Title

Adaptively Operating a Fixed-percent Environmental Flow Budget with a Functional Flows Approach

Author
Murdoch, Lindsay E

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Adaptively Operating a Fixed-percent Environmental Flow Budget with a Functional Flows Approach

By

LINDSAY E. MURDOCH

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Approved:

Jay Lund, Chair

Sarah Yarnell

Jon Herman

Committee in Charge

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Abstract

Keywords: Operations research, budget-based environmental flows, functional flows, hydrologic seasonality and interannual variability, river management, Bay-Delta Plan

This thesis introduces the Functional Flows Adaptive Implementation Model (FFAIM), a framework for distributing a variable environmental flow budget throughout the year using a Functional Flows approach to prioritize key features of the natural flow regime that structure hydrologic seasonality for healthy ecosystem self-regulation. This framework provides (1) continuous scaling of functional environmental flow schedules by water year percentile and (2) an optimization structure for real-time adaptive operation of an annually varying environmental flow budget with periodically updated unimpaired flow forecasts. This functional flow implementation shows how unimpaired flow forecasts can inform environmental flow operations that preserve natural patterns of interannual and seasonal flow variability with a limited proportional environmental flow budget. This framework is demonstrated for the Lower Tuolumne River to shape and shift flows in accordance with the 2018 Water Quality Control Plan for the San Francisco Bay/Sacramento-San Joaquin Delta Estuary or Bay-Delta Plan (Bay-Delta Plan).

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Lastly, none of this would have been possible without the unwavering support of my family. To Constance (and Oxxo), who weathered frustrations, sleepless nights, and missed meals. Your encouragement and patience have been my pillars of strength.

Terminology

Adaptive implementation: A planning process in which decisions are regularly updated as improved information becomes available.

Bulletin 120 (B120): A regular publication by California's Department of Water Resources that includes water supply forecasts and other important hydrological data derived from recent Sierran snow surveys.

Environmental flow: The quantity and timing of water flows required to maintain the components, functions, processes, and resilience of aquatic ecosystems and sustain the goods and services they provide to people. (TNC, 2018).

- **instream flow**: the total water retained in channels for a variety of purposes that provides ecological benefits
- **ecological flow**: interchangeable with environmental flow, emphasizing the focus on ecological outcomes of managed flows
- **functional flow**: the water retained in a river that supports distinct flow components proven to be critical for maintaining baseline ecological functionality, as described in Yarnell et al. 2015

Exceedance probability: The likelihood that a specific condition (e.g., unimpaired flow volume, water year percentile) will be exceeded in a given time period.

Flood control operations: Water management strategy and actions taken to minimize the risk of flooding, such as pre-storm reservoir releases to increase storage capacity.

Flow budget (also "environmental flow budget"): A water volume made available annually for environmental purposes, perhaps set as a percent of unimpaired flow. Here, this flow volume refers to 40% of the unimpaired flow in a river from February through June, as directed in the Bay-Delta Plan.

Flow Regime: The variability of flows, both seasonally and interannually, quantified by magnitude, frequency, timing, duration, and rates of change of flows. For managed flows, "flow regime" references the range of flow schedules over multiple seasons and years, reflecting variability across wet and dry years as well as seasonally.

Flow Schedule: A time series of regulated daily streamflows, often expressed in an annual or seasonal hydrograph.

Functional Flow Component: A portion of an annual hydrograph that provides a distinct ecologic, geomorphic, or biogeochemical function (Yarnell et al. 2015). In California, five functional flow components are well recognized (Yarnell et al. 2020; https://ceff.ucdavis.edu/functional-flows-approach; Stein et al. 2021):

- *Fall pulse flow*: Coincides with the first or second major storm in the fall
- *Wet season peak flows*: Coincides with the most significant flashy winter storms
- *Wet season baseflow*: Sustained by overland and shallow subsurface flow in the periods between winter storms, computed as the 10th percentile of wet season flows
- *Spring recession flow*: Represents the transition from the wet to dry season and is characterized by a steady decline in flow from elevated spring flows over weeks to months

- *Dry season baseflow*: Sustained by groundwater inputs to rivers, computed as the 50th percentile of dry season flows

Functional Flow Metrics: Quantitative measures of flow characteristics (*timing, duration, frequency, magnitude, or rate of change)* for each of the five functional flow components. A subset of these descriptive metrics can be used to define a functional flow schedule.

Functional Flow Regime Index (FFRI): The linear relationship between each magnitude metric and the annual flow volume expressed as a percentile over the period of record that indicates variation across wet and dry annual conditions.

Hedging: A strategy used in water management to minimize risks from water scarcity or surplus, often by conserving water in the short term to increase water available for potential future shortages.

Holistic environmental flow approach: A broad category of environmental flows in which the natural hydrological regime is used to develop a flow strategy that maintains desired, ecologically significant features to protect flow benefits for the entire ecosystem, rather than a few indicator species (Arthington 1992).

Operating Year (OY): The operating year for FFAIM decisions is February-January. Example: OY2020 is February 2020 – January 2021. Not to be confused with water years (WY), which begin on October 1st of the prior year.

Percentile: A statistical measure indicating the value below which a given percentage of observations falls within a group of observations.

Unimpaired flow: theoretically available water supply assuming existing river channel conditions without storage, diversions, imports, and exports. Daily and monthly unimpaired flow estimates are posted on CDEC as "full natural flow" (FNF).

Water year percentile: The percentile of annual flow volume in a given year, used to provide a continuous alternative for discrete water year types (i.e., "critically dry," "dry," "below normal," "above normal," and "wet" in California). Water year percentile is an easily interpretable numeric identifier, where higher numbers (>50) indicate wetter years and lower numbers (<50) indicate drier years. In the Tuolumne River case study, the water year percentiles are computed as the empirical frequency of annual volumes between 1987 and 2021.

Water year type: A coarse categorical classification of water years based on hydrological conditions (e.g., critical dry, dry, below normal, above normal, and wet). In California's Lower San Joaquin River Basin, these conditions are defined using the 60-20-20 index. More information can be found here:

(https://cdec.water.ca.gov/reportapp/javareports?name=WSIHIST)

Introduction

In recent decades, approaches to managing river flows for environmental purposes have changed with our deepening understanding of the interplay between streamflow and ecological systems (Tharme 2003; Williams et al. 2019; Acreman and Dunbar 2004). Initially, environmental flow efforts sought to provide fixed bare minimum flows, presuming that critical low baseflows would be enough to support river ecosystems. Although these provided some protection, minimum flows alone were usually insufficient to revitalize desired fish populations (Williams et al. 2019). Subsequent flow initiatives sought to identify additional flow needs, including seasonal pulse flows, corresponding to different life stages of target species (e.g., Trinity River Restoration Program). Given the dependencies of target species on broader ecosystem communities of organisms, this strategy, while an improvement, is also usually insufficient to support desired species and broader ecosystems (Arthington et al. 1992, 2006).

Today, environmental flow strategies are shifting to more holistic, ecosystem-centered approaches that factor in the critical roles of flow in regulating physical, chemical, and biological feedbacks (Tharme 2003). This evolution has been driven by recognition of sometimes intricate feedbacks between the entire flow regime and its seasonal and interannual variability in shaping habitat and species composition and populations (Bunn and Arthington, 2002). Understanding that native species have co-evolved with seasonal and interannual flow patterns (Bunn & Arthington 2002; Gasith & Resh 1999), including intermittent exposure to high and low-flow extremes, unimpaired historical hydrology (Lytle & Poff 2004) can provide a starting place for environmental flow planning. The native ecosystem evolved into these historical natural flow patterns. The progression from rudimentary minimum flow initiatives to more holistic, ecosystem-based approaches reflects both mechanistic and empirical advances in environmental understanding and management (Williams et al. 2019).

This thesis introduces the Functional Flows Adaptive Implementation Model (FFAIM), a framework for operating a variable environmental flow budget throughout the year using a holistic environmental flows approach. The Functional Flows approach (Yarnell et al. 2015) prioritizes seasonal features of the natural flow regime known to influence ecogeomorphic responses and equips managers with a structure to prioritize flows to these key flow components of demonstrated ecological importance. This thesis provides and demonstrates steps to develop a functional flow regime for a particular river with an adaptive planning approach that allows managers to operate to functional flow schedules using a forecasted environmental flow budget based on a percentage of unimpaired flow (%UF) before the budget is thoroughly known. The resulting FFAIM framework is quite flexible. Functional flow metrics are estimated from available historical flow estimates, which can be adjusted to better fit within highly altered channel forms and flood management requirements. As channel structure evolves or new data and information become available, these metrics can be adjusted for geomorphology and other factors.

The following four chapters are a roadmap for designing and applying an operational functional flow regime. The first chapter presents background information on the Functional Flows approach employing the California Environmental Flows Framework (CEFF) and introduces an environmental flow budget proposed for the Lower San Joaquin tributaries in the Bay-Delta Plan. The second chapter outlines a process for designing a continuous, scaled functional flow regime that is flexible enough to be applied across rivers. The third chapter considers how this flow regime could inform real-time management, using probabilistic optimization and forecasting to support adaptive decision-making as the %UF budget volume evolves. Chapter four presents results from a Tuolumne River case study of adaptive functional flow implementation. A final chapter on future work and conclusions completes the thesis.

1. Background and Project Overview

Flow is fundamental in river regulation. A river's flow drives its physical structure, provides cues for organisms in its ecosystem (e.g., migration and spawning), and creates longitudinal and lateral connectivity for food, migration, and suitable habitat (Bunn & Arthington 2002). These aspects make environmental flow regulation essential for protecting riverine habitats and ecosystems. Environmental flow protections have improved in recent years but typically fail to adequately foster ecological health (Arthington 2006). The Natural Flow Paradigm (Poff 1997) posits that native ecosystems have co-evolved with local natural flow regimes. Hence, deviations from natural flow regimes degrade habitat and impact species composition (Richter et al. 2012). Increasingly, the entire range of historical flow variability is being recognized for its integrating role and empirical representation of complex intertwined feedbacks in aquatic ecosystems for river management (Lytle & Poff 2004; Biggs et al. 2004).

Restoring the historical flow regime is unrealistic in most river systems, where mixed-use management constrains the availability of water in the system (Acreman et al. 2014). Competing demands for limited water reduce the available water quantity and change the quality (including temperature) and timing of river flows (Bunn & Arthington 2002). Naturally, dynamic channel geometry has also been reshaped and stabilized by human manipulation, resisting channel-moving high flows and disrupting pre-development sediment regimes (Meitzen et al. 2013; Moyle & Mount 2007). Habitat restoration in these modified systems provides a patchwork of high-quality habitat interspersed with heavily impacted reaches that respond differently to flow-related inputs of water, sediment, and nutrients (Whipple & Viers 2019).

In the Fall of 2021, California's State Water Resources Control Board approached the Center for Watershed Sciences at the University of California, Davis with the challenge of developing an adaptive planning method to meet flow objectives outlined in the Bay-Delta Plan by allocating an environmental flow volume on three tributaries of the Lower San Joaquin River. The goal was to improve environmental outcomes by shaping and shifting wet season runoff throughout the year. The Functional Flows approach provides a well-documented scientific basis for how to preserve vital ecological aspects of flow—*seasonality* and *interannual variability*—even with diminished flow volume. The following sections provide context for the State's efforts and the Functional Flows approach.

1.1 Flow-budget approach and the Bay Delta Plan

On December 18, 2018, the State Water Resources Control Board (SWRCB) amended the 2018 Water Quality Control Plan for the San Francisco Bay/Sacramento-San Joaquin Delta Estuary or Bay-Delta Plan (Bay-Delta Plan) to include new environmental flow objectives for the Lower San Joaquin River (LSJR) and its three salmon-bearing tributaries (Stanislaus, Tuolumne, and Merced Rivers) "for the reasonable protection of fish and wildlife beneficial uses" (SWRCB-BDO 2018). The SWRCB allocated 40% of unimpaired flows (within an adaptive range of 30 to 50 percent estimated at the rim reservoir on each tributary) from February through June to meet the objectives. Compliance with these flow objectives is measured at the mouth of each tributary, near their confluence with the San Joaquin River mainstem.

Many approaches could be chosen to allocate this environmental flow budget operationally. By default, the Bay-Delta Plan specifies that sufficient water be bypassed to achieve 40 percent of unimpaired flow (40% UF) at the three compliance stations using a 7-day rolling average described in (SWRCB-BDO 2019). This 7-day averaging period seeks a balance between faithfulness to the natural flow of that year and operational ease (SWRCB-BDO 2019). The averaging period helps operators prepare for the coming week by sacrificing strict adherence to daily flow changes (SWRCB-BDO 2018; Gartrell 2023).

The Bay-Delta Plan also allows for shifting and shaping the 40% UF environmental flow budget via “adaptive implementation.” This thesis develops and demonstrates an adaptive implementation method using an annually varying proportional environmental flow budget. Specifically, using a Functional Flow approach, we show how an environmental flow budget can be distributed operationally throughout the year. Specific functional flow components, proven to support critical ecosystem functions, are prioritized over less impactful flow features.

The Functional Flow approach allows high-flow components to exceed 40% of the estimated magnitude and to backstop minimum baseflows throughout the year (40% of the lowest flow days, even with a 7-day rolling average applied, might be lower than desirable). The Functional Flows Adaptive Implementation Model (FFAIM) is a seasonal operations model that uses external unimpaired flow forecasts to predict the 40% UF budget and to recommend functional flow schedules, as updated runoff conditions evolve.

The flow objectives in the Bay-Delta Plan are constructed as a system-wide approach rather than focusing on a particular piece of infrastructure. The program is structured to use downstream compliance points for each tributary and a combined compliance point just below the Stanislaus confluence at Vernalis (Figure 1). While the 40% UF budget is taken from the Bay-Delta Plan, FFAIM's method of shaping and shifting a variable water budget could be applied to any river basin where water can be stored across seasons and downstream flow can be controlled.

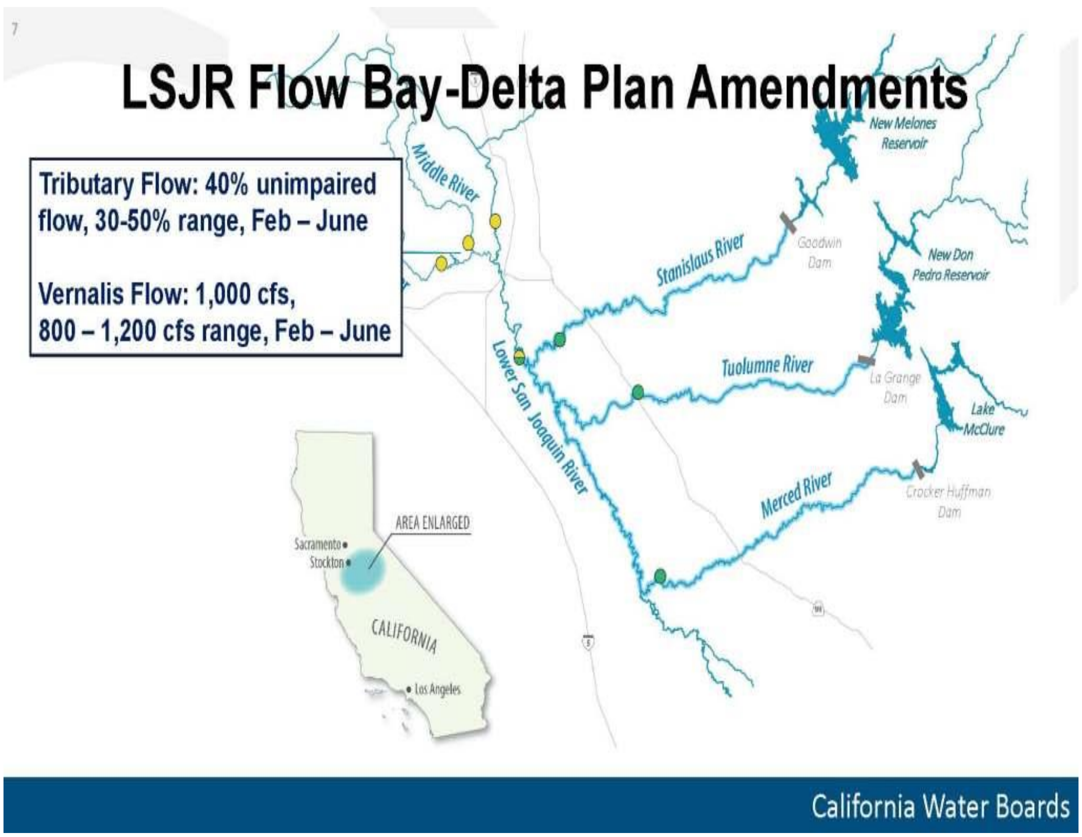


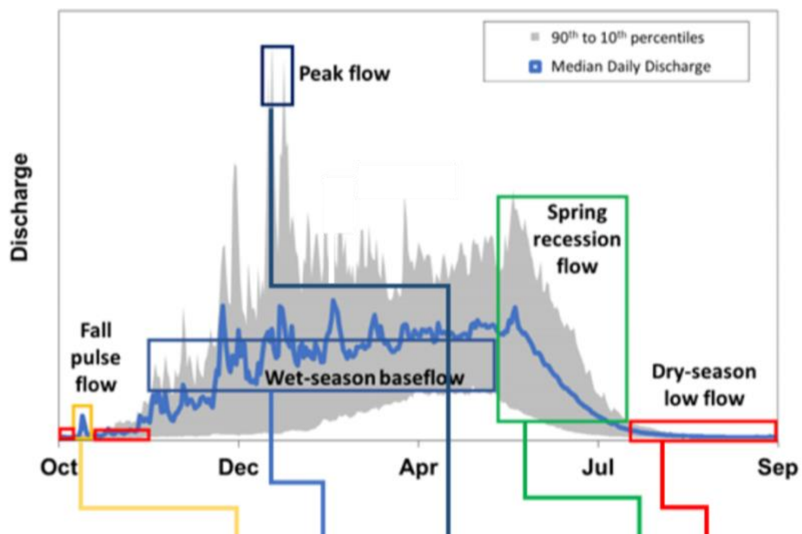
Figure 1: Lower San Joaquin River map with three tributaries: Stanislaus, Tuolumne, and Merced Rivers. Flows downstream of three rim dams are regulated for downstream compliance points (green circles). Additional requirements exist at Vernalis, downstream of the final major tributary confluence (green and yellow circle). (Source: SWRCB-BDO 2018)

1.2 Functional Flows and CEFF

Policy and management discussions often reduce flow-ecology relationships to highly simplified cause-and-effect relationships that inadequately describe population responses to flow (DeFries & Nagendra 2017). Aquatic ecosystems are highly variable with dynamic feedbacks (Anderson et al. 2006) with physical modifications, sedimentation, water quality, bioenergetic cycles, and other factors interacting to produce ecosystem responses (Yarnell & Thoms 2022). Climate change will alter these effects and interactions (Horne et al. 2019). Assessing these interdependent factors is costly, data-intensive, time-consuming, and involves many uncertainties (Acreman & Dunbar 2004). Instead of focusing on individual species-specific responses to flow, it is likely faster to take a holistic, empirical approach that integrates the physical and biogeochemical mechanisms by which flow acts on the landscape and produces cascading ecological responses.

The Functional Flows approach posits that each river has a characteristic flow pattern that provides the foundation of functionality. This pattern varies somewhat from year to year, maintaining interannual diversity in these flow-driven functions. This departs from the idea that a singular *minimum flow* can sustain a riverine environment, instead upholding that both seasonal and interannual variability regulate ecological feedbacks. If managers have only a reduced amount of water in a river, each year's hydrologic signature must be represented to sustain the myriad of regulating functions performed by river flow.

