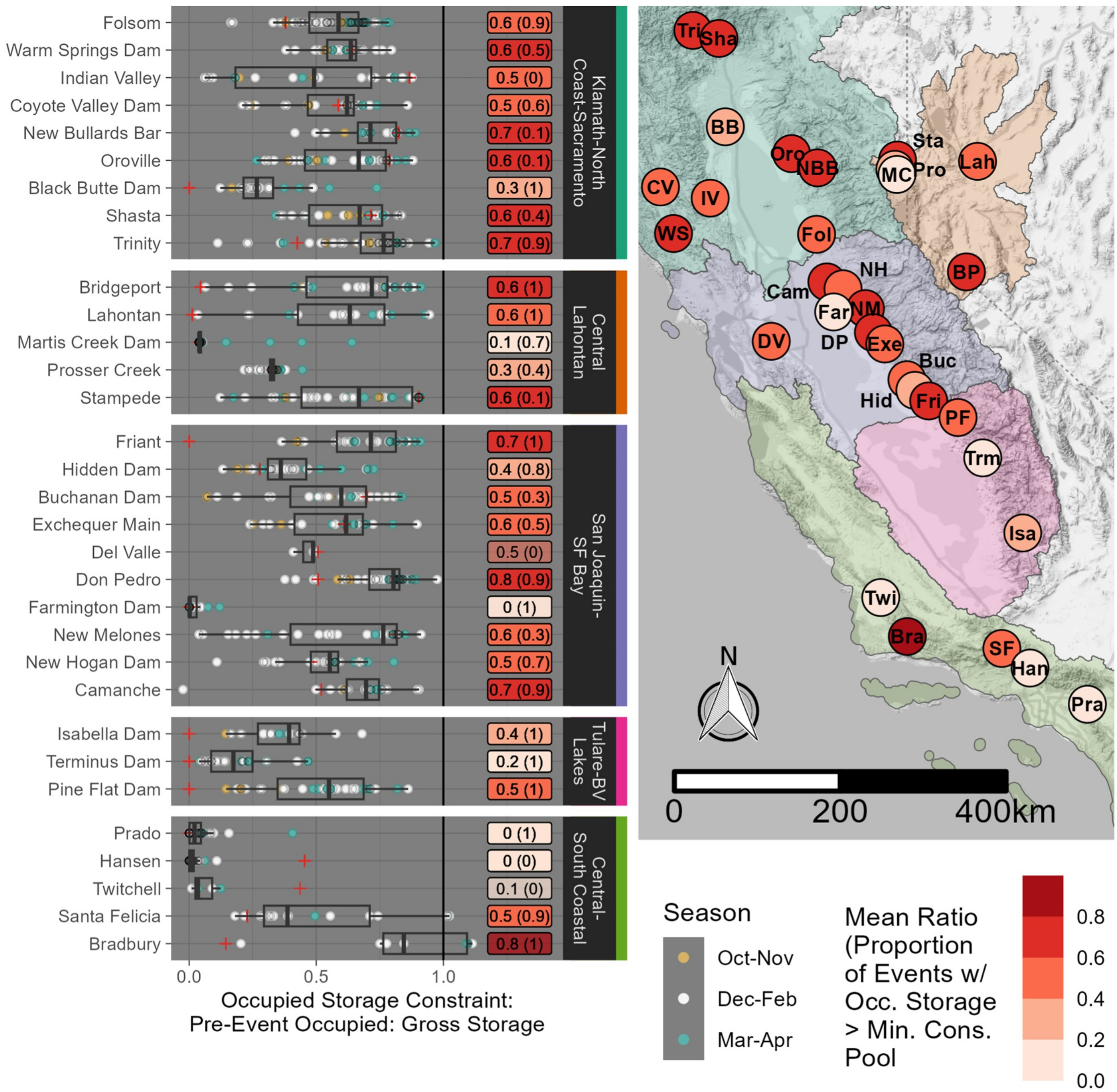

Figure 9. Occupied storage constraint, calculated as the ratios of occupied to gross storage on the day the flow event begins. The average ratio across the top 10% events at each site are shown to the right. Numbers in parentheses indicate the proportion of events when occupied storage was greater than the minimum conservation pool (points falling to the right of +). Because the size of the conservation pool can vary seasonally at some sites with smaller conservation pools in the springtime (green points), the occupied storage is more often larger than the minimum conservation pool during this time of year. The map shows site locations, colored by the mean ratio. See Table 1 for site abbreviations.