The Functional Flows approach is a holistic method to restore more natural and ecologically functional flows by prioritizing seasonal flow-features that regulate ecosystem functions (Yarnell 2015; Williams et al. 2019). The Functional Flows approach shifts the focus from single-species management to flow-regulated ecogeomorphic processes (e.g., sediment movement, water quality maintenance, environmental cues for native aquatic species) that support ecosystem health (Grantham et al. 2020). Functional flows are discrete aspects of the natural flow regime with documented relationships with ecological, geomorphic, or biogeochemical processes in riverine systems (Yarnell et al. 2015). A Functional Flows approach prioritizes preserving natural variation in functional flow components relative to other aspects of the flow regime. Functional flow components can be abstracted from archetypical seasonal patterns derived from local climate and geology (Lane et al. 2018). In California, five functional flow components critical for supporting ecosystems in rivers and streams have been identified: *fall pulse flow, wet-season peak flows, wet-season baseflow, spring recession flow, and dry-season baseflow* (Yarnell et al. 2020). Details on ecosystem functions provided by each functional flow component are included in Appendix A. These five functional flow components can be described by a suite of *functional flow metrics* relevant to aquatic and riparian communities in California's Mediterranean-climate river systems (Yarnell et al. 2020) (Figure 2).



	Functional Flow Components				
Flow Characteristics	Fall Pulse	Wet Baseflow	Peak Flow	Spring Recession	Dry Low Flow
Magnitude	X	X	X	X	X
Timing	X	X	X	X	X
Duration		X	X	X	X
Frequency			X		
Rate of Change				X	X

Figure 2: Functional flow components (boxes) for a mixed rain-snowmelt runoff system in California with key flow characteristics for each flow component (table). The blue region represents the 50th percentile daily discharge range. Gray shading represents 90th to 10th percentile daily discharge ranges for the record. after Yarnell et al. (2020).

The California Environmental Flows Framework (CEFF)(ceff.ucdavis.edu) provides guidance for developing and implementing a site-specific Functional Flows approach. CEFF was created in broad collaboration with resource agencies, academia, and non-governmental organizations in 2021 as a scientifically defensible environmental flow framework that can be rapidly adopted across California (Stein et al. 2021). CEFF provides modeled estimates of functional flow metrics for all streams in the state based on observed values of functional flow metrics under natural reference conditions (Grantham et al. 2022). These natural reference conditions can be used directly as the basis for ecological flow criteria (Section A). Historical and ongoing land use and channel activities degrade physical, chemical, and biological conditions in many rivers. In such cases, the natural ranges of functional flow metrics may be less effective in supporting ecosystem functions. For example, channel incision may reduce the ability of wet-season peak flows to inundate the floodplain or maintain geomorphic complexity. In such cases, ecological flow criteria may need to be adjusted to support ecological functions in altered channels (Section B). CEFF also provides guidance on considering ecological flow criteria in the context of other non-ecological management objectives, assessing potential trade-offs between water allocations, and determining appropriate environmental flow recommendations and management strategies (Section C).

This thesis presents one method to design and operate an environmental flow regime, using water year percentile and flow budget availability as the primary drivers of seasonal and interannual variability. Using a Functional Flows approach to design the environmental flow regime provides considerable flexibility and adaptability. A seasonal operations model, FFAIM, employs this approach to guide adaptive seasonal operations during any given year, updating operations and environmental budget volumes as the water year develops using probabilistic seasonal flow forecasts. At its core, FFAIM's flow regime design is a hydrologic desktop method, using historical hydrologic estimates to understand local flow seasonality and interannual variability (Acreman 2004). Within this framework, there are substantial opportunities to adjust metrics to account for non-flow deviations from reference conditions that may require additional data and periodic modification via adaptive management.

If we wait for the moment when everything, absolutely everything, is ready, we shall never begin.

Ivan Turgenev (1877)
Virgin Soil Ch. 21

2. Designing a Functional Flow Regime from Hydrologic Data

2.1 Purpose

Most environmental flow regulations for the Lower San Joaquin River and its tributaries represent interannual variability using a few discrete water year types. These include water rights decision 1641 (link) for Vernalis minimum flows, FERC minimum flows on the Merced and Tuolumne Rivers, and the 2019 Biological Opinion minimum flows on the Stanislaus River. Furthermore, the seasonality represented by these flow prescriptions targets baseflows and pulsed flows to support a few target species during particular life stages (Hankin et al. 2010). While well-meaning, this coarse representation falls short in three ways: (1) it represents only part of the natural variability (especially at the low end), (2) it misses critical flow features of natural seasonality, and (3) it tends to focus on flows for particular species of interest and falls short of flows that might support interconnected ecosystem processes.

To address these shortcomings, we propose instead continuously scaling environmental flows by historical return intervals of flow-driven functions and more comprehensive seasonality (i.e., early rain-driven runoff in the wet season, spring snowmelt, and low flows in the dry season). This application of the Functional Flows framework better represents and supports the natural variability of major functional flow components while allowing some other flow features, such as minor rain events, to deviate more from natural conditions.

Figure 3 compares three alternative environmental flow regimes with unimpaired flows. Figure 3a illustrates a baseflow-only environmental flow approach, which omits major natural flow peaks with scientifically demonstrated ecological functions. Figure 3b shows an alternative operation as a daily percent of unimpaired flows. This yields a miniaturized hydrograph, which is unreliable for providing critical ecological functions of high peak flows and baseflows. Figure 3c is a functional flow regime that prioritizes natural flow features, seasonal baseflows, and significant peaks nearer to their natural levels at the expense of flows and peaks at other times. The functional flow regime offers a compromise that supports the natural magnitudes of critical flow features and water diversions commensurate with a %UF approach.

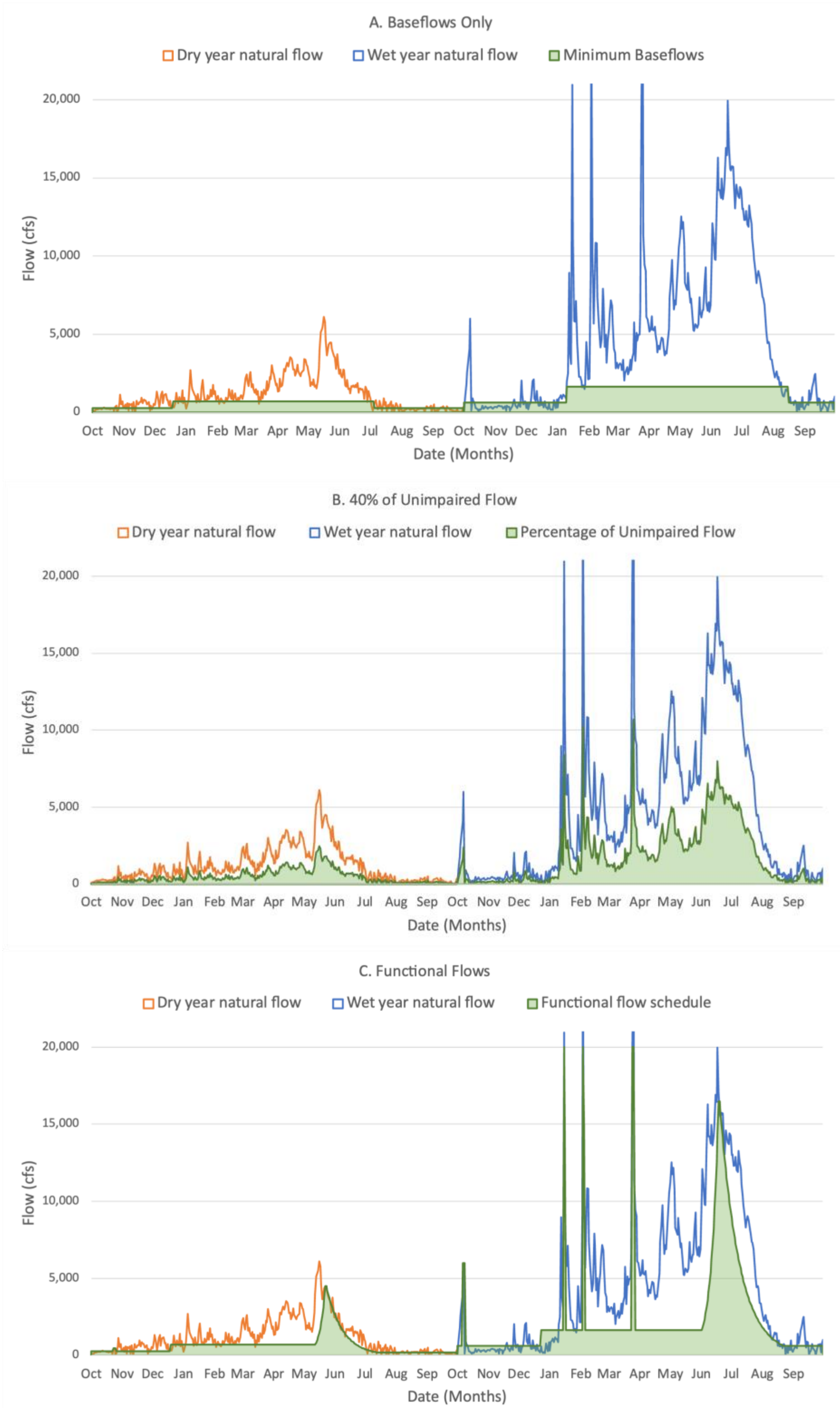


Figure 3: (A) Baseflows, (B) 40% FNF, and (C) functional flow hydrographs compared to the natural flow in dry (1988) and wet (1998) water years on the Tuolumne River. Functional flows preserve the spring and wet season peaks and maintain a baseflow set to the 10th percentile magnitude of wet season flows and 50th percentile of dry season flows.

Together, the suite of functional flow metrics and their temporal variations can be combined into a functional flow regime to represent a broader and more detailed spectrum of water year conditions (Figure 4). Functional flow components prioritize the timings and magnitude of environmental flows to regulate high-quality habitat. Specifically, baseflows during dry and wet seasons ensure year-round habitat connectivity, while the spring pulse/recession mirrors the gradual flow decline typical of snowmelt. The fall pulse, simulating the initial runoff event from the first autumn storms, is a precursor to seasonal transitions. Wet season peaks in wetter years reflect intense wet season storms, disrupting regular flow patterns, mobilizing sediment, and fostering structural diversity. The magnitude, timing, and duration of each flow component varies across years depending on runoff conditions. The resulting functional flow regime includes minimum seasonal flows that vary with the water year percentile, maintaining distinctive functional signatures for each year.

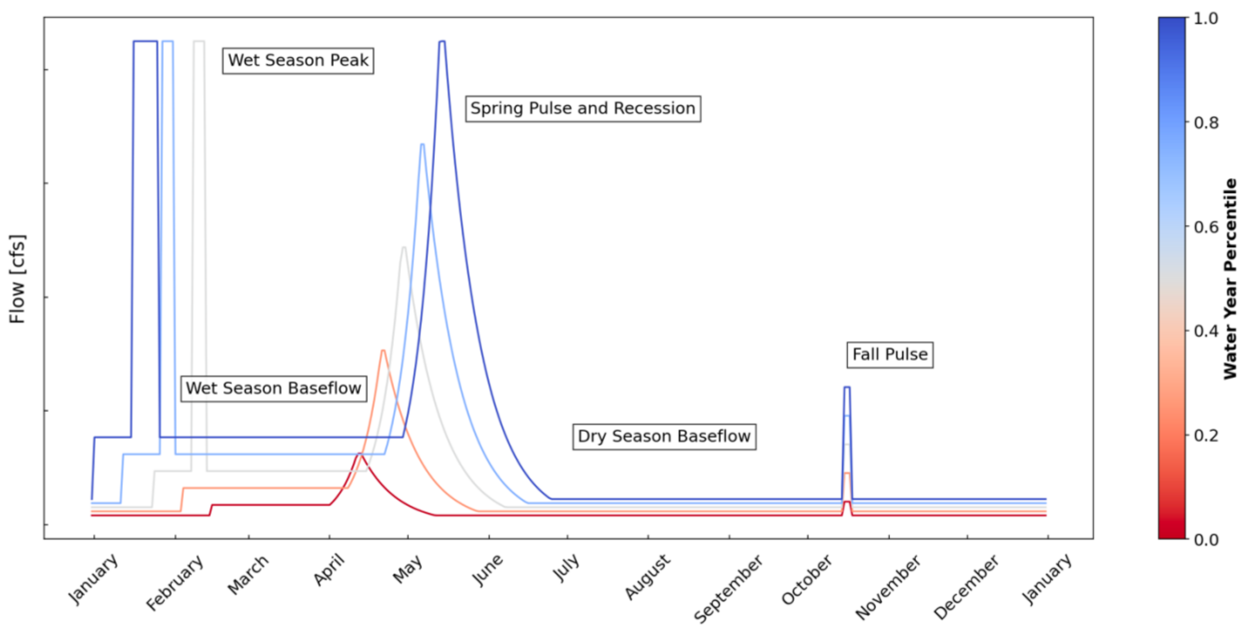


Figure 4: Illustrative hydrographs showing how functional flow schedules might vary flow components by water year percentile, creating a diverse functional flow regime over many years.

The following section presents a method to distribute a limited environmental water budget across an operating year while preserving seasonality and interannual variability. The range of natural functional flow metrics characterizes historical flow variance. We use this historical variability to identify functional flow metrics that correlate to water year percentile (representing wetter and drier years). We then identify patterns in these metrics useful for designing and varying flow schedules to represent the diversity of flows across a broader range of water year types.

2.2 Designing Functional Flow Schedules to Represent Interannual Variability

Figure 5 outlines the general process for developing and assembling a set of annual functional flow schedules as inputs to the Functional Flow Adaptive Implementation Model (FFAIM) for a particular stream location. Step 1 computes functional flow metrics (FFMs) that quantify the variability of flow characteristics of each functional flow component. Step 2 adjusts the FFMs to account for factors that may limit the effectiveness of the natural range of FFMs to support ecosystem functions, such as physical habitat alterations, competition from non-native species, or water quality impairments. Step 3 develops relationships between the functional flow metrics and annual flow volumes to reflect variation in flow characteristics across wetter and drier years. In Step 4, the resulting relationships are assembled into a range of functional flow schedules. Operational environmental flows are chosen by matching functional flow schedules to forecasted flow budgets. Chapter 3 will further detail how these flow schedules are used within FFAIM to suggest real-time decisions.

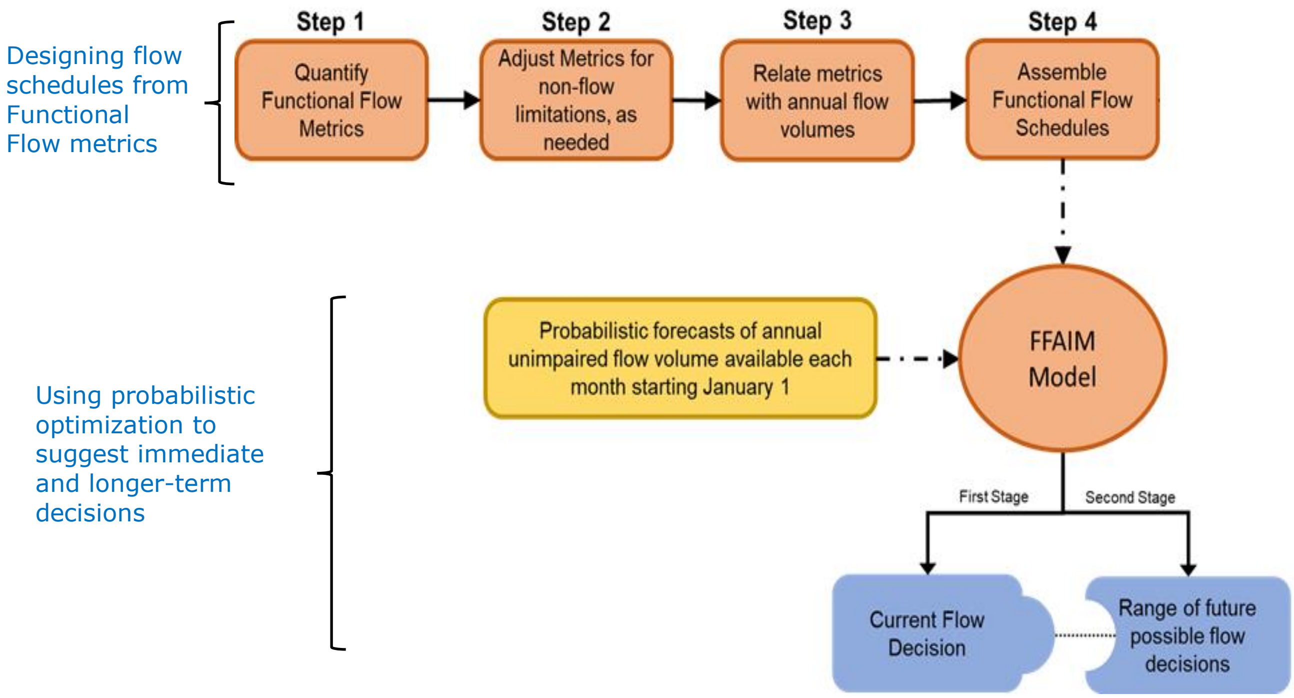


Figure 5: Process for developing the Functional Flows Adaptive Implementation Model (FFAIM) for a stream location. See text for details on each numbered step.

Step 1: Quantify functional flow metrics

The Functional Flows approach begins with distilling information from the natural flow regime (represented by a long period of estimated daily unimpaired flows) to quantify the variability of functional flow metrics (CEFF Section A). Functional flow metrics for California rivers can be readily computed from historical daily unimpaired flow estimates (such as daily full natural flow (daily FNF) data from the California Department of Water Resources (CDEC; https://cdec.water.ca.gov/reportapp/javareports?name=FNF) using the Functional Flows Calculator API client package (R-based script publicly available via eflows.ucdavis.edu). This calculator applies signal processing (Patterson et al. 2020) and streamflow characterizations (Lane et al. 2018) to identify interannual distributions of descriptive metrics of the five functional flow components. When historical unimpaired flow estimates are unavailable, modeled estimates are publicly available on the Natural Flows Database for all of California (hosted by The Nature Conservancy at rivers.codefornature.org).

Step 2: Adjust functional flow metrics for physical, regulatory, biological, or water quality limitations.

While the concept of the *natural flow regime* has contributed significantly to the environmental flow assessment, there are various practical and theoretical reasons why natural flows might be an imperfect blueprint for planning environmental flows. The flow and form of California's rivers are heavily modified by land and water development and are unlikely to be entirely restored to their historical condition. However, opportunities exist to restore a river's flow-driven functions even with these new channel realities.

Functional flow metrics (from Step 1) can be adjusted to account for factors, such as altered channel conditions, flood flow regulations, and water quality impairment, that limit the effectiveness of the natural range of flow metrics to produce the desired physical, chemical, and biological functions (Stein et al. 2021; CEFF Section B). When designing an environmental flow regime, there may be justification for deviating from the natural range of functional flow metrics and adding additional flow features. Planners should be mindful of the following considerations that might warrant metric shifting as they begin to design and revise operational functional flow regimes:

> **Altered channel morphology.** Historical and ongoing land and water management have often altered physical conditions from pre-development times. For example, large dams

modify the geochemical and physical conditions of the downstream channel, often changing the shape of the river from a shallow, meandering, and wide channel with flows frequently connected to the floodplain to a deep, incised, and narrow channel (Meizan et al. 2013). The physical channel form dictates habitat availability, hydraulic suitability, floodplain activation thresholds, and transport and deposition dynamics (Meizan et al. 2013). Any deviation from the most recent flow paradigm will likely alter downstream geomorphology such that morphological adjustments should be considered ongoing and experimental.

Sediment availability. Dams interrupt longitudinal sediment transport regimes by blocking sediment and enabling the accumulation of fine-grain material (Graf 2006). The buildup of these fines, which is detrimental to aquatic habitats (Chapman 1988), can be mediated by high flows and restoration practices (e.g., gravel augmentation on the Tuolumne River; FERC OEP 2019). The natural timing and magnitude of high-flow events might be altered to maximize the effectiveness of sediment projects and promote habitat creation.

Composition of lotic and riparian communities. Whereas native species are adapted to the natural flow regime, highly altered flows allow for the establishment of non-native species (Bunn and Arthington 2002). Natural flows alone may be insufficient to halt the loss of native species; instead, active management will be required to protect critical strongholds where natives are likely to bounce back (Propst et al. 2008). Particular conditions may be imposed (e.g., maximum rates of change to limit stranding, coordinating riparian planting, and over-bank flows) to protect native refugia and give natives an advantage over their competitors.

Chemical and thermal conditions. Reduced flow magnitudes concentrate solutes, possibly impacting the ability of baseflows to meet chemical objectives (Bradley et al. 1990). Dams influence a river's thermal regime by altering downstream flow magnitudes (affecting the river's heat capacity) and selectively releasing water from the reservoir's temperature-stratified layers. Adjusted flow magnitudes or timing might better mimic the historical temperature conditions below the regulating dam, though this would require additional understanding of the reservoir's construction, operation, and limnology (Olden & Naiman 2010).

Channel capacity and human safety concerns. Dams and managed flows have encouraged floodplain development and the construction of flood-control structures to protect urban and agricultural communities (Auerswald et al. 2019). Public safety mandates hard capacities on channel flow, limiting flow magnitudes (e.g., maximum flood control operating flows set by the U.S. Army Corps of Engineers). Furthermore, levees concentrate flows into artificially narrow channel forms, impeding pulse flow attenuation and water storage in the floodplain (Serra-Llobet et al., 2022).

Reservoir operation and construction. The operation and original design of dams may limit the design of environmental flows below a regulating dam. Flood control operations might result in early wet season releases to make room in the reservoir to store incoming storms, which may result in hastening and capping peaks from storm events. Efforts to reintroduce high flows may also be limited by penstock capacity, outlet capacities, and the willingness to use spillways (Richter & Thomas 2007).

Climate non-stationarity. Flow metric adjustments may be required to support native or novel ecosystems in a climate-altered future. Higher temperatures, changes in

> precipitation, and resulting changes in land and water management are likely to change the ability of the river to support different mixes of native and non-native species and ecosystems. Managers will have to confront difficult decisions, such as the validity of historical reference conditions in the face of the new climate normal (Betancourt 2012; Horne et al. 2019).

Adjustments made to natural functional flow metrics can reduce environmental effectiveness. It is, therefore, prudent to discuss potential tradeoffs and enact monitoring plans and adaptive management to limit unintended consequences and improve outcomes over time (Poff et al. 2018).

Alteration of functional flow metrics also poses practical concerns for flow regime design. Even the simple decision to limit flow magnitudes for channel capacity and flood control can introduce tradeoffs with other flow metrics. For example, when reducing spring peak magnitudes, flow designers must choose between preserving either ramping rates, duration, or both (Figure 6). While these decisions will likely have ecological consequences, excessive attention to detail can prolong iterative planning cycles and delay substantive methodological and ecological improvements.

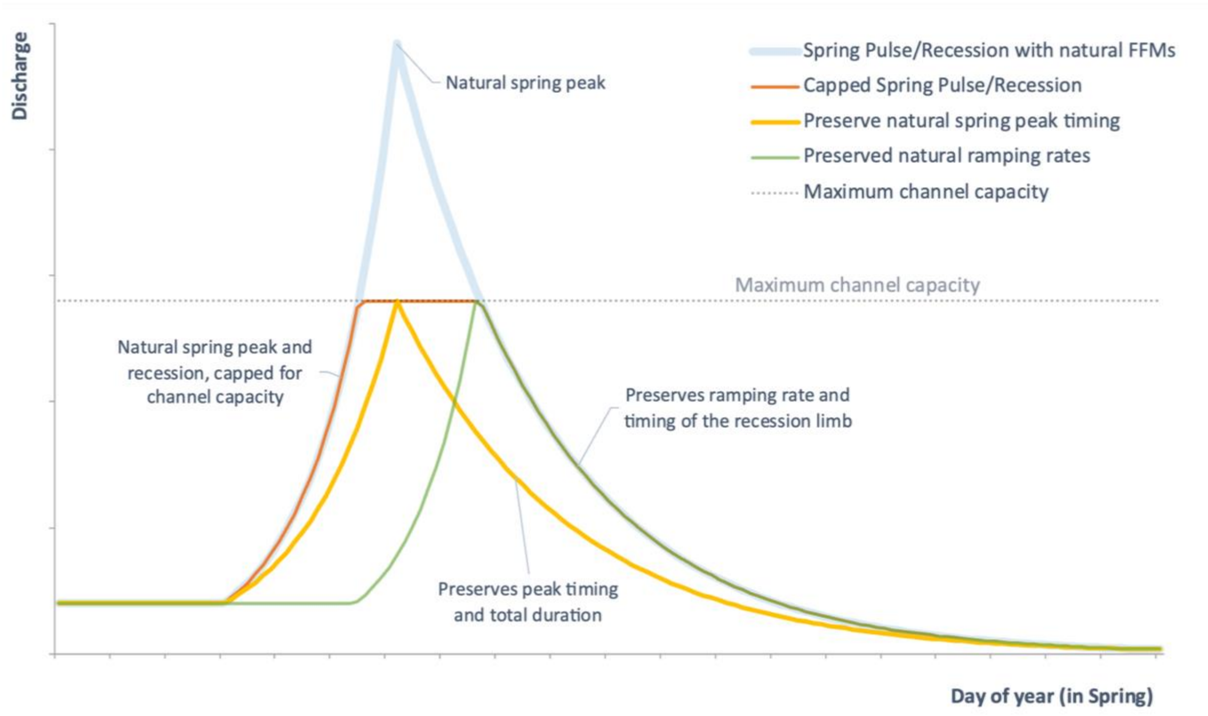


Figure 6: Three examples of spring pulse and recession design in a system with a regulated maximum flow.

Step 3: Create Water Year Percentile-Functional Flow Metric curves to create a Functional Flow Regime Index (FFRI).

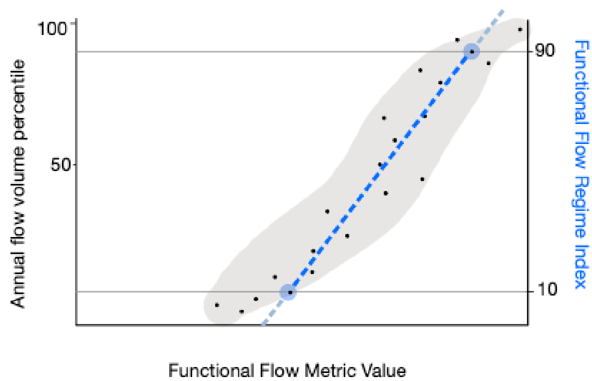
In most Californian streams, functional flow metric values vary across individual water years with climate conditions (Grantham et al. 2022). Wetter years typically have larger flows and longer durations of wet season and spring flows, while drier years typically have lower flow magnitudes and longer dry season durations. Similarly, wetter years have more annual runoff volume, while drier years have less. A functional flow regime index (FFRI) that links particular metrics to water year percentiles is used to design flow schedules with different water volume requirements.

Replicating natural interannual variability begins by examining how functional flow metrics naturally vary with annual flow volume. The FFRI links these two statistics to represent interannual variation in the functional flow regime. By using annual flow volume as a percentile, the modeler can easily reference the ideal frequency with which the metrics should occur over a span of years. Some functional flow metrics do not correlate with annual flow volume, such as those related to individual storm events (e.g., peak frequency, fall pulse timing, etc.). Many of these metrics still fall within a range of values in the natural flow regime and modelers should consider whether and how to vary these. The reasoning used to vary individual metrics directly affects the water volume needed for a functional flow schedule to match target water year percentiles.

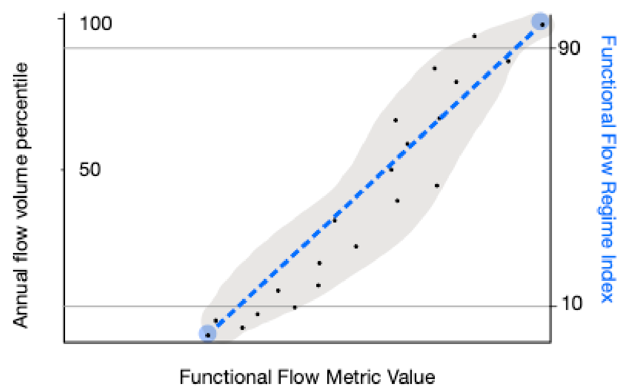
There are infinite ways to represent relationships between water year percentile and functional flow metrics mathematically and graphically. Hydrologic data often has outliers, and the record of daily unimpaired flow estimates is relatively short. Some judgment is needed to "fit" these relationships, particularly concerning extreme values. All "fits" are approximate. The following are a few ways to represent interannual variability of metrics, showing the flexibility in developing FFRI relationships and ways to represent annual flow volume-metric relationships:

> **Linear "fits"**. Linear methods offer a straightforward fitting solution, particularly suitable for cases with modest historical data or cases where extreme events have less significance (e.g., intense high and low-flow events might excessively stress ecosystems). One approach to mitigate severe stressors involves managing metrics within the 10^{th} and 90^{th} percentiles, excluding the less common and more extreme tails (for which little data exists). The central portion of a cumulative distribution often can be approximated adequately by a straight line, connecting endpoints at the 10^{th} and 90^{th} water year

percentiles (refer to Figure 7a). Opting for the 10th and 90th percentiles as endpoints is advantageous because they are prominently featured in the Functional Flows Calculator API output. Alternatively, the Functional Flow Regime Index (FFRI) could be configured to encompass the entire metric range, including edge cases observed within the available data (refer to Figure 7b) or a simple regression fit of non-extreme events (however defined).



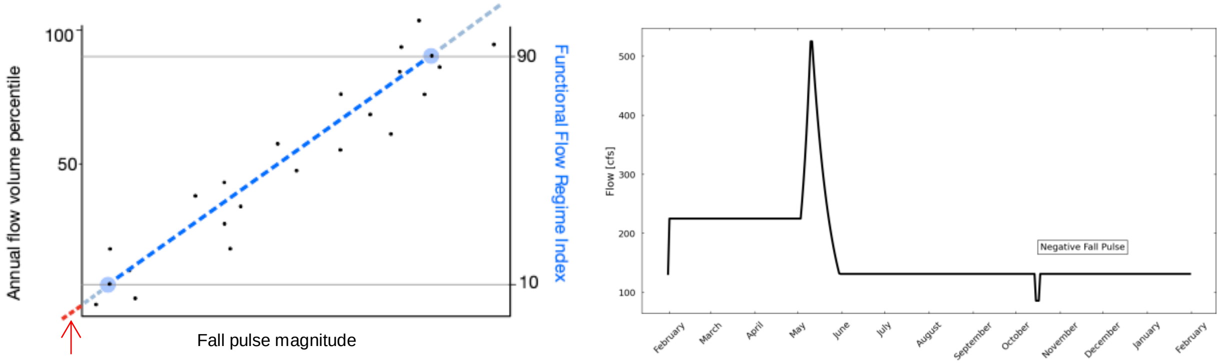
(a)



(b)

Figure 7: Two examples of how a linear fit could represent the relationship with water year percentile. (a) estimates metric values that more commonly occur (between the 10th and 90th water year percentiles), minimizing risk of stress-inducing flows. (b) estimates the entire range of metric values, including extremes (>90th and <10th water year percentiles).

These linear relationships only apply within the endpoints and should not be extrapolated beyond those bounds (e.g., linear fit in Figure 7a no longer represents the observed trend outside the 10th and 90th water year percentiles). Modelers should be clear about the range in which FFRIs are reasonable. Figure 8 shows an extreme case where a linear relationship produces an unsatisfactory hydrograph outside the suitable range. In this case, the fall pulse, which is usually additive to the dry season baseflow, becomes negative for very low FFRIs (in this example, FFRIs less than 5). Figure 8b shows the *anti-pulse* that takes shape in the annual hydrograph of an extremely dry year if extrapolation is used.

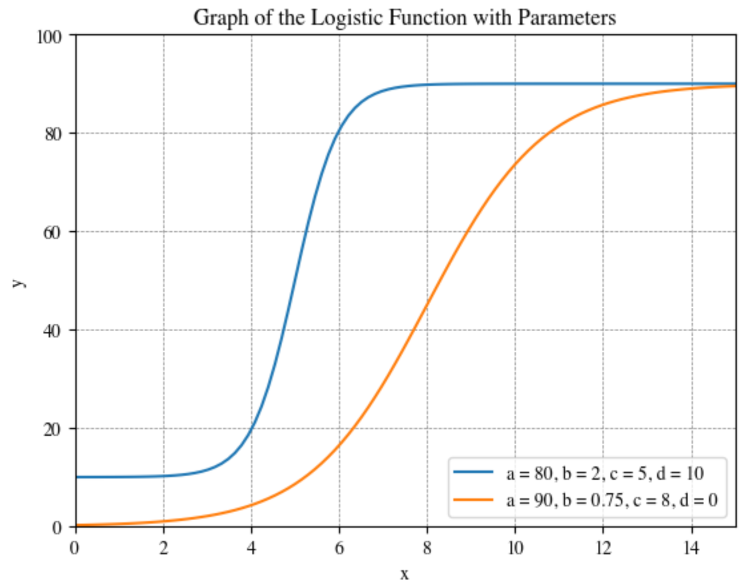


(a) (b)

Figure 8: Flow metrics extrapolated outside of the intended range can produce curious hydrographs. (a) shows a linear representation between annual flow volume percentile and fall pulse magnitude. Blue highlighted circles are endpoints of a reasonable range of the FFRI-metric relationship. Red dotted line shows where positive FFRI values produce negative flow metric values. (b) shows a hydrograph of an FFRI from this red region. Extrapolating for a small positive FFRI causes a negative fall pulse.

Sigmoidal "fits". Sigmoidal functions produce S-shaped curves with a single inflection point, often used to capture monotonic non-linear relationships. These can be particularly useful for representing low-likelihood edge cases. But metric values outside the natural range will remain problematic and data-sparse. Logistic, Gompertz, and Weibull sigmoidal functions are discussed below:

Logistic functions can help capture edge cases and are intuitively parameterized. The logistic function asymptotes are equidistant from the inflection point creating a symmetrical curve, making these functions especially good for metrics distributed normally between clearly defined upper and lower bounds. Figure 9 gives the equation of a logistic function with different parameterizations. Figure 10 shows how the logistic function might fit historical data for a relationship between the water year percentile and a functional flow metric.



$$y = \frac{a}{1 + e^{-b(x+c)}} + d$$

Where parameters > 0:
$(a + d)$ is the upper asymptote
b controls the growth rate
c shifts the curve on the x-axis
d is the lower asymptote

Figure 9: Equation and parametrization of the logistic function.

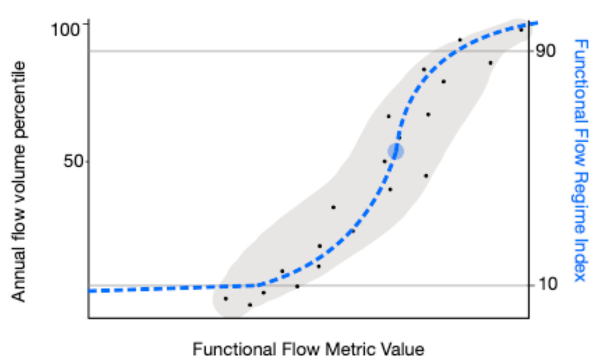
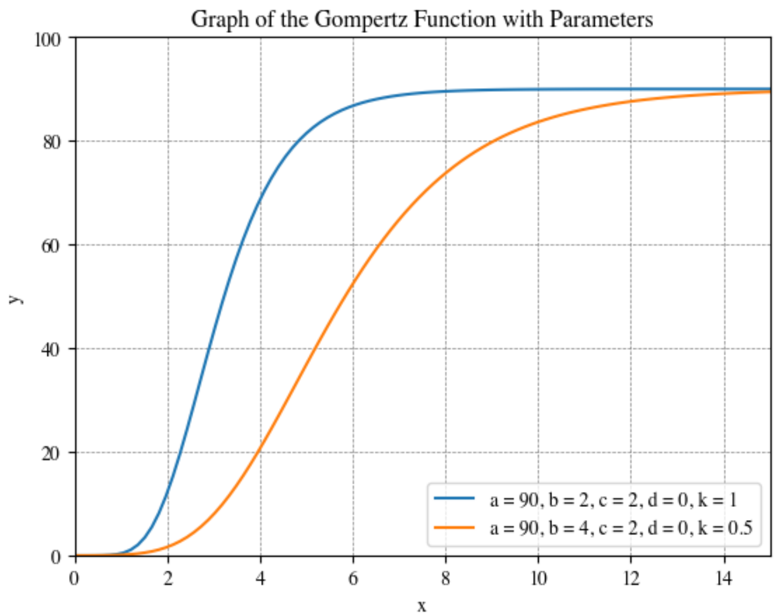


Figure 10: Conceptual example of how a logistic function might be fit to functional flow metric data (plotted by water year percentile) to define an FFRI.

Gompertz functions similarly fit logistic functions but differ in allowing asymmetry around the inflection point (Figure 11, Figure 12). Gompertz functions are ideal for representing skewed data with a lower limit (such as zero) and gradually decreasing frequency toward the upper tail. This is particularly useful in modeling flooding, where more accurate representations of upper extremes are necessary. Figure 11 gives the Gompertz function with example parameterizations. Figure 12 shows how the function might fit historical data for a relationship between the water year percentile and a functional flow metric.



$$y = ae^{-be^{-k(x-c)}} + d$$

$(a + d)$ is the upper asymptote
b is the growth rate
k shifts the inflection point in the x-direction
c shifts the curve on the x-axis
d shifts the curve on the y-axis

Figure 11: Equation and parametrization of the Gompertz function.