(Figure 7). We note here that (a) the occupied storage values used are from one day prior to the start of the inflow event and thus do not represent how much flow was released prior to that date in anticipation of the storm, and (b) the operational flexibility metric assumes that releases are made at the governing release rate for the duration of the storm, which may not reflect operational rules, as any additional downstream runoff generated during the event could add to this flow and would result in exceedences of thresholds used to establish the governing release.

3.3. Summary of Physical Constraints

The PCA (Figure 11; Table S3 in Supporting Information S1) illustrates relationships among the four physical constraints metrics and historical climatology of the top 10% historical events, and although we do not include

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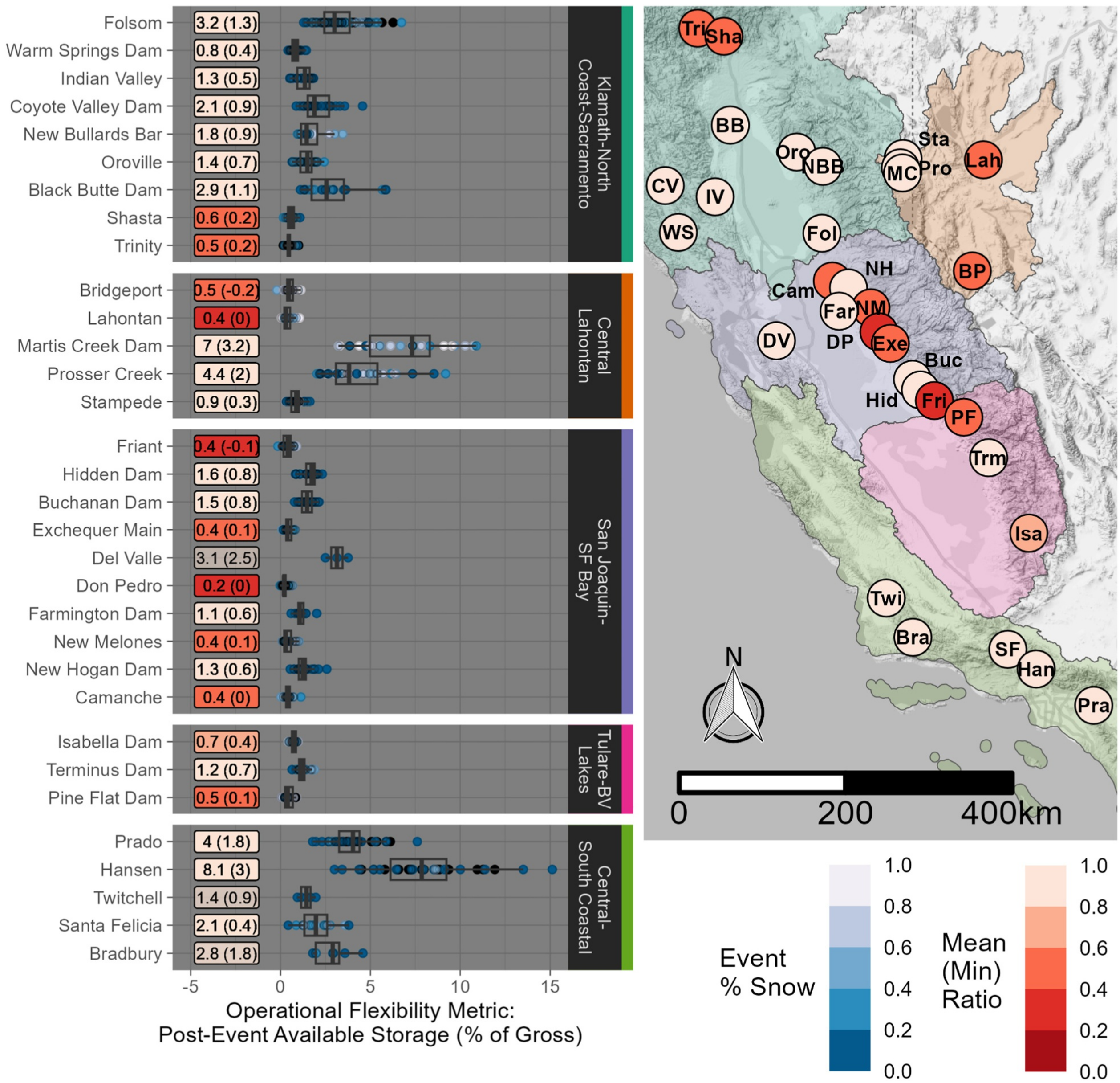