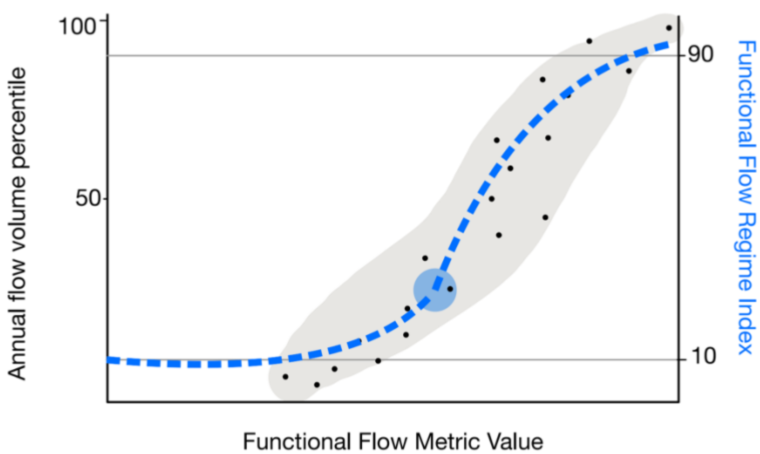
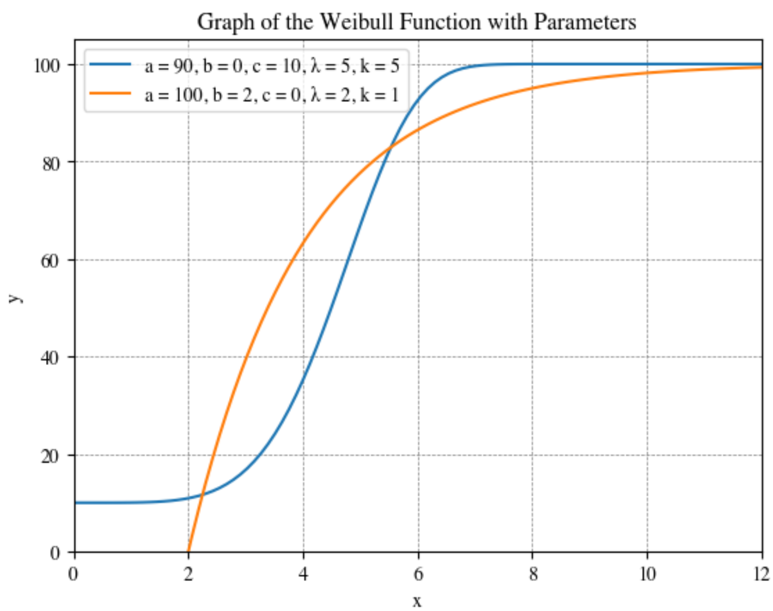


Figure 12: Conceptual example of how a Gompertz function might be fit to functional flow metric data (plotted by water year percentile) to define an FFRI.

Weibull functions have even more versatility because they can be parameterized to include both exponential (when $k = 1$) and sigmoidal functions (when $k > 1$). This expands the modeler's ability to fit observed relationships and set hard minima for particular metrics. Additional model constraints may be needed to ensure water availability for such metric minimums. Figure 13 gives the equation and example parameterization for the Weibull function. Figure 14 shows how the function might fit historical data for a relationship between the water year percentile and a functional flow metric.



$$y = a * exp\left[-\left(\frac{x-b}{\lambda}\right)^k\right] + c$$

$(a + c)$ is the upper asymptote
b shifts the curve on the x-axis
k is shape parameter
λ is the scale parameter influencing the spread
c shifts the curve on the y-axis

Figure 13: Equation and parametrization of the Weibull function.

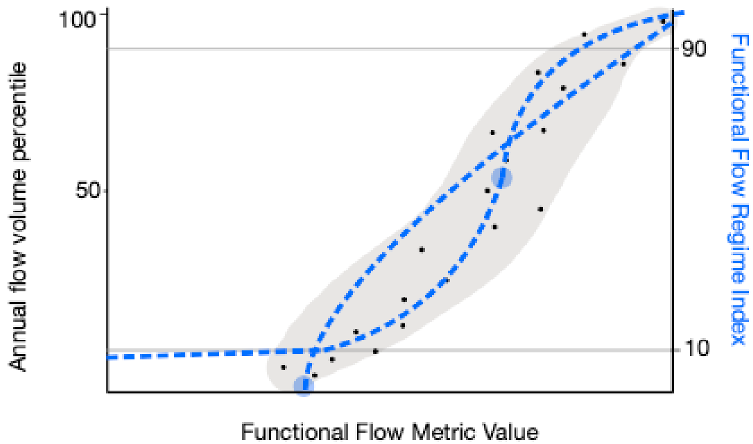


Figure 14: Conceptual example of how a Weibull function might be fit to functional flow metric data (plotted by water year percentile) to define an FFRI.

These methods for determining functional flow metric scaling by water year percentile also can be applied to metrics not correlated to water year percentile to scale the variability with the flow budget. This should be especially considered for flow metrics and flow functions that contribute relatively little to the total annual volume. For example, the fall pulse, usually caused by a modest storm near the end of the dry season, can be random with respect to total annual volume. The modeler may still favor larger fall pulses in wet years (with larger flow budgets) and smaller in dry years (with lower flow budgets). Good judgment is imperative when defining the variance pattern of such metrics where data fitting is impossible.

Step 4: Assemble functional flow schedules as inputs to FFAIM

The results from steps 1-3 provide inputs needed for FFAIM to assemble functional flow schedules and define a broader functional flow regime across a spectrum of years. The associated functional flow metrics can be combined to create a functional flow schedule or annual functional flow hydrograph for any operating year for a given annual unimpaired flow volume.

Each annual flow volume has a percentile x, generally with a corresponding FFRI x, with corresponding values for the FFRI metrics: m_1, m_2, m_3, such as flow rate, duration, and ramping rates, summarized in Equations 1 (g_n is the relationship defined in Step 3). These functions are presented mathematically in Appendix B, so each FFRI x has a corresponding set of metrics [m_1, m_2, m_3] and a resulting water volume for that function.

$$\begin{gathered} m_1 = g_1(FFRI_x) \\ m_2 = g_2(FFRI_x) \\ \dots \\ m_n = g_n(FFRI_x) \\ \hat{m}_{FFRI_x} = [m_1, m_2 \dots m_n] \end{gathered} \tag{1}$$

Scaled magnitude metrics ($\hat{m}_{FFRI_x}$) are combined with the remaining metrics needed to produce a daily flow schedule, *q(t)* for the corresponding $FFRI_x$, in Eqn. 2:

$$q(t) = f\left(\hat{m}_{FFRI_x}, t\right) \tag{2}$$

The daily flow function specifies the daily flow rate ($q(t)$) for the vector of magnitude metrics. Combining these daily flow rates over an operating year produces a functional flow schedule. Figure 15 shows an example of a functional flow regime (i.e., the spectrum of functional flow schedules for a range of annual flow volume percentiles) that can be produced with the flow metric specifications used for the Tuolumne River example. These flow schedules are input into FFAIM's decision support effort, described in the following section.

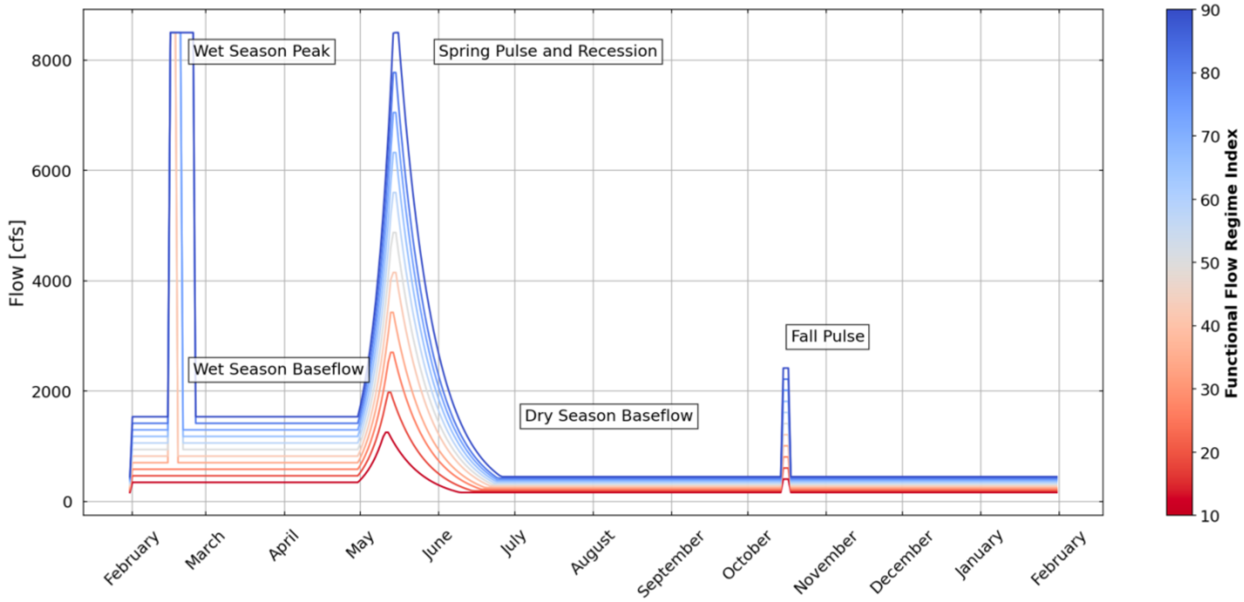


Figure 15: These hydrographs show a spectrum of designed functional flow schedules with drier flow schedules (red) and wetter flow schedules(blue). While similar to Figure 4, this flow regime does not show varied timing of flow components due to differing flow design choices.

2.3 Discussion

The Functional Flows approach provides a flexible, science-based framework for allocating limited water to the most functionally essential flow components. The steps outlined above present how to design a Functional Flow regime using water year percentile to vary flow features from year to year. This method offers a path to implementing budget-based functional flows where each flow schedule requires a unique flow budget. CEFF provides a process for establishing goals and functional flow criteria but stops short of dictating how functional flows should be designed and implemented, leaving flexibility to adjust to the river system of interest. The abovementioned steps are one way to design an environmental flow regime for a particular river. The resulting flow regime consists of flow schedules that restore variability to the five most critical functional environmental flow components within and across years. Because historical unimpaired flows are the primary data for flow magnitudes, monitoring and adaptive management are needed to restore desired flow-driven functions in existing channels without undue stress on the ecosystem at high and low flows. Specific management objectives may require additional flows at particular times.

The approach to designing a functional flow regime outlined above addresses a gap in regulatory flow approaches that provide flow schedules for a few discrete year types. Refocusing on annual flow percentile (a continuous representation of year types) eliminates coarse gaps in flow magnitudes and directly links flow metrics to their desired interannual frequency. This gives managers a reference to identify underrepresented flows, which may occur more often in a changing climate. Furthermore, the unitless FFRI value can help meaningfully compare flow schedules across rivers.

3. FFAIM: Integrating Uncertainty into Environmental Flow Operations

3.1 Purpose

The prior section described how to build functional flow schedules by water year percentile. To apply these flows operationally, managers often must begin to provide water downstream before the ultimate flow budget volume is known. Probabilistic optimization methods use estimates of likely unimpaired flows to suggest immediate-term decisions, while preparing for a range of future scenarios given seasonal flow uncertainties. Monthly unimpaired flow estimates are available for a range of exceedance probabilities for the Lower San Joaquin from several sources (including DWR's Bulletin 120 Forecast Breakdowns and the National Weather Service's CNRFC).

FFAIM balances the benefits of decisions needed today against the risk of not having enough water for the future using a stochastic two-stage optimization approach implemented in Python (using the Pyomo optimization package). There are several ways to frame such an objective, a focus of future study. In this example, the primary model objective is to maximize the average minimum FFRI of flows across two stages—the current decision period (first stage) and probability-weighted potential functional flow schedules for the remainder of the year (second stage)—so flow commitments made early in the season do not excessively reduce environmental flow functionality later in the year. Precisely, the optimization balances the highest achievable flow magnitudes in the first stage (using the FFRI) with the likely flow magnitudes and future FFRI for probabilistic unimpaired flow forecasts for the remainder of the year, such that the largest average annual functional flow schedule is achieved across the entire year given the likely range of environmental water budgets. The identified potential functional flow schedules use magnitude metrics with the same FFRI across flow components and include all metric inputs established in Step 3.

As the season progresses with monthly forecast annual flow data, the model subtracts prior allocations from the remaining flow budget, adjusts the possible future functional flow schedules to match the new forecast expectations, and updates functional flow schedule recommendations for the remainder of the operating year.

3.2 Methods: FFAIM formulation, variables, and constraints

FFAIM makes recommendations across two stages: the immediate operating period decision and optimized operations for each forecasted budget for the rest of the operating year based on probabilistic future unimpaired flow forecasts. Because the volume of water can be computed across any period of interest within a year by summing daily flows for any percentile hydrologic condition, the model can quickly compute volumes used in the first (present) and second (future) stages, which are re-defined each time the model is re-run with updated forecasts and probabilities. Stages are defined by their timing: t_0 is the beginning of the current decision period, t_1 is the end of this decision period, and t_f is the end of the operating year[1], the volume used by a two-part flow schedule is given in Eqn. 3:

$$V_k = \int_{t_0}^{t_1} f\left(\widehat{m}_{FFRI_{stage1}}, t\right) dt + \int_{t_{1+1}}^{t_f} f(\widehat{m}_{FFRI_{stage2,k}}, t) dt \tag{3}$$

[1] FFAIM's stage timings are flexible, allowing the user to adjust timings for any forecast availability delays and other operational requirements or opportunities (such as a storm). The only exception is the Spring Pulse, which must fall entirely into a single stage. FFAIM is constrained to ensure that the maximum duration of the spring pulse will fit into a single stage by modifying defined stage timing inputs.

or, more concisely:

$$V_k = V_{stage\ 1} + V_{stage\ 2,k} \tag{4}$$

A unique operating year water volume, V_k, exists for each forecast scenario, k. The volume of water in the first and second stages of the operating year sum to the predicted volume of water available for the remainder of the operating year. The volume in stage one, when an immediate operational decision is made, remains the same for all forecasts, resulting in a single decision volume for the immediate period, $V_{stage\ 1}$. However, a range of possible volumes exists for the remainder of the year, $V_{stage\ 2,k}$, for each discrete flow forecast provided.

The forecasted flow budgets for the entire operating year, $Flow\ budget_k$, for each forecast k, are model inputs specifying how much water is available for each event, V_k. Each annual flow budget k, is the sum of water allocated in earlier periods, plus water allocated in the two stages (summing to V_k), plus any carryover storage, minus any other contributions, as shown in Eqn. 5:

$$Annual\ flow\ budget_k = prior\ allocations + V_k + CS_k - other\ contributions \tag{5}$$

Every time the model is re-run to update the recommended flow schedule, the model considers how much of the water budget has already been used for instream flows ($prior\ allocations$). These prior decisions are combined with the total volume of the recommended flow schedule (V_k) and excess water that could be stored for future use (CS_k). V_k and CS_k are solved for by the optimization model and vary with different flow budget scenarios *k*. There may also be other sources of water for the flow schedule ($other\ contributions$), such as borrowed or purchased water. For the Tuolumne River, a portion of the February through June flow budget volume is added to the minimum required FERC baseflows in July – January. In very wet years, when the budget satisfied the largest modeled flow schedule (i.e., where magnitude metrics all have an

FFRI of 90), surplus water could be allocated to CS_k. This accounts for all environmental water available to the model.

Two terms, AF_k and RF_k, balance the immediate need for functional flows and the need to use some of the February-June flow budget in the remaining months of the operating year. Equation 6 defines the *remaining functional performance,* RF_k, for each forecast scenario k. The *remaining functional performance* is the FFRI for the metrics in stage two, for each forecast scenario *k*.

$$RF_k = FFRI_{stage2,k} \tag{6}$$

The *annual functional performance,* AF_k, describes the <u>minimum</u> FFRI cross both stages (immediate decision and future possible flows) for each forecast scenario k. The *annual functional performance* for scenario k is defined in Eqns. 7 and 8, which is satisfied by the minimum FFRI of the two stages:

$$AF_k \leq FFRI_{stage1} \tag{7}$$
$$AF_k \leq FFRI_{stage2} \tag{8}$$

These terms, AF_k and RF_k, are included in FFAIM's objective function and drive the model to maximize and balance allocations within and across both stages.

FFAIM optimization and objective function

FFAIM's main objective is to efficiently allocate water in immediate and later decisions given a range of likely flow budgets so that flow commitments made early in the operating season do not unreasonably reduce the ability to support functional flows in later months. This objective is expressed mathematically in Eqn. 9:

$$Maximize\ Average\ Value\ of\ Annual\ FFRI = Max \sum_k p_k [w_k AF_k + rRF_k] \tag{9}$$

with decision variables:

AF_k is the minimum FFRI across the current *decision* and *remaining* future periods with forecast scenario k

RF_k is the FFRI of the *remaining* periods achievable with forecast scenario k

and constants:

p_k is the probability of forecast scenario k

w_k is a cautionary weighting of extreme forecast scenarios k (average to 1)

r is a small constant (<1) to balance the relative importance of AF_k and RF_k.

FFAIM's objective function operates on two weighted decision variables: AF_k and RF_k. The main objective is to maximize the worst-performing flow component FFRI averaged across two periods for each flow forecast budget. The *annual functional performance,* AF, maximizes the minimum FFRI achievable across two stages (Eqns. 7 and 8). For drier forecast scenarios, the remaining stage FFRI limits AF_k. For wetter forecast scenarios, the current decision stage FFRI limits AF_k. This objective tends to raise the FFRI for the current decision period and the rest of the operating year to a maximum achievable annual FFRI.

The objective is maximized so the annual functional performance will have a more natural distribution across years despite having environmental flow budgets that are substantially less than unimpaired flows. Larger percent-flow budgets may require that this objective be changed.

Where the current decision period limits AF_k, the second objective is to manage the rest of the flow budget and to maximize the remaining season FFRI (Eqn. 6). For wetter years, this ensures that the additional water is put to good ecological use for the remainder of the year.

The optimization balances achievable FFRI in the immediate decision period among the possible FFRI projected by forecasts so high instream flows early in the operating season are less likely to harm performance later in the operating season if conditions become dry. Parameters *w* and *r* allow for expression of risk and operating preferences.

Parameters and operational model tuning

Four parameters can be set and adjusted by modelers: p_k, w_k, and r_j. The probability weights, p_k, weigh the range of possible budgets according to their likelihood. Modelers should keep these probabilities consistent with forecasted exceedance probabilities. The risk tolerance weights, w_k, are cautionary to emphasize any additional concern with performance under extreme events beyond their probability weights (low or high flow). w_k = 1 if probability weight is sufficient, w_k> 1 could add additional weight for drier years, w_k < 1 would reduce weighting for less concerning year-types. In this model, w_k = 1 for every k. The weight r_j is to be <1 to give more weight to annual FFRI but still some weight to the remainder of the operating year in case the year becomes wetter.

Using FFAIM for adaptive implementation

As the year progresses, new (and more accurate) unimpaired flow forecasts become available. With each updated seasonal flow forecast (e.g., monthly), FFAIM is re-run for the remainder of the operating year, subtracting water from the budget already allocated and suggesting a flow decision for the next period. Over the course of the operating year, the flow budget is allocated month-by-month until the budget is finalized and flow decisions are made for the remainder of the operating year. These periodic decisions combine to form the final adaptive flow schedule (Figure 16).

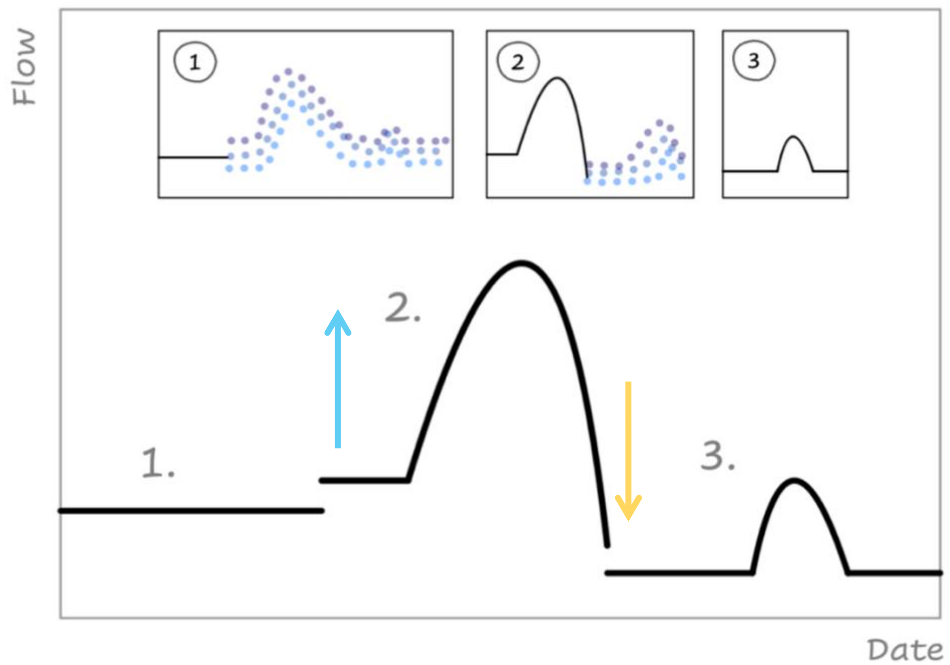


Figure 16: Conceptual figure of the accumulation of flow decisions made from sequential runs with updated forecasts. Model run 1 makes an immediate term flow recommendation and outlines a range of likely future recommendations (blue dotted region). Run 2, with updated flow forecasts, recognizes higher flow forecasts, and recommends a higher flow. Run 3, the final flow budget is known and the model recommends for the remainder of the operating year, now expecting a drier year. The year's adaptive flow schedule, in retrospect, is the combination of FFAIM's flow recommendations. The stepwise behavior results from updated forecasts and past recommendations.

Incorporating water borrowing (and associated costs) for the driest scenarios

The upper and lower ends of the flow forecast (the 0.10 and 0.99 exceedance probabilities) can result in extreme flow schedule prospects in the second stage. Suppose the model finds an FFRI below ten for the second stage given a 99th percentile predicted flow budget due to extremely dry conditions. In that case, the model suggests a stage one flow magnitude of the 10th percentile to avoid extreme adverse ecological impacts, hoping that future forecasts or other sources will provide enough water for this requirement. Alternatively, This water "borrowing" might be sufficiently discouraged by implementing a penalty or additional weight in the objective function weighting that discourages the model from recommending stage one flows that deplete water that might be saved for the second stage for extreme scenarios.

Conversely, if more water is available than required for the 90th percentile flow volume, the model allocates the additional flow to the future as 'carryover storage.' Although simply applied here, rules for carryover storage could be adjusted in practice to allow for small carryover volumes in wetter years (e.g., 60th to 90th water year percentile) that would help to hedge against dry early season conditions in later years (Wu 2023).

3.3 Differing responses to volume in imbalanced stages

The objective function described above efficiently allocates water to the stage where additional water brings the biggest functional flow improvement (i.e., the most significant response in FFRI). In practice, this desire to maximize AF_k may come at the expense of hedging (i.e., restraining allocation of the flow budget in preparation for drier possible scenarios) in favor of wetter stage 1 recommendations early in the operating season. In each model run, an objective function that gives wetter flow schedules greater "value" will allocate the flow budget to the stage where it can achieve the wettest water year percentiles with the least volume allocation.

To highlight this behavior, a modeling experiment explored how stage-related volume sensitivity influences FFAIM's recommendations. A simplified flow regime consisting only of a wet season baseflow was set to vary linearly between 344 cfs (corresponding to an FFRI of 10) and 1534 cfs (corresponding to an FFRI of 90). We then consider two-stage duration delineations, using the stage duration as a proxy for the stage-related volume sensitivity (where it takes more budget volume to increase FFRI in a longer-lasting stage). The first case is a balanced two-month model, consisting of a one-month February decision stage (stage 1) and a one-month future stage (stage 2). The second is an imbalanced five-month model, consisting of a one-month February decision (stage 1) followed by a four-month future stage. These different stage durations affect the maximization of the primary objective function (maximizing the weighted average of AF).

Parameter values were set as described below. p_k, which sets the probability weighting of the different exceedance forecasts, is defined as follows:

Table 1: Probability weight (p_k) values corresponding to Bulletin 120 forecast exceedance probabilities.

Forecast Exceedance Probability

	99th percentile	90th percentile	75th percentile	50th percentile	25th percentile	10th percentile	$\sum_k p_k$
p_k	0.10	0.15	0.25	0.25	0.15	0.10	1.0

Some extra weight (0.01) is apportioned to the 0.99 exceedance probability, $p_{0.99}$, because this forecast is assumed to cover the region between 1 and 0.90 exceedance probabilities. This weighting tends to overweight the dry end of expected values, such that the probability-weighted average is slightly below the median 0.50 exceedance forecast. The sum of probability weights for the six exceedance forecasts is one.

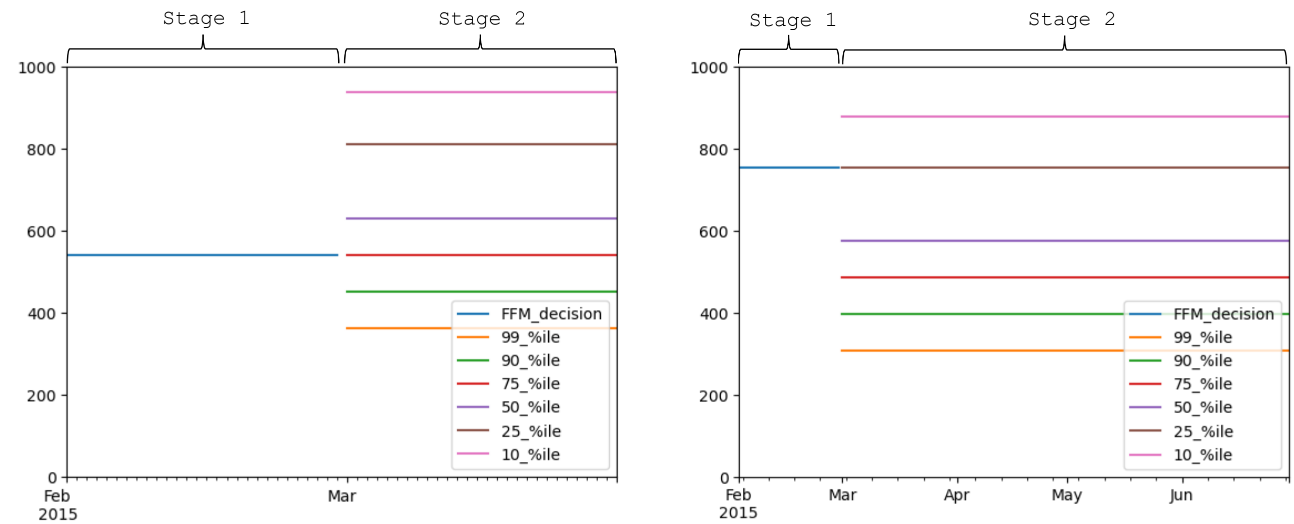
On the other hand, the supplemental cautionary weight for different forecasts, w_k, is set as follows.

Table 2: Cautionary weight (w_k) values are held constant across exceedance probabilities.

	Forecast Exceedance Probability						
	99th percentile	90th percentile	75th percentile	50th percentile	25th percentile	10th percentile	$avg(w_k)$
w_k	1.0	1.0	1.0	1.0	1.0	1.0	1.0

The w_k values equal one across all six exceedance forecasts. No cautionary weighting or water borrowing was used to keep flow schedules above an FFRI of 10 for this exploratory exercise.

Using these values, these model runs explore the effects on modeled recommendations. Figure 17a shows the two-month treatment, where the model recommended stage 1 flows from the 0.75 exceedance budget. In this example, the duration ratio is 1:1 and the value of additional volume (to attain higher FFRI) is the same. Figure 17b shows the results of the 5-month model, where the stage duration ratio is 1:4. In this example, the model recommended stage 1 flows from the 0.25 exceedance probability budget. In this case, the model dismisses presumptions about the expected budget, preferring the relative certainty of substantially higher flows in stage 1 versus saving the same volume to achieve minimally higher flows in the second stage.



(a) *(b)*

Figure 17: Model results from two wet season baseflow model experiments that differ in stage 2 duration. When stage 1 and stage 2 have the same duration (a), the model recommends immediate flows for the 0.75 exceedance probability budget. When stage 2 is much longer (b), the model recommends immediate flows from the 0.25 exceedance probability.

In practice, the model efficiently maximizes the minimum FFRI across the two stages. In the 5-month example, the annual minimum FFRI (the minimum between two stages) can be so much higher in stage 1 (per additional unit of volume) that gains from increasing the stage 1 FFRI outweigh the losses from letting stage 2 dictate the minimum annual FFRI for higher UF budget possibilities (recall that AF_k is the minimum of stage 1 and stage 2 for each k from Eqns. 7 and 8). Table 3 shows the 2-month model's corner point solutions ("possible outcomes"), given the range of forecasted budgets. Table 4 shows all possible outcomes for stage-wise volume allocation in the 5-month model, given the forecasted budgets. The 2-month model, where both stages are equally balanced, recommends either a 50th or 75th percentile (k) flow decision (both produce the same objective value, $\sum_k p_k AF_k = 20.9$). This makes sense given the p_k-weighting scheme sets up either forecast scenario to equal the average. In contrast, the 5-month model optimizes to the 0.25 exceedance probability to achieve a higher weighted annual minimum FFRI ($\sum_k p_k AF_k = 23.9$). The difference between the two optimization experiments is that the imbalanced 5-month optimization can increase stage 1 FFRI with less depreciation of stage 2 FFRIs relative to the perfectly balanced 2-month model.

Table 3: The decision space for the 2-month experimental model. The model tends toward six corner solutions that satisfy the budget volume constraints (light yellow) and chooses one solution that maximizes objective function (orange). Yellow highlights illustrate how FFAIM makes decisions given exceedance probabilities. The 2-month experimental volume maximizes the probability-weighted average AF by recommending either the 0.50 or the 0.75 exceedance stage 1 FFRI. An infeasible outcome, in which the model decision corresponds to the 0.10 exceedance forecast produced and FFRI <0 for the 0.99 exceedance budget.

		Infeasible Outcome		Possible Outcome 1		Possible Outcome 2		Possible Outcome 3		Possible Outcome 4		Possible Outcome 5	
Exceedance probability	p_k	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI
0.1	0.1				41		46		50		53		60
0.25	0.15				32		38		41		44		47
0.5	0.25	unfeasible		32	20	26	26		29	20	32	17	35
0.75	0.25				14		20	23	23		26		29
0.9	0.15				8		14		17		20		23
0.99	0.1		<0		2		8		11		14		17
	Primary Objective Value: $\sum_k p_k AF_k$	**NA**		**17.9**		**20.9**		**20.9**		**19.4**		**17**	

Table 4: The decision space for the 5-month experimental model. The model tends toward six corner solutions that satisfy the budget volume constraints (light yellow) and chooses one solution that maximizes objective function (orange). Yellow highlights illustrate how FFAIM makes decisions given exceedance probabilities. The 5-month experimental volume maximizes the probability-weighted average AF by recommending the 0.25 exceedance stage 1 FFRI.

		Possible Outcome 1		Possible Outcome 2		Possible Outcome 3		Possible Outcome 4		Possible Outcome 5		Possible Outcome 6	
Exceedance probability	p_k	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI
0.1	0.1	44	44	38	46	28	48	23	50	18	51	13	52
0.25	0.15		36		38		40		41		42		43
0.5	0.25		24		26		28		29		30		31
0.75	0.25		18		20		22		23		24		25
0.9	0.15		12		14		16		17		18		19
0.99	0.1		6		8		9		11		12		13
	Primary Objective Value: $\sum_k p_k AF_k$	**22.7**		**23.9**		**22.8**		**20.9**		**17.4**		**13**	

Ideally, FFAIM would recommend decisions that match the most likely predicted budget—using the given p_k weighting scheme, this would fall between 0.75 and 0.50 exceedance forecasts. The balanced 2-month model makes a reasonable, moderately conservative choice given the limited information about the flow budget. The 5-month model is more reckless, recommending a decision corresponding to the drier 0.25 budget—increasing the likelihood of having less water to release in the second stage. The pattern observed in this experiment proliferates in operational models, where FFAIM tends to recommend less prudent high stage 1 flows in early runs, forcing the model to compensate and release lower than ideal flows later in the season.

3.4 Using w_k weights to manage stage-related volume sensitivity

An imbalance between the two model stages creates a tendency to recommend wetter year flows early in the operating year. One way to promote saving in early runs is to modify the w_k values in the objective function, adding weight to drier forecast scenarios that counterbalances the sensitivity of FFRI to changes in volume. If it takes more water to effect change in stage 1 than in stage 2, greater weight would be put onto drier forecast scenarios. To illustrate this, we revisit the 5-month experimental model with two w_k weighting schemes:

Table 5: Moderate and heavy w_k weighting schemes. Grey highlights indicate large weights (>1.0) for dry forecast events (k).

	w_k by Forecast Exceedance Probability						
	99th percentile $w_{0.99}$	90th percentile $w_{0.90}$	75th percentile $w_{0.75}$	50th percentile $w_{0.50}$	25th percentile $w_{0.25}$	10th percentile $w_{0.10}$	$avg(w_k)$
Moderate weighting of dry scenarios	1.90	1.50	1.0	1.0	0.50	0.10	1.0

Heavy weighting of dry scenarios	1.90	1.75	1.50	0.50	0.25	0.10	1.0

Table 6 shows the optimized stage 1 and 2 FFRI results given the different w_k weights. With no weights, the model optimizes to the 0.25 exceedance probability, recommending a stage 1 FFRI of 38. The medium weighting model makes a more conservative decision, an FFRI of 28, corresponding to the 0.50 exceedance probability forecast. The heavy-weighting alternative results in an FFRI of 23, corresponding to the drier 0.75 exceedance probability event k. This heavy-weighting alternative distributes flows across two stages identically to the 2-month model (with a budget scaled up to account for the extended duration). Figure 18 and Figure 19 show the 5-month experimental results with medium and heavy weighting of dry scenarios.

Table 6: FFAIM recommendations for four experiments: the balanced stage 2-month model, the 5-month model without w_k weighting, the 5-month model with moderate w_k weighting, and the 5-month model with heavy w_k weighting. With increasing weight on drier forecast scenarios, 5-month model stage 1 recommendations become drier until recommended flow schedule FFRIs match the 2-month model.

	2-mo. model, $w_k = 1, \quad \forall k$		5-mo. model, $w_k = 1, \quad \forall k$		5-mo. model, *moderate* weighting of dry scenarios		5-mo. model, heavy weighting of dry scenarios	
Exceedance probability	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI	Stage 1 FFRI	Stage 2 FFRI
0.10	23	50	38	46	28	48	23	50
0.25		41		38		40		41
0.50		29		26		28		29
0.75		23		20		22		23
0.90		17		14		16		17
0.99		11		8		9		11

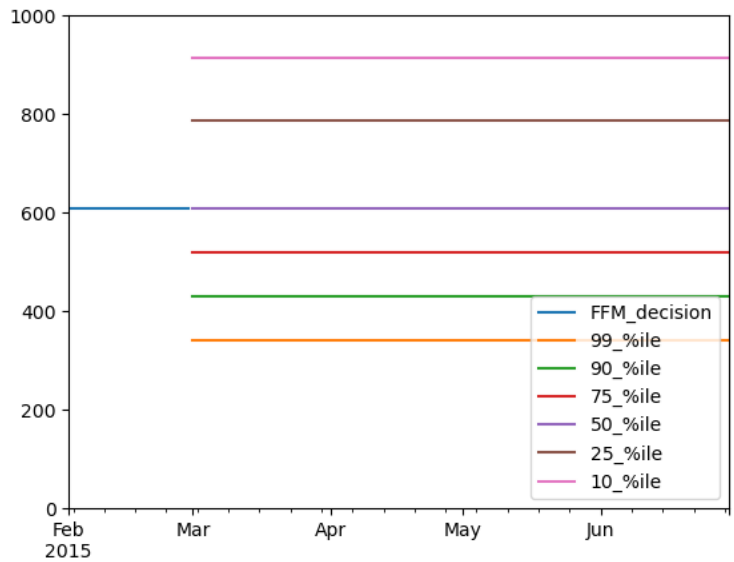


Figure 18: Hydrograph of the 5-month model flow recommendations using medium w_k weighting of dry scenarios

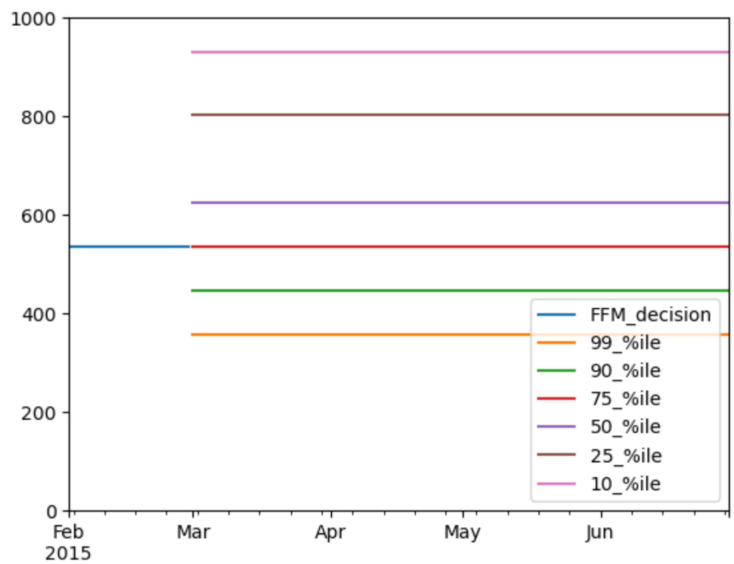


Figure 19: Hydrograph of the 5-month model flow recommendations using heavy w_k weighting of dry scenarios

There may be other ways to account for the imbalance in volume sensitivity across two stages that promote hedging. One possibility is to calibrate w_k using historical simulations to promote the dispersal of FFRIs across runs to match historical water year percentiles. This method requires that historical forecasts are available and would require re-calibration for each determination of stage date ranges and changes to manually-input metrics. Furthermore, because the optimization tends toward discrete corner points, several sets of w_k weights can produce similar results. A more convenient option might be to formulate weights at runtime, determined mathematically as a function of $\frac{\Delta\, FFRI}{\Delta Volume}$ of each stage. Other objective functions that reflect the expected value of the final flow budget could be considered. These and other alternatives can be a focus of future research.

4. FFAIM on the Tuolumne River, a Case Study

4.1 Introduction

The Lower Tuolumne River watershed is a mixed rain-snowmelt-driven system typical of Mediterranean-montane rivers in California. Altering the natural hydrology, the Tuolumne River has a large lower-elevation reservoir that captures winter runoff and spring snowmelt for later release to lowland areas in the dry season (Figure 35). Extensive agriculture and cities in the lowlands depend on reservoir releases for their water supply delivered through a network of canals. The river through the lowlands also supports a diverse native aquatic community adapted to the strongly seasonal climate and streamflow conditions. The Federal Energy Regulatory Commission (FERC) requires minimum environmental flow releases to maintain the stream perennially for these aquatic communities. These minimum flows are sometimes supplemented with modest seasonal flow pulses that vary by water year type (wet, moderate, or dry) to support anadromous fish migration.