Figure 10. The Operational Flexibility metric calculated as post-event available storage as a ratio of gross storage. Post-event available storage is calculated by subtracting the sum of pre-event occupied storage and event net flow from gross storage. Values greater than or equal to 1 indicate 100% of gross storage could be available post-event because more water can be released over the duration of the event than combined event inflow and pre-event occupied storage. Numbers closer to zero indicate little remaining storage available post-event. Numbers on the left indicate the mean (minimum) post-event available storage at each site. Points falling to the left of the red + indicate those events during which encroachment of the maximum flood pool occurred. The map shows site locations, colored by the mean post-event available storage ratio. See Table 1 for site abbreviations and Figures S9a and S9b in Supporting Information S1 for site-specific relations between operational flexibility, event inflow, and occupied storage.

results based on analysis of all events, we verified that our choice of using the top 10% does not materially change the outcome; that is, the groupings of reservoirs relative to constraints is consistent, whether using all events or just the top 10%. The first principal component explains 39% of the variance among sites and represents a gradient of operational flexibility whereby greater flexibility corresponds with drier sites with less snow-dominated precipitation, and lesser release and occupied storage constraints. The second component explains an additional 23% of variance and represents a gradient from larger to smaller flood storage constraints, with wetter, more rain dominated sites corresponding with larger occupied and flood storage constraints, lesser release constraints, and more operational flexibility. The opposing directions of the release constraint and % snow vectors with the