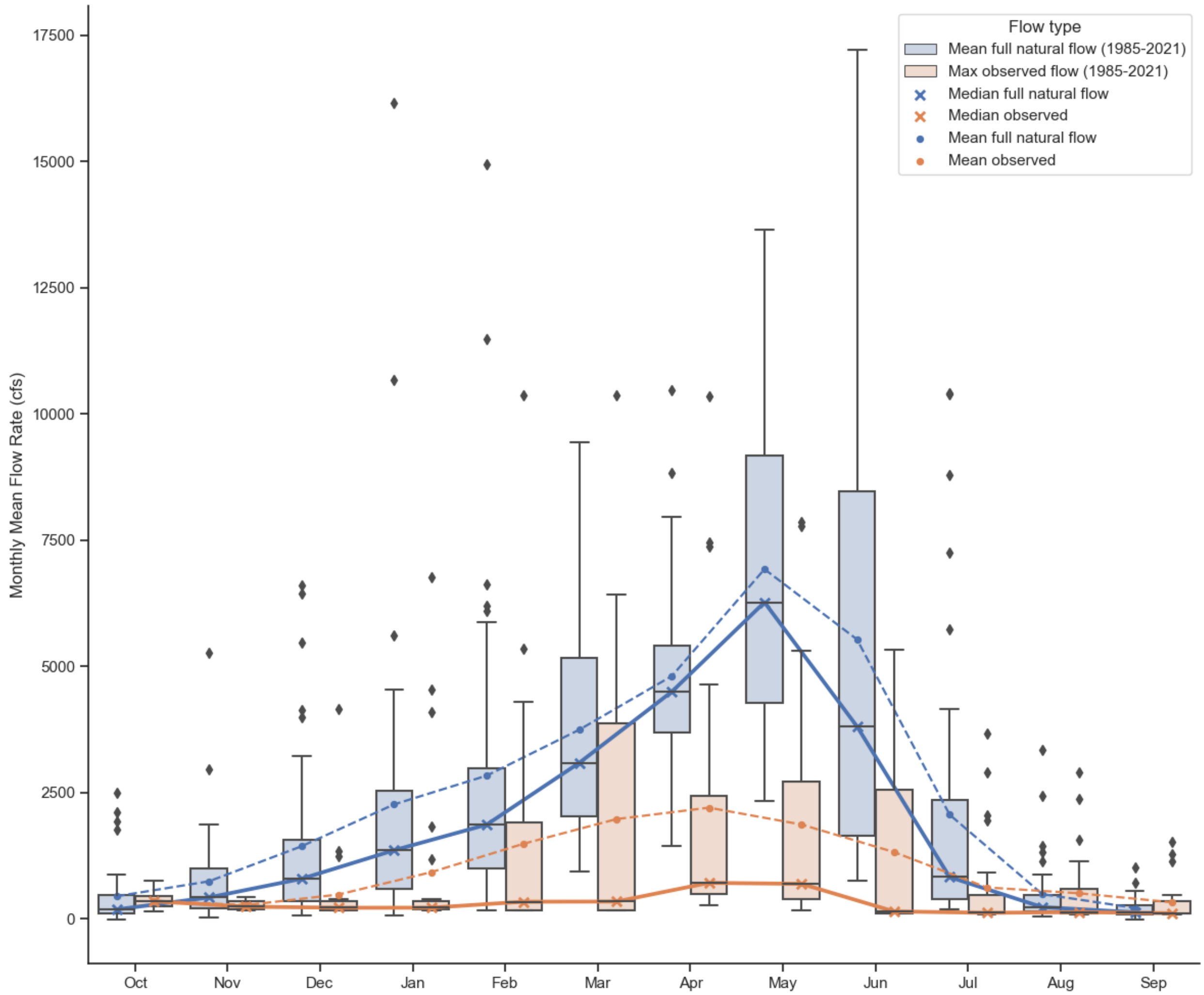


Figure 20: Monthly mean full natural flow rate (blue) and monthly mean observed flow (orange) on Tuolumne River at La Grange ('TLG'). Box plots indicate the historical variability for each month.

The 2018 Bay-Delta Plan is a significant expansion and reorientation of existing minimum baseflows, committing to keep 40% of February-June unimpaired flow (UF) in the channel. By default, this flow prescription would bypass through New Don Pedro on a 7-day rolling average. FFAIM proposes an adaptive alternative that prioritizes functional flow components and reshapes the 40% UF budget throughout the year.

The FFAIM methods presented here are explored for the Lower Tuolumne River, CA. First, a functional flow regime—the set of idealized annual environmental flow schedules for each water year percentile—is developed using the approach outlined in Chapter 2. The functional flow regime developed for the Tuolumne River continuously scales four flow component magnitudes, leaving some metrics (e.g., timing, rate of change) constant for operational simplicity and flexibility. This flow regime is then tested by exploring how interannual variability is determined by the available flow budget and by exploring the sensitivity of these results to small changes in functional flow metrics and components.

Next, the optimization formulation described in Chapter 3 is applied to seasonal operation of environmental flows using a fixed 40% percent of each year's February – June runoff. The FFAIM model updates decision recommendations monthly, using probabilistic seasonal flow forecasts from DWR Bulletin 120. Each month, an allocation is made for the current month using newly available forecast information, leaving the remaining environmental water budget for the rest of the operating year. Operations for the remainder of the operating year are adjusted adaptively using later runoff forecast updates.

4.2 Designing an FFRI-indexed functional flow regime for the Tuolumne River

The Tuolumne River Functional flow regime created for this case study was constructed using the process outlined in *Figure 5*. The following subsections illustrate how the general process for refining a functional flow regime outlined in Chapter 2 could be applied to a specific reach. The flow regime was designed to fit within a February-January operating year (OY). The resulting flow regime illustrates the approach's flexibility without over-complication. Once the flow regime and its appropriate metrics have been identified, we show how the regime relates to the environmental flow budget and explore how to (1) choose a %UF budget or (2) evaluate the effectiveness of an existing flow budget (i.e., 40% UF February-June, as identified in the Bay-Delta Plan) to meet interannual functional flow criteria.

Step 1: Quantify Functional Flow Metrics. Functional flow metrics were computed for the Tuolumne River using historical (1987-2022) calculated daily full natural flow (FNF) data from CDEC (gage ID: TLG-8, estimated by the California Department of Water Resources). The calculated daily FNF time series reasonably estimates unimpaired flow, but the calculation methods occasionally result in unrealistic values, particularly during the summer (Pulido et al. 2022). Missing, zero, and negative daily FNF values were replaced with more reasonable values, estimated by Kalman Filter Imputation (using the imputeTS package in R: http://steffenmoritz.github.io/imputeTS/). The time series was then input to the Functional Flows Calculator API client package (R-based script publicly available via eflows.ucdavis.edu) to obtain functional flow metrics for each year and a distribution of values for each metric (expressed as percentiles) across the available period of record expressed as percentiles. Output from running calculated daily FNF data through the Functional Flows Calculator API appears in Appendix C.

Step 2: Adjust metrics for physical, regulatory, biological, and water quality limitations. The Tuolumne River has changed from its historical condition in numerous ways. Substantial channel incision, riparian development, blocked access to upstream coldwater habitats, shifted timing of coldwater flows, and disconnected floodplains provide poor habitat conditions for native species. These physical changes limit the effectiveness of the natural range of flow magnitudes to provide hydraulic conditions and quality suitable for salmonids, geomorphic diversity, or riparian succession.

Furthermore, some regulations limit the maximum of high flows (wet season peaks and spring pulse magnitudes). The U.S. Army Corps of Engineers limits high flow releases from New Don Pedro Project to 9,000 cfs below Dry Creek (Ch. 6, Bay Delta Plan). We thus chose to apply a 500 cfs cushion and limit high flow magnitudes to 8,500 cfs. Figure 21 compares historical unimpaired flow frequency with regulated historical reservoir outflows. These flows would provide useful geomorphic functions (e.g., deep scour and floodplain resetting) but are often incompatible with human activities. So, we scaled down spring peak magnitudes, as shown in Figure 22.

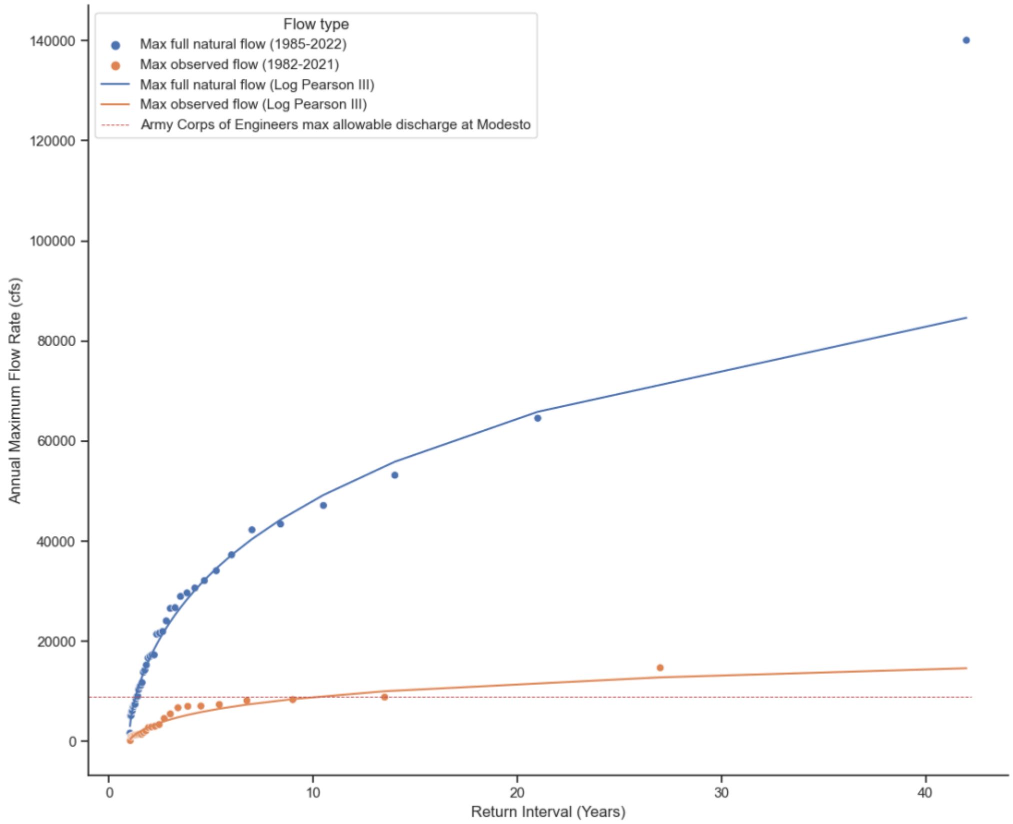


Figure 21: Annual maximum flow return intervals for full natural flow and observed Tuolumne River flow near La Grange.

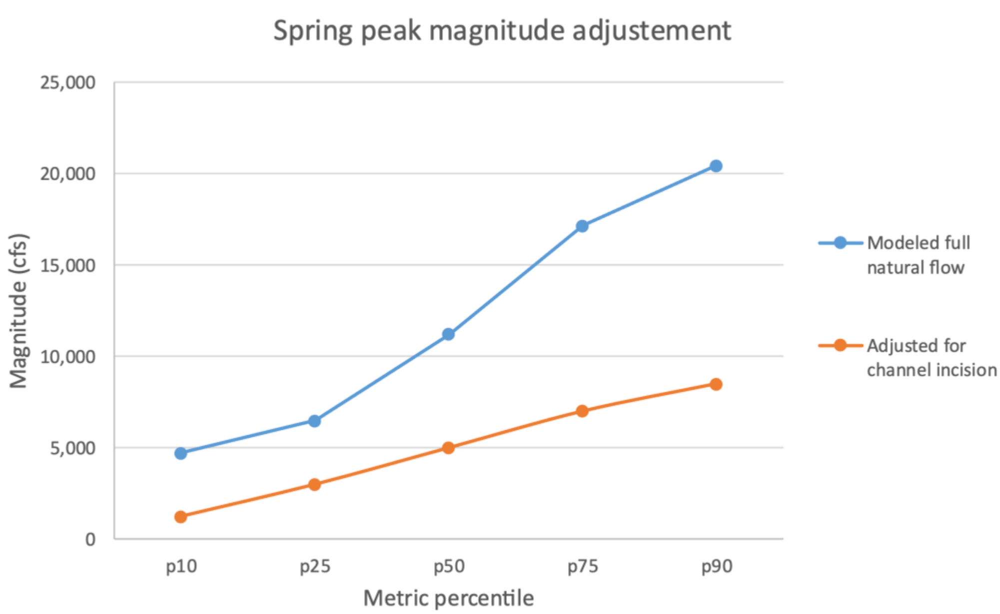


Figure 22: Adjusted range of the maximum magnitude of spring peak and recession to account for channel capacity limits. Percentiles of the metric value over the period of record are on the X-axis. Blue line is spring peak magnitude values calculated from daily full natural flow. Red line is adjusted for today's incised channel.

Step 3: Create Water Year Percentile-Functional Flow Metric curves to form a Functional Flow Regime Index (FFRI). In the Tuolumne example, we scale four *magnitude* functional flow metrics (wet season baseflow, spring recession, dry season baseflow, and fall pulse magnitudes) using only *linear FFRI relationships*. The wet season peak magnitude is not considered for continuous scaling because the natural ranges of 2-, 5-, and 10-year flood events were outside the channel capacity limit. We focus on representing flows between the 10th and 90th water year percentiles to not reproduce years likely to stress the native ecosystems, particularly in a system already pressured by drought and depleted instream flows. High flow years (>90th water percentile) have a high likelihood that operations will be driven by flood control and not require scarcity-driven functional flow shaping.

Three functional flow magnitude metrics (wet season baseflow, spring pulse, and dry season baseflow) (Figure 23, Figure 24, and Figure 25) had clear correlations to the water year percentile because each contributes significantly to annual flow volume. Fall pulse magnitude data lack a clear correlation with water year percentile; however, we also used an FFRI-style relationship to continuously scale fall pulse magnitudes within the 10 to 90 range (Figure 26). This allows FFAIM to recommend larger fall pulses in years with a larger environmental flow budget.

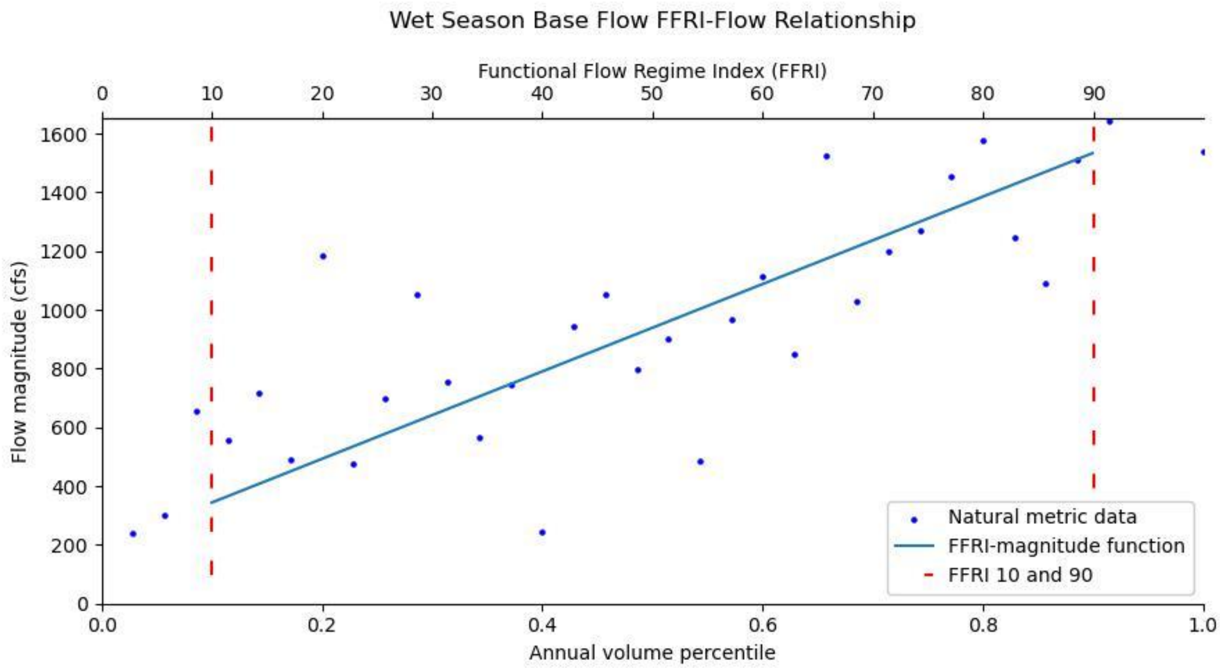


Figure 23: Functional Flow Regime Index (FFRI) values for wet season baseflow magnitude metric, as a water year percentile over the period of record, limited to 10th-90th percentiles.

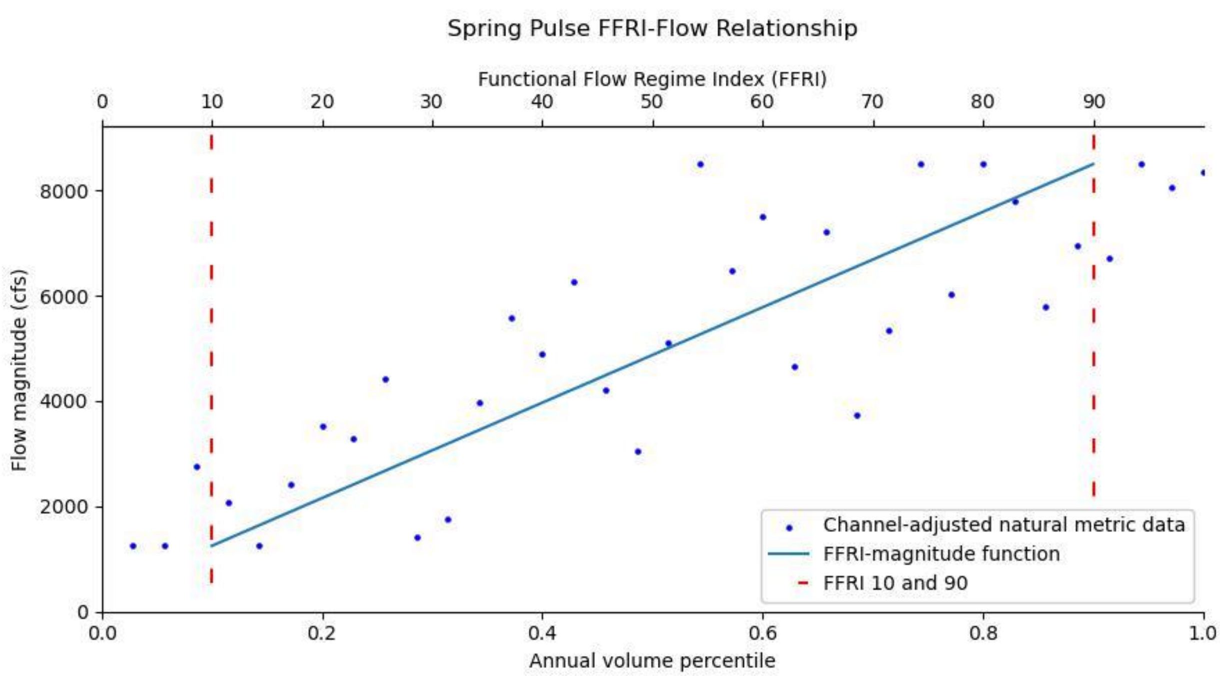


Figure 24: Functional Flow Regime Index (FFRI) values for spring pulse flow magnitude, as a water year percentile over the period of , to 10th-90th percentiles. Spring magnitudes shown are adjusted down to fit channel capacity limits in Figure 22.

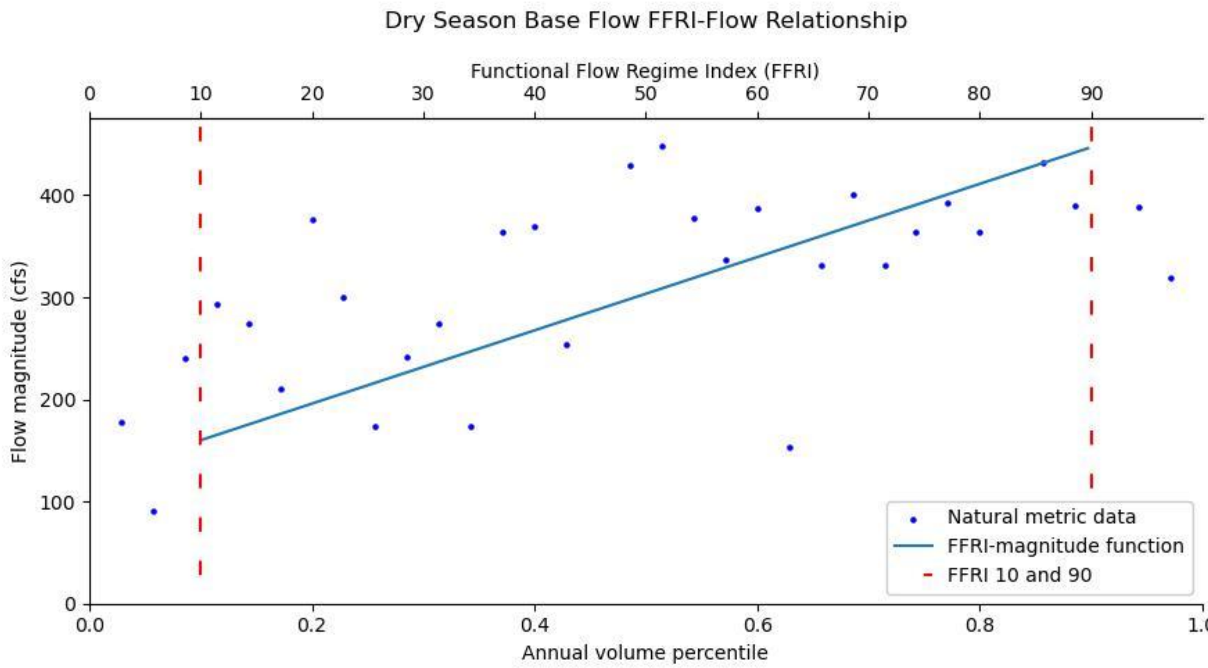


Figure 25: Functional Flow Regime Index (FFRI) values for dry season baseflow magnitude, as a water year percentile over the period of record, limited to 10th-90th percentiles.

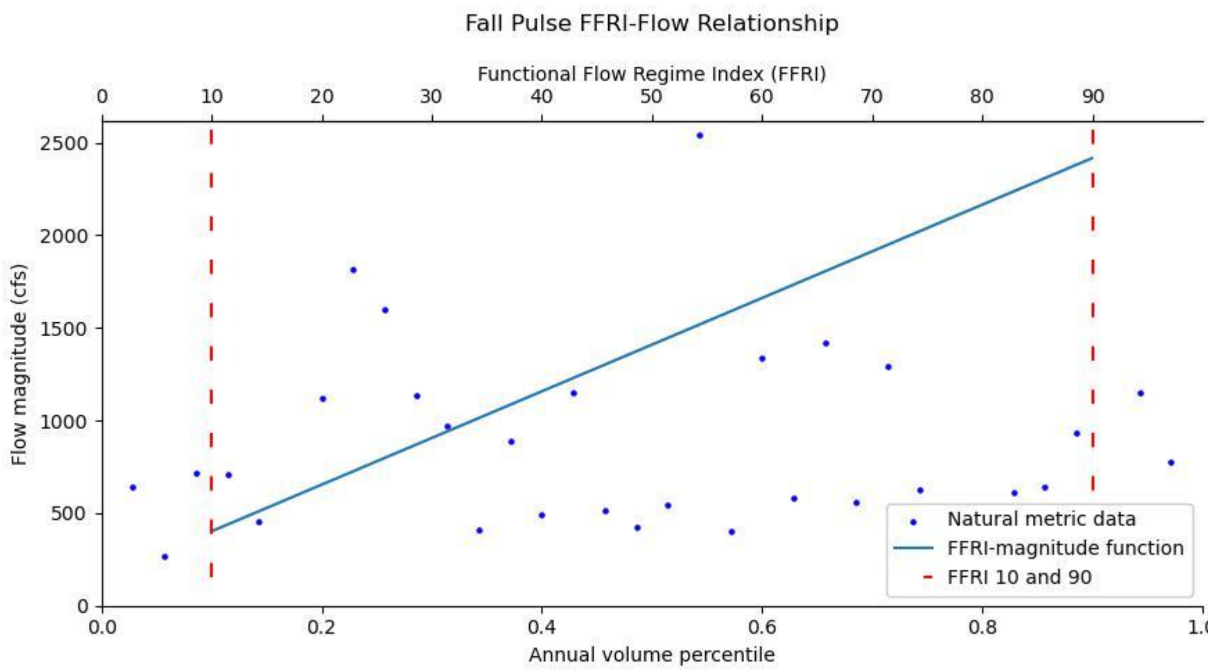


Figure 26: Functional Flow Regime Index (FFRI) values for fall pulse magnitude, as a water year percentile over the period of record, limited to 10th-90th percentiles. The relationship a poor fit, but shows how fall pulse magnitudes are scaled in FFAIM so the central range is included across FFAIM's flow schedules.

The wet season peak also varies from year to year but is not determined by an FFRI. The wet season peak magnitude was set to the maximum allowable flow in the channel for public safety (Bay-Delta Plan, Ch. 6). The wet season peak duration varies between 0, 3, 5, and 10 days based on budget volume (or expected budget volume in the decision stage) according to the distribution of cumulative February-June volumes in the historical record (Figure 27). The total duration of the wet season peak can be divided into multiple peak events in post-processing if desired. Operational limitations likely will determine peak flow ramping rates and can be added in post-processing (outside the scope of this example).

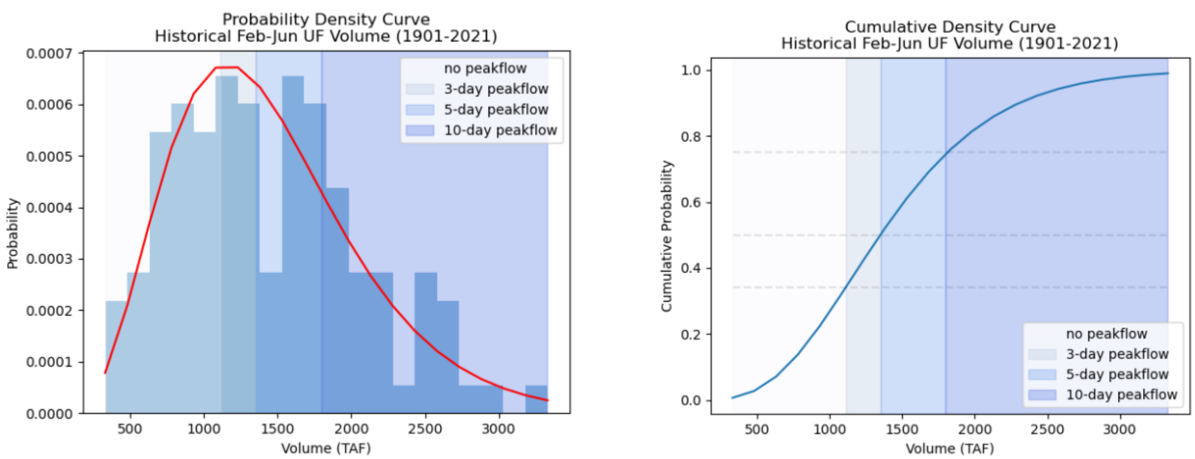


Figure 27: Peak flow durations vary with historical distribution of wet season flow volumes. Highlighted regions represent 34-50th percentile water years, 50th-66th percentile water years, and 66th-100th percentile water years. Durations are decided based on expected value of February-June flow (from forecasts)

The remaining metrics are either manually input into the model at runtime (such as timing metrics for each flow component and rate of change metrics) or result from combinations of other flow components (e.g., duration metrics can be computed from timing metrics). These remaining metrics were held constant at reasonable values for the natural system and operational constraints. Further explanation for the Tuolumne River application is in the FFAIM Technical Report (Yarnell et al. 2024).

Step 4: Assemble functional flow schedules as inputs to FFAIM. For the Tuolumne River case study, four magnitude metrics were used in the FFRI functions described in Eqn. 1, and 12 functional flow metrics were set manually or calculated (Table 7).

Table 7: Summary of how function flow metric values are determined in the Tuolumne FFAIM model case study.

Flow component	Metric	Relation-type	Description
Wet season baseflow	Magnitude	Scaled with annual flow volume (FFRI)	Varies within adjusted range, following patterns identified in the natural flow regime
	Timing	Manual input	February 1, start of OY
	Duration	Calculated from timing metrics	Until start of Spring Recession
Wet season peak	Magnitude	Manual input	8,500 cfs, the maximum channel flow
	Timing	Manual input	February 17, easily shifted
	Duration	Ruleset	0, 3, 5, or 10 days
	Frequency	Ruleset	0 or 1 event
Spring peak/recession	Magnitude (at peak and start of recession)	Scaled with annual flow volume (FFRI)	Varies within adjusted range, following patterns identified in the natural flow regime
	Timing (at start of recession)	Manual input	May 4
	Duration	Calculated from timing and rate of change metrics	Until start of Dry Season
	Rate of Change	Manual input	13% per day up-ramp 7% per day down-ramp
Dry season baseflow	Magnitude	Scaled with annual flow volume (FFRI)	Varies within adjusted range, following patterns identified in the natural flow regime
	Timing	Calculated from timing and rate of change metrics	When spring recession equals baseflow magnitude
	Duration	Calculated from timing metrics	Until start of Wet Season baseflow
Fall pulse	Rate of Change	Manual input	Held constant
	Magnitude	Scaled with annual flow volume (FFRI)	Varies within adjusted range
	Timing	Manual input	October 15th, consistent with FERC-mandated fall pulses

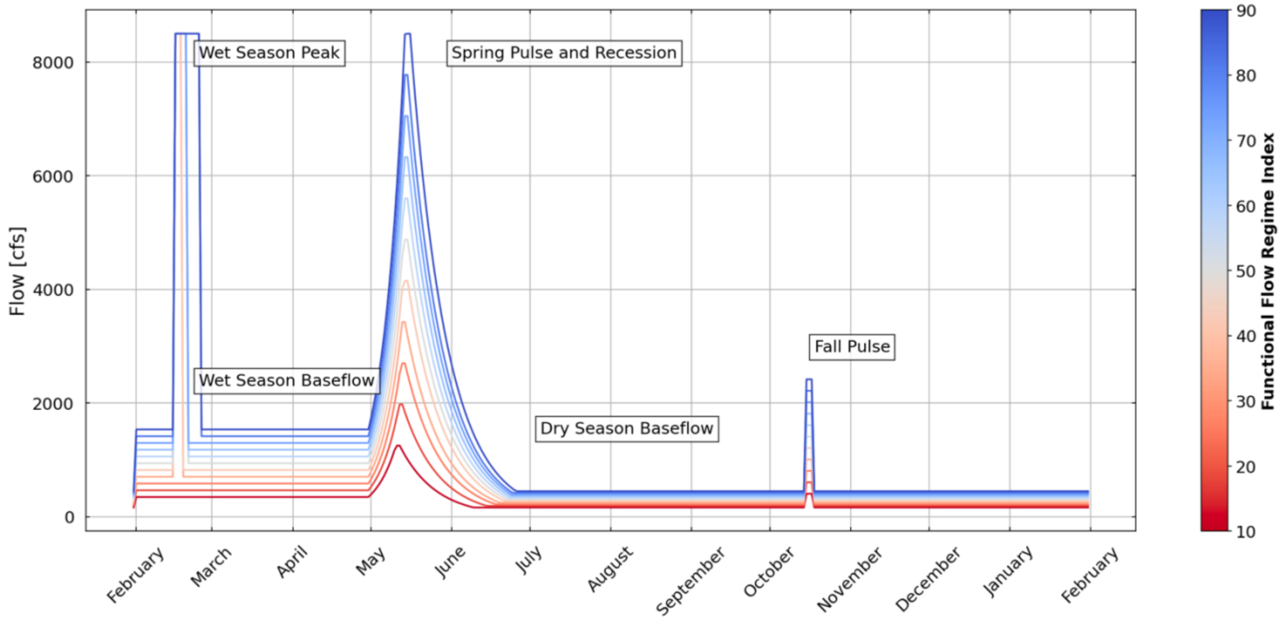


Figure 28: The functional flow regime considered by FFAIM for the Tuolumne River. 11 hydrographs represent functional flow schedules for 10th to 90th water year percentiles.

4.3 Tuolumne River Functional Flow Regime: Results and Discussion

Before implementing the functional flow regime operationally, clear connections are needed with the flow budget. A functional flow regime should reflect natural seasonal and interannual variability by accurately representing the historical variation of water year percentiles across years. Although some metrics prescribed by FFAIM might not align with the natural metrics in a single year, prioritizing consistency in interannual variability seems more critical ecologically than strict alignment in a specific year.

The few decades of available hydrologic data constrain our assessment of interannual flow variability in the Tuolumne River. Generally, shorter periods of data provide a less comprehensive picture of historical variability and especially diminish the ability to represent extreme events. Paradoxically, climate change in California is tending to exacerbate hydrologic extremes, decreasing the frequency of "normal" water years. Figure 29 highlights the temporal availability of different data sources for the Tuolumne River. Recent years tend to over-represent dry years compared to the longest records of unimpaired flow volume (1901-present). The FFRI values are developed from annual volume percentiles from 1987-2021. Results would differ if daily unimpaired flow estimates were available over another period.

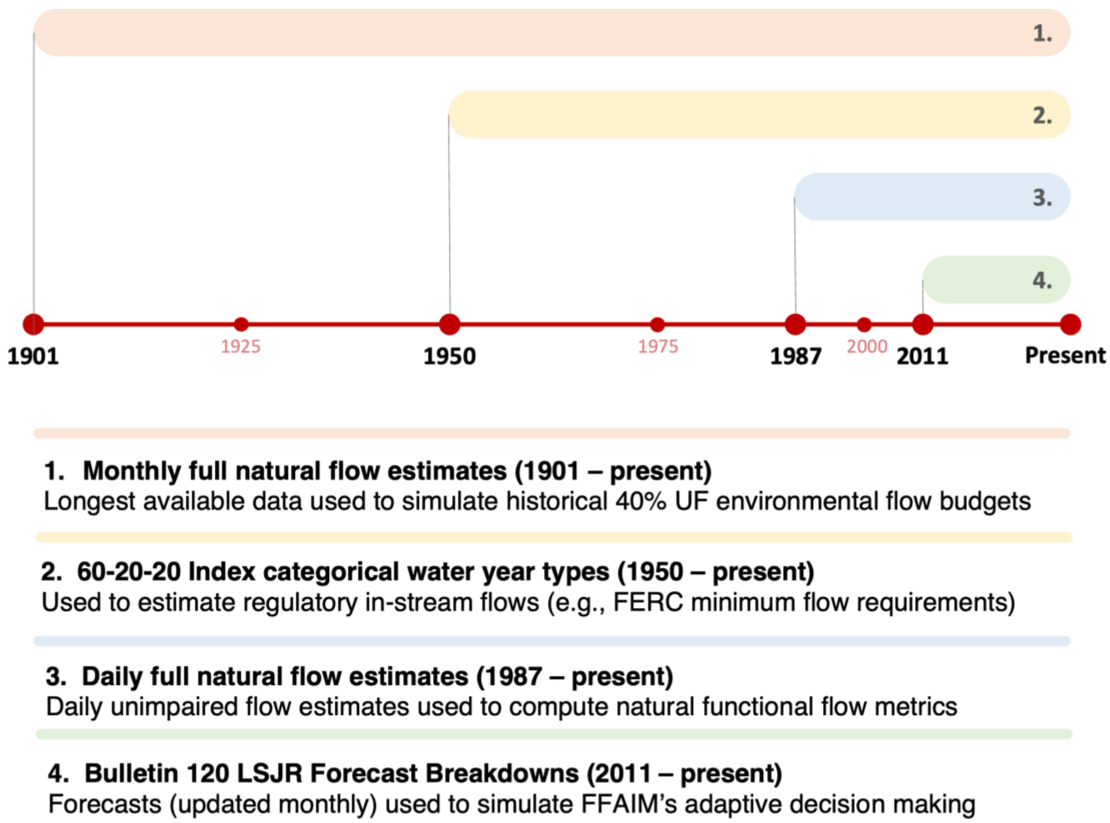


Figure 29: Durations of data for different hydrologic data sources used in Tuolumne River FFAIM simulations. (Monthly and daily FNF data are available via 'TLG' station query on CDEC (https://cdec.water.ca.gov/dynamicapp/selectQuery). Historical Bulletin 120 LSJR Forecast Breakdowns and 60-20-20 Indices are also posted on CDEC with Bulletin 120 resources (https://cdec.water.ca.gov/snow/bulletin120/).)

Given limitations in our understanding of historical (and future) flow variability, we can begin to explore how the flow budget controls FFAIM's functional flow recommendations. Monthly unimpaired flow estimates from 1901 allow us to simulate flow budgets for 123 years. We term these “perfect foresight” schedules because they represent what might be implemented if the total flow budget could be known in February, at the beginning of the operating season. Using these data, we can explore different flow budgets, the influence of additional flows, and the sensitivity of the functional flow regime to changes in input values. All of this, of course, is subject to the usual concerns about climate change, another topic for further research.

Identifying and evaluating different flow budgets. The flow budget is used to select a particular operational flow schedule from the functional flow regime. Over time, environmental flow recommendations should be managed to provide functional flow distributions statistically similar to natural flows. This requires suitable total environmental flow budgets. The Bay Delta Plan specifies an annual flow budget: 40% of unimpaired flow from February to June. Figure 30 shows FFRI distributions for a variety of February-June %UF with perfect foresight, compared to a hypothetical uniform distribution – the hypothetical distribution by which each FFRI occurs at roughly the same frequency as its corresponding water year percentile.