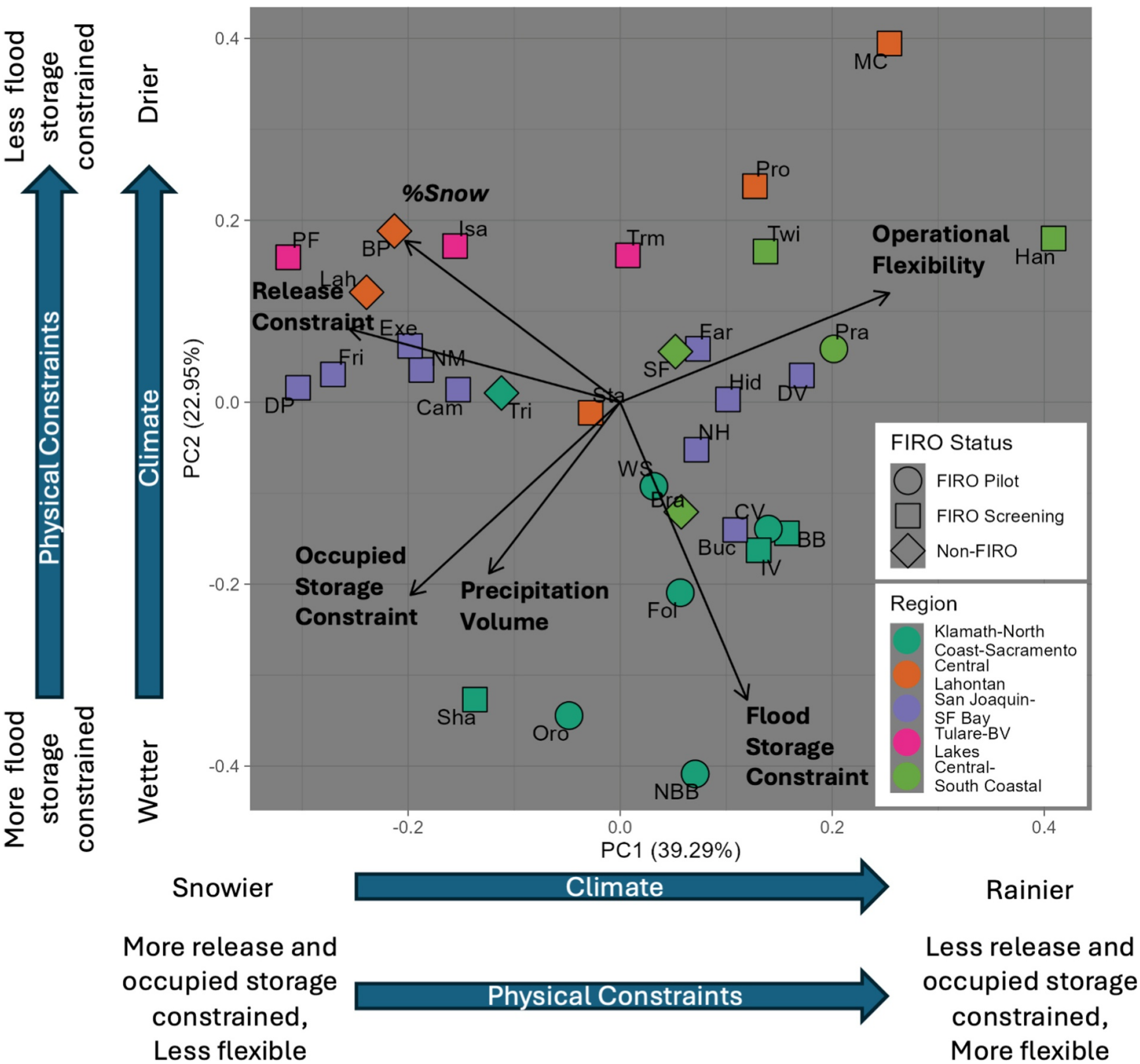

Figure 11. Principal Components Analysis (PCA) bi-plot visualizing variability in average values of physical constraint metrics (Table 2) for the top 10% events and correspondence with precipitation volume and the proportion of precipitation falling as snow for the same events. All values were standardized to a mean of zero and standard deviation of 1. The PCA results table is in Table S3 of Supporting Information S1. An alternative visualization with points colored by dam primary purpose is in Figure S10 of Supporting Information S1.

operational flexibility vector indicates that release constraints are a significant control on operational flexibility and that these constraints correspond with snowier sites. Using an alternative visualization of the PCA based on dam primary purpose as defined in the NID (Figure S10 in Supporting Information S1), groupings related to the primary purpose of dams are evident --dams with hydroelectric power generation as their designated primary purpose (Trinity, Shasta, New Bullards Bar, Folsom, New Melones, Don Pedro, Exchequer Main) tended to have lower flexibility and dams with primary purposes of flood risk reduction tended to have higher flexibility due to larger and smaller volumes of pre-event occupied storage, respectively. That said, release constraints at the snowier sites with flood risk reduction as their primary purpose (Friant, Pine Flat, Lahontan, and Isabella) are distinctive, as these have lower flexibility relative to other flood risk reduction dams, indicating that operational flexibility corresponds with historical climatology moreso than primary purpose in this study region. There is no strong relationship between potential water supply benefits, as indicated by flood storage capacity, and operational flexibility but spatial patterns are evident (Figure 12), and although snowier sites tend to have less flexibility, they span a range of potential water supply benefits.

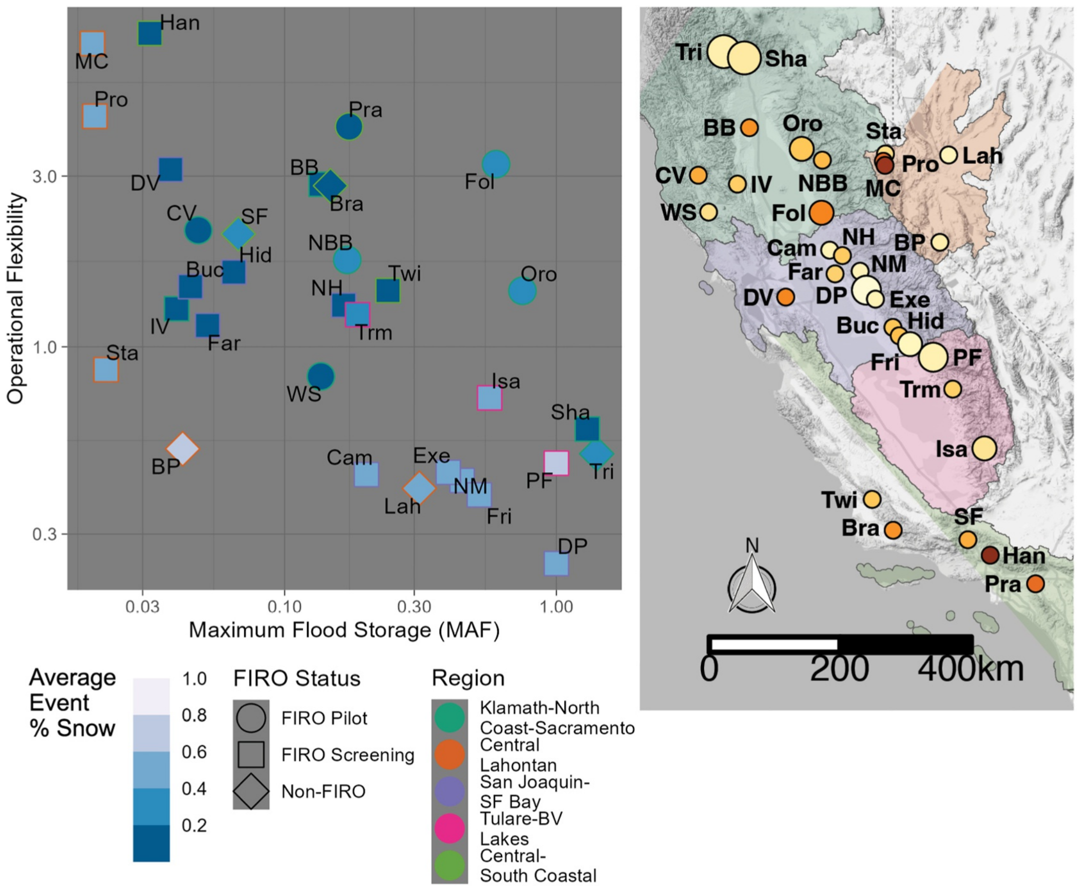

Figure 12. Maximum flood storage (proposed proxy for potential water supply benefit) and operational flexibility (the degree to which physical constraints pose challenges to implementing Forecast-Informed Reservoir Operations given the lead time required for safe implementation).

4. Discussion

4.1. Event-Scale Precipitation and Reservoir Inflow Volume Coupling Varies Regionally

Forecasts that can reliably give reservoir operators sufficient time to release stored water in anticipation of inflows is a key requirement for FIRO (Yeates et al., 2026). The FIRO screening process included assessments of weather forecast skill across the US (Cordeira et al., 2025) which provide early indications of site suitability, but water (i.e., reservoir inflow) forecast skill was not quantified due to a lack of a suitable archive of nationally consistent hydrologic reforecasts necessary to complete hydrologic forecast evaluations at ~600 FIRO screening candidate sites. Although streamflow forecast skill was also not explicitly addressed in this study, understanding relations between streamflow and precipitation products provides important perspectives that are relevant to understanding FIRO site suitability. First, we identify the degree to which precipitation and streamflow are coupled across different watersheds by examining how much runoff ratios vary among events in each watershed. In watersheds where these are more variable, and therefore precipitation and streamflow are less tightly coupled, the skillfulness of streamflow forecasts may differ from that of weather forecasts and assessments of streamflow forecast skill will be especially important at these locations. Second, we identify the land surface (i.e., soil moisture) and meteorological (i.e., precipitation phase) factors that have the greatest correspondence with this coupling. This provides an early indication of where more ground observations may be required to better understand hydrologic states and processes and the types of observations (e.g., soil moisture, freezing levels) that are most likely to lead to improvements in streamflow forecasts. While our sensitivity analysis indicated that runoff ratios and peak precipitation to peak inflow lag times were fairly robust to event separation parameterizations (See Text S1, Figures S1 and S2 in Supporting Information S1), our use of a single method for event separation and our selection of precipitation data result in estimates that may not be replicated using a different method or data set.

Similarly, the relations of precipitation phase and antecedent soil moisture to flow components (runoff ratio, quickflow, total event volume) based on WLDAS may differ with use of a different data set. Thus, we emphasize here that prioritizing where ground observations would be most beneficial for FIRO should include additional exploration of how the results reported here vary as a function of these alternatives, given known inconsistencies among different gridded climate data sources (Mankin et al., 2025), and the potential sensitivities of runoff ratio values and lag times to event separation approaches.

Finally, the workflow developed in this study, which uses publicly available data on reservoir hydrology (Steyaert et al., 2022), meteorological (Pierce et al., 2021) and land surface conditions (Erlingis et al., 2021), an automated baseflow separation algorithm (Giani et al., 2021, 2022), and reservoir operations data compiled as part of the FIRO screening process, provides a scalable approach for quantifying watershed responses and operational constraints at the early stages of FIRO site suitability assessments. Having this information earlier in the process can provide additional insights to inform FIRO priorities, planning, and strategies.

Many state and federal dam operations in our study region rely on weather and streamflow forecast ensembles from the National Weather Service California-Nevada River Forecast Center (CNRFC) for decision making. Ensemble streamflow forecasts are derived from the Hydrologic Ensemble Forecast Service (HEFS), which uses weather forecast information as inputs to represent meteorological uncertainties but does not currently account for uncertainties in land surface conditions (e.g., snowpack, soil moisture) or freezing levels (CNRFC, 2025). Retrospective analyses of HEFS forecast and hindcast ensemble skill conducted for basins under consideration for FIRO have identified underdispersion and underprediction biases in cases of high flow events (Albano et al., 2023; Brodeur et al., 2025; Prado Dam Steering Committee, 2023). Results from these studies and those presented here highlight the need for improved representation of antecedent land surface conditions and precipitation phase, given these are key factors driving streamflow generation. This is being addressed across the state of California (Curtis et al., 2019) and in several FIRO Pilot project watersheds, where instrumentation has been installed to help verify forecasts, and provide observations of soil moisture, stream flow and precipitation phase that can help to improve hydrologic states and process understanding, ultimately resulting in better hydrologic forecasts of these events.

4.2. Lag Times Between Peak Precipitation and Reservoir Inflows Are Short and Variable

Both precipitation and streamflow forecast uncertainties and reservoir-operations risk tolerances are larger at longer lead times (Delaney et al., 2020). Risk tolerances vary from reservoir to reservoir depending on storage-volume availability, constraints on the volume of water that can be released, and the amount of time required for released waters to clear the channel downstream. The combination of these factors leads to differences in the skillful-forecast lead times required for safe implementation of FIRO. Peak precipitation to peak reservoir inflow lag times were assessed in this study to determine whether additional lead time could be available for water releases, beyond that provided by the precipitation forecast. Lag times typically varied between 0 and 5 days, with longer lag times occurring during longer duration storms and at sites with significant upstream storage (Table S1 in Supporting Information S1), where management interventions likely influence the hydrologic response timing. Because we only looked at the largest 10% of events, our lag time estimates are biased toward longer lags (Sivapalan, 2006). The median lag time at most sites is one day, suggesting that the daily resolution data we used in this study was too coarse to capture the sub-daily lag times that likely exist at some sites during some events. Overall, our results for this region suggest that hydrologic lag times are unlikely to reliably provide additional lead time for reservoir releases on the order of days beyond that provided by precipitation forecasts, but additional lead time on the order of hours could be possible. If sub-daily additions to lead times for reservoir releases would provide advantages for FIRO operations, studies using sub-daily precipitation and streamflow data could help to understand potential for this. For FIRO applications, we encourage further detailed study of lag times, as those quantified here are likely sensitive to the data sets and methodological approach used. We also note that the relatively short lead times observed in this study are due to the small watershed size (102–16,766 km^2; see Table S1 in Supporting Information S1) and high topographic relief (watershed average slopes range from 6° to 25°; see Table S1 in Supporting Information S1), and thus results are not indicative of whether lag times could offer advantages for FIRO in large, low relief basins elsewhere.

4.3. Storage and Release Constraints Differ Across Snow- and Rain-Dominated Basins

Results based on the four physical constraint metrics demonstrate how storage and release limitations of reservoir infrastructure correlate with historical dominance of rain and snow (Williams, 1997). Wetter rain-dominated sites in the northern CA basins tend to have greater inflow to flood storage ratios. Because of the simplifying assumption of maximum flood storage used here, the flood storage constraint metric could be considered a best-case, given that flood storage at many sites varies seasonally and/or based on longer-term forecasted inflows (Institute for Water Resources, 2016). Smaller available flood storage volumes during other times of year would result in greater flood storage constraints that may increase non-linearly, depending on reservoir geometry and upstream watershed characteristics (Evangelista et al., 2025; Gabriel-Martin et al., 2019). Despite this, our operational flexibility metric results suggest that most of these wetter, rain-dominated sites have sufficient release and gross storage capacities to safely accommodate historical inflows under current operational rules, assuming the ability of these reservoirs to instantaneously release water at the governing release rate. FIRO viability has been demonstrated (Coyote Valley, New Bullards Bar, Oroville) or an assessment is ongoing (Warm Springs) in four of these basins, all of which had relatively high operational flexibility scores in this study. Similarly, high operational flexibility scores were identified for sites in the California South Coastal region, where FIRO viability has been demonstrated at Prado. In this region, greater flexibility is afforded by reservoirs holding little pre-event water and having storage and release capacities that are much larger than inflows. In contrast, snow-dominated watersheds exhibit greater release constraints, as they were designed to accommodate snowmelt-driven flooding, which generally occurs at a slower rate relative to rain-driven flooding. Although the simplifying assumptions regarding reservoir release capacities that were applied here, including the ability to instantaneously release water at the governing release rate (see Section 2.3.2) result in conservative, best-case estimates of Operational Flexibility that deserve further consideration, our results suggest that requirements and approaches for safe implementation of FIRO could differ across climatological gradients of water availability and dominant precipitation phase and general guidance on FIRO viability and strategies could be inferred based on these regional patterns.

4.4. Snow-Dominated Basins Have Less Operational Flexibility

Our operational flexibility metric quantifies how the largest storm inflows in historical records (1950–2019) relate to gross storage capacities, release constraints, and available reservoir space, which all contribute toward determining the lead times necessary for reservoir releases to occur at rates that minimize downstream flood impacts while also avoiding exceedance of reservoir storage thresholds. The results presented here confirm the intuitive conclusion that creation of FIRO space to hold more water in flood storage in reservoirs with low operational flexibility may be more challenging and require longer lead times than has been the case for the higher flexibility reservoirs where previous FIRO pilot studies have been conducted (Figure 1, Figure 13). Of the seven reservoirs with the largest water supply storage capabilities that were included in both our study and the screening process, Oroville and Folsom are among the most operationally flexible and FIRO pilot studies have been completed at both sites. In contrast, more snow dominated sites such as Shasta, Don Pedro, New Melones, New Exchequer and Pine Flat, exhibit lower operational flexibility, albeit none of the 27 sites that were included in both our study and the FIRO Stage A screening process were identified as having “Prohibitive” barriers to FIRO.

The generally lower operational flexibility observed at snow-dominated reservoirs in the San Joaquin is likely to result in more significant water management challenges in the future, as warming climate and changing interactions between the snowpack and extreme precipitation are likely to result in larger inflows (Davenport et al., 2020; Musselman et al., 2018). Most of these reservoirs are operated to reserve flood storage space conditioned on the amount of precipitation forecasted or observed over a defined time period to accommodate increased flood risks driven by antecedent land surface conditions (rain-flood conditional space), while others are operated to maintain storage space depending on snowpack volume (snowmelt conditional space). These operational rules are based on historical climate. In the case of the latter, application of current operational rules under a warmer climate with more rain and less snow could significantly increase flood risk, as a smaller snowpack would allow more water to be held in the reservoir during wintertime, when larger inflows due to more precipitation falling as rain, rather than snow, are still most likely to occur. At the same time, larger and earlier releases of water from the reservoir to mitigate against these flood risks, elevates risks of water supply shortages (Cohen et al., 2020). A recent assessment of climate change adaptation strategies to address flood risk, water supply, and ecological vulnerabilities on the Merced River (New Exchequer, a low operational flexibility site in our study) demonstrated that the greatest benefits are achieved by creating additional space in both the flood storage and conservation pools and combining FIRO and Managed Aquifer Recharge strategies. This is achieved by pro-actively transferring conservation pool water downstream to be used for aquifer recharge through releases that are independent of storm forecasts. This is beneficial because the implications of constrained release rates are less consequential if releases can be made outside the forecast window and the reservoir can accommodate greater increases in storage volumes because more storage is available. Because the downstream channel capacity is a key constraint at New Exchequer (Figure 6), investments in downstream water distribution infrastructure that release stresses on the main channel provided additional water supply benefit (California Department of Water Resources, 2024). As is occurring at New Bullards Bar and Folsom reservoirs, creation of outlets that can release water at lower elevations provides greater flexibility to release water well before storage capacities are met (US. Army Corps of Engineers, 2023; Yuba Water Agency, 2025). The strategies above provide examples of ways to reduce storage and release constraints through infrastructure investments such as (a) identifying alternative storage space for conservation pool water, (b) investing in downstream flood managed aquifer recharge, and (c) downstream channel, reservoir outlet (e.g., AR Control Spillway on the Yuba River), and/or conveyance infrastructure improvements that enable larger safe releases to occur. While these investments may be needed at sites with lower operational flexibility, updating reservoir operational rules based on contemporary understanding of storage and release targets, snowpack conditions, and weather forecasts can all help to optimize FIRO implementation without physical infrastructure change.

5. Conclusions

In this study, we present an approach for quantifying the operational flexibility of reservoirs in mountain regions of California and Nevada and identifying key factors that mediate precipitation-runoff generation. Key contributions of this work are as follows:

- We developed an operational flexibility metric to quantify the relative flood buffering capacity of reservoirs based on historical inflows, available storage, and release constraints. Operational flexibility varies across climatological gradients, with snow-dominated basins exhibiting the least flexibility. This result is largely driven by greater governing release constraints at snow-dominated sites, where the amount of water that can be released from reservoirs is more limited relative to those in rain-dominated basins where most FIRO pilot studies have been conducted. A warming climate will further challenge this flexibility, indicating that inclusion of projected changes in temperature and streamflow regimes will be an important component of evaluating FIRO viability in these watersheds. Moreover, FIRO efforts in snow-dominated basins will likely need to be coupled with other adaptation strategies.
- FIRO relies on weather and water forecasting (American Meteorological Society, 2020). Regional and CONUS-wide assessments of weather forecast skill have been conducted as part of the FIRO screening process (Cordeira et al., 2025), but assessments of streamflow forecast skill have not yet been completed. We quantified event-scale relations between precipitation and streamflow (runoff ratios) to provide an early indication of the degree to which precipitation forecasts might serve as reliable proxies for streamflow forecasts and the types of observations (e.g., soil moisture, precipitation phase) that best explain variations in runoff ratios. Our results can be used to prioritize investments in streamflow forecast skill evaluations and installation of ground observation networks in basins where they are most likely to improve situational awareness of flood risks, and may ultimately contribute to improvements in streamflow forecast skill.

This work is not intended to eliminate potential FIRO candidates and also does not replace the detailed analyses and stakeholder outreach needed to assess FIRO viability. Rather, through the use of an automated baseflow separation algorithm, readily available streamflow and reservoir storage data, gridded climatological data sets, and information compiled during FIRO screening this analysis can be scaled across many sites to provide additional insights at earlier stages of the screening process. The FIRO Stage A screening process of the national portfolio of USACE dams used several criteria to identify barriers to FIRO and is now complete (Yeates et al., 2026). Our study builds upon these results by providing additional perspective on how physical constraints vary across different historical climate regimes and what challenges, opportunities, and investment priorities may be as additional sites are considered for FIRO.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

Streamflow and storage information from ResOps (Steyaert et al., 2022), reservoir attributes from the National Inventory of Dams (U.S. Army Corps of Engineers, 2022), meteorological data from WLDAS (Erlingis et al., 2021) and the extreme-preserving precipitation data set (Pierce et al., 2021), and code to run the baseflow separation analysis (Giani et al., 2022) are available from links found in source references. Input and output data from the event separation analysis, as well as the code developed to summarize and analyze operational flexibility and watershed response metrics can be found here: https://doi.org/10.5061/dryad.n5tb2rc84.

Acknowledgments

Funding for this work was provided by the US Army Corps of Engineers, Engineer Research and Development Center through grant agreement number W912HZ1920011 and the National Science Foundation through award number 2429901. The authors wish to thank several colleagues, including T.C., M.E., S.F., R.H., R.M., A.M., A.B.M., and R.W, whose perspectives helped to contextualize the results presented here, three anonymous reviewers whose suggestions helped to improve this manuscript, and Lori Fulton, who provided graphics support.

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