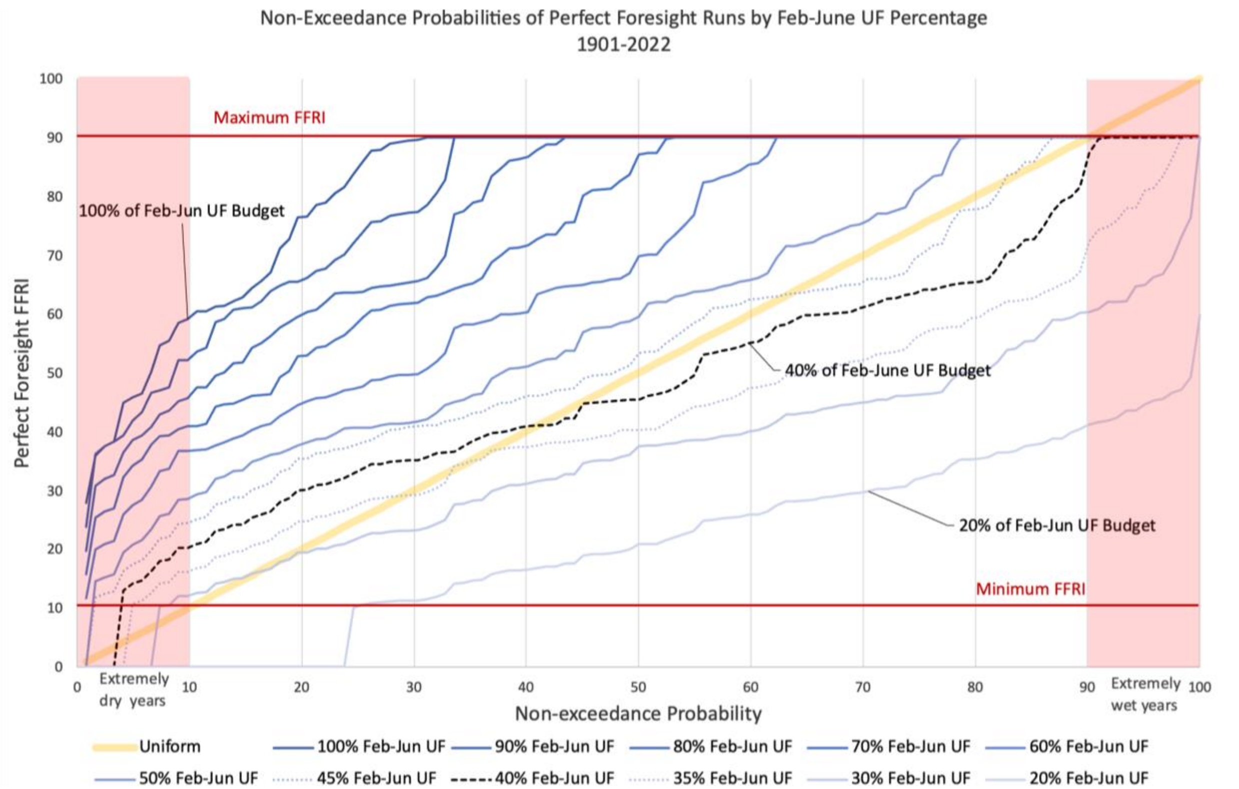


Figure 30: 1901-2022 Perfect foresight simulation FFRIs for different % UF flow budgets, based on historical February-June monthly FNF. The uniform distribution (yellow) indicates an ideal uniform interannual distribution of FFRI schedules.

Budgets below 40% seem insufficient to meet the desired range of frequencies in the functional flow regime. The 20% UF budget consistently falls below the uniform distribution, resulting in lower-than-desired FFRIs across all years. For this budget, 25% of years will need more water to meet the minimum functional flow regime. Functional flow schedules are designed to recommend flow schedules that we are reasonably confident will not pose undue stress to impacted ecosystems. For this reason, we focus on managing within the 10-90th percentiles of the natural range of metrics.

Figure 30 shows the 45% UF budget results in appropriate wetter year FFRIs (or water year percentile), and 35-40% UF budgets do the same for drier year flows. This moderation of flows also provides a cushion for effects of adaptive operation, explored in later sections. Because

FFRIs poorly describe flow schedules outside of the 10-90 range, results in the driest probability range are not included. The first instance of an FFRI 10 indicates the percentage of years where the flow budget is expected to be insufficient for minimum dry-year functional flows. In the 40% UF example, we expect that 3%-4% of years might have insufficient flow to meet the minimum functional flow schedule (with an FFRI of 10).

Increasing the environmental flow budget percentage decreases the risk of having insufficient water in the driest years. However, too much water in the budget results in FFRIs consistently above the uniform distribution (50-100% UF), mainly because the model tries to maximize FFRIs. This does not mean these budgets are inferior to alternatives closer to the uniform distribution, only that flows might be overallocated to the major functional flow components considered here. The functional flows approach helps managers assess the bare minimum recommended seasonal distribution of flows throughout the year and maintain some semblance of a particular year's seasonality. If a particular budget produces FFRIs greater than the water year percentile, it might be an opportunity to introduce additional flow features into the functional flow regime (e.g., additional peaks in the wet season, flashier escalating wet season flows leading up to the spring pulse, banking some environmental water for drier years, etc.).

Flow schedules in the 40-50% UF range seem a reasonable fit for our functional flow regime. The 40-50% UF budgets reduce the risk of insufficient water in dry years and provide close to the appropriate frequency of functional flow magnitudes across years. Areas where these curves fall below the uniform distribution, are opportunities for tweaks that could be addressed by additional flows or metric adjustments described below.

Assessing the value of additional flow contributions. While not considered in the results presented here, the Bay Delta Plan offers the opportunity to consider the additive benefit of existing environmental flows during the July-January period. On the Tuolumne, the Federal Energy Regulatory Commission sets existing minimum instream flows that vary by 60-20-20 water year type index (see detailed description in Yarnell et al. 2024, FERC-OEP 2019). Figure 31 shows the shift in the non-exceedance curve of the perfect foresight FFRIs when these additional environmental flows are added. With additional FERC flows added, the 40% UF curve provides a much better match to the uniform distribution while still boosting flows in the driest years.

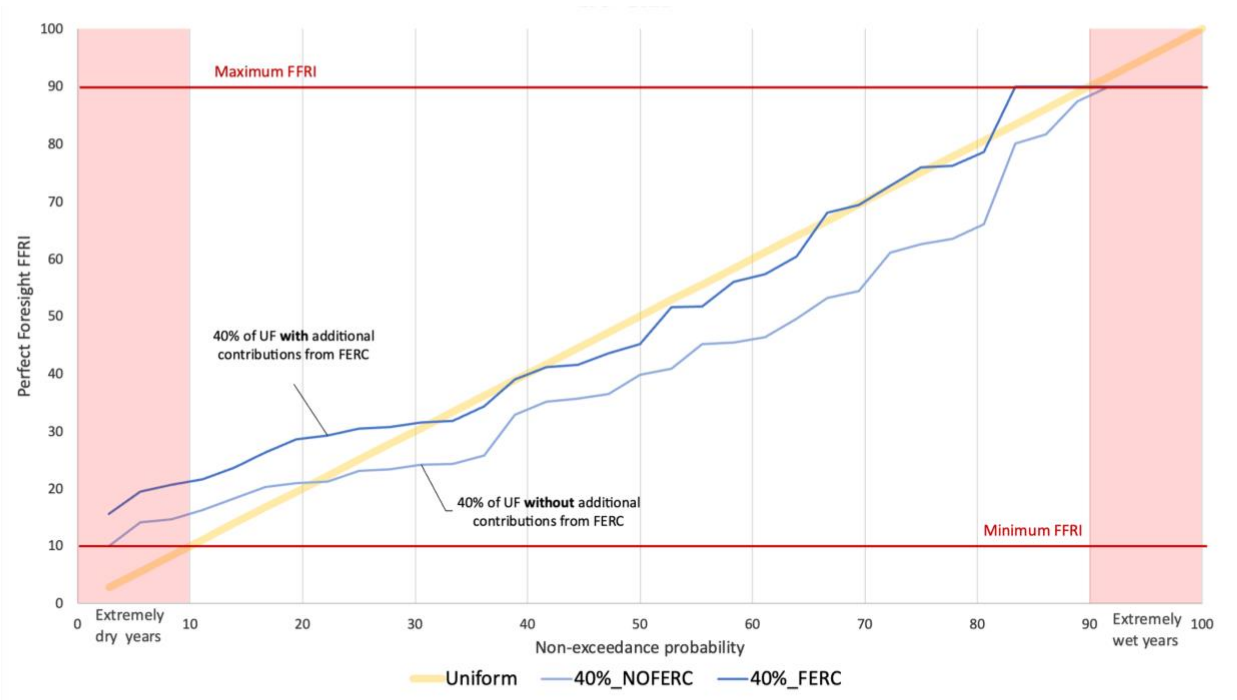


Figure 31: Non-exceedance probabilities of 40% Feb-Jun UF budget with and without FERC contributions from Jul-Jan added by water year type, based on 1987-2022 budget estimates.

Modifying functional flow metric input values. One advantage of this approach is its structural flexibility. The functional flow regime created for the Tuolumne contains many functional flow metrics assigned a reasonable value at runtime. FFAIM is designed to employ manually input metrics for operational flexibility (e.g., if a forecast update is delayed, to coordinate timings with observed climate and hydrology, etc.). Figure 32 shows how changing metric inputs might alter the frequency of FFRIs, holding the budget percentage constant. Increasing the duration of the wet season baseflow component by one month decreases FFRI for all non-exceedance probabilities. This is an example of how changes to individual metric inputs can alter how FFAIM replicates natural interannual variability.

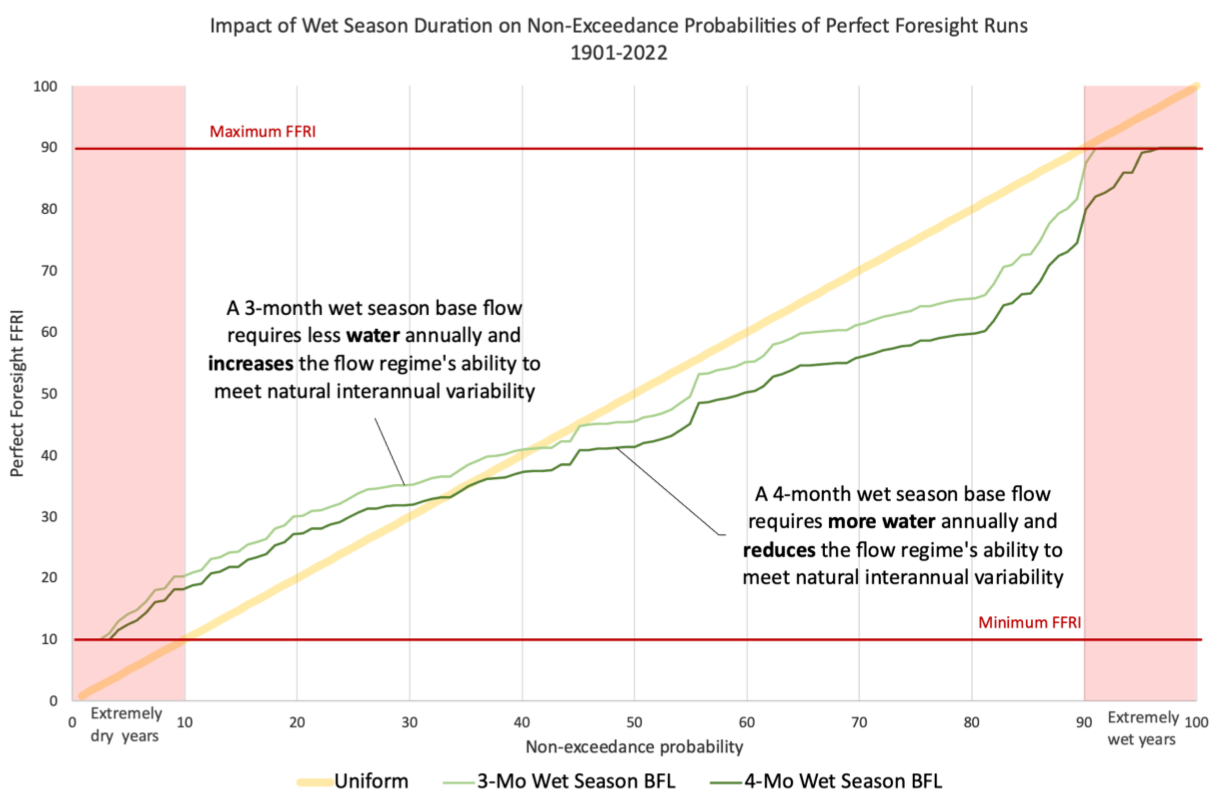


Figure 32: Non-exceedance probabilities of FFRI for 40% Feb-Jun UF budget with 3-month and 4-month wet season baseflows, based on 1901-2022 budget estimates.

4.4 Use of FFAIM for Adaptive Implementation on the Tuolumne River

FFAIM is an adaptive operation model that uses flow budget forecasts to predict the year's environmental flow budget and recommends immediate-term flows that maximize the minimum annual FFRI across two stages, considering consequences on the rest of the operating year. For the Tuolumne River case study, the beginning of the operating year is set to begin February 1st, corresponding with the first sufficiently accurate flow forecast. FFAIM is run each month, from February to May, with updated Bulletin 120 unimpaired flow forecasts and known past monthly streamflow decisions to make a current month flow recommendation and update the range of future functional flow schedules for the remainder of the operating year. Historical Bulletin 120 forecast updates are documented online and available for 2011-present (https://cdec.water.ca.gov/snow/bulletin120/). Results presented here document OY 2011 to OY 2022, **without** additional weighting parameters (w_k = 1 for each k) and **without** supplemental flows in the dry season (i.e., no calibration or budget contributions from FERC that are included in Yarnell et al. 2024).

Monthly flow forecasts. To estimate the environmental flow budget for the Tuolumne River, FFAIM uses publicly available historical unimpaired flow forecast breakdowns from Bulletin 120 (accessed at: https://cdec.water.ca.gov/cgi-progs/prev_forecat_discussion_ss/SJWSI.pdf). Alternative probabilistic seasonal unimpaired flow forecasts could come from the National Weather Service California-Nevada River Forecast Center (CNRFC) or other sources. However, the DWR Bulletin 120 forecasts are California's most commonly used seasonal flow forecasts. The Bulletin 120 "San Joaquin Water Year Forecast Breakdown" provides a range of forecast annual unimpaired flows discretized into six potential outcomes, based on exceedance probability, for each month. The exceedance probability of a particular unimpaired flow volume is the percent likelihood that the volume will be equaled or exceeded (e.g., a 0.90 exceedance probability has a 90% chance of being equaled or exceeded). Six exceedance probabilities are included in Bulletin 120's forecast breakdowns: 0.99 (driest), 0.90, 0.75, 0.50, 0.25, and 0.10 (wettest).

Table 8 shows an example Bulletin 120 February 1st forecast breakdown for the Tuolumne River for 2021. Forecast flow volumes for February through June for each exceedance probability were totaled, multiplied by 40%, and input to FFAIM as the range of potential environmental flow budgets (Table 9). Each month, a new Bulletin 120 supplied updated flow forecasts and the prior month's unimpaired flow volume became known, providing updated inputs for FFAIM. Over time, the environmental flow budget became less uncertain and narrowed towards the actual budget amount, known on July 1st (Figure 33). In practice, Bulletin 120 is released several days into the month. However, to simplify the demonstration simulations in this report, we assumed forecasts were available on the 1st of the month, and FFAIM was run accordingly.

Table 8: February 1, 2021 San Joaquin Water Year Forecast Breakdown, predicting monthly unimpaired flow for the Tuolumne River below La Grange.

2021 SAN JOAQUIN RIVER WATER YEAR FORECAST BREAKDOWN
February 1, 2021

Tuolumne River below La Grange Reservoir Unimpaired Flow [taf]

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	WY	Apr-Jul	
99%	6	1	14	17	55	81	132	199	132	26	5	2	670	489	
90%	6	1	14	17	67	105	188	286	188	38	7	3	920	700	
75%	6	1	14	17	85	125	219	338	219	44	8	4	1,080	820	
50%	6	1	14	17	104	153	250	380	250	50	10	5	1,240	930	65%
25%	6	1	14	17	125	180	306	463	306	65	12	6	1,500	1,140	
10%	6	1	14	17	151	224	363	535	362	90	15	8	1,785	1,350	
												1966-2015 avg	1,909	1,193	

Table 9: Tuolumne River monthly flow forecast distributions for February 1, 2021 (see Table 8 above) used to predict the environmental flow budget and associated functional flow schedules in FFAIM during the February, 2021 model run.

Exceedance probabilities	Feb UF (TAF)	Mar UF (TAF)	Apr UF (TAF)	May UF (TAF)	Jun UF (TAF)	Total Feb-Jun UF (TAF)	Flow budget (40% of Feb-Jun UF) (TAF)
0.10	151	224	363	535	362	1,635	654
0.25	125	180	306	463	306	1,380	552
0.50	104	153	250	380	250	1,137	454.8
0.75	85	125	219	338	219	986	394.4
0.90	67	105	188	286	188	834	333.6
0.99	55	81	132	199	132	599	239.6

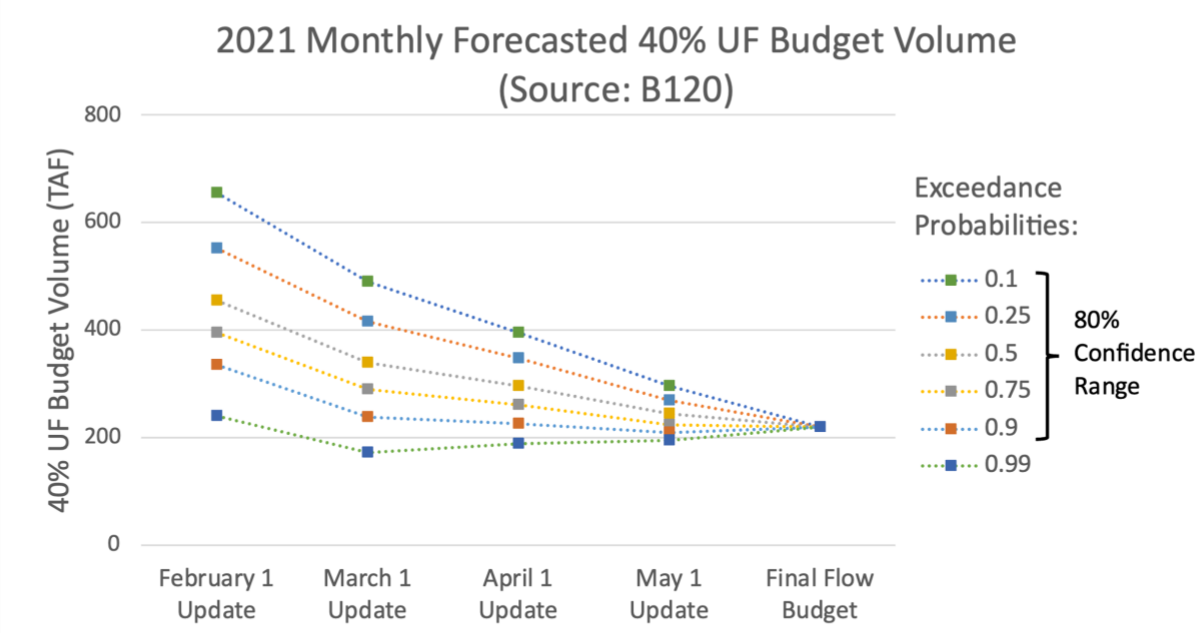


Figure 33: 2021 Environmental flow budget forecasts updated monthly for the Tuolumne River. Estimated flow budgets becomes more certain with each month, until the final known flow budget on July 1. February 1 Update budget volumes are those calculated in Table 8.

To better understand Bulletin 120's accuracy, we can consider how well early flow budget forecasts predict the final flow budget across years. Figure 34 shows the median predicted flow budgets across four updates compared to the final flow budget. Forecasts become more accurate as the wet season progresses, except for one March forecast update in 2017 – an already difficult year to predict because it was very wet. Figure 35 shows the forecast error more explicitly, confirming that forecasts consistently overpredict the budget in drier years and underpredict in wetter years (as one would expect) (Harrison & Bales 2016), apparent in critical dry ('C') and wet ('W') years.

For FFAIM, this offers little hope of using weights to improve the reliability of forecasts. In February of dry years, the flow budget might be overestimated by more than 200 TAF (Figure 35), increasing the likelihood of FFAIM over-releasing flows early in the season (beyond the potential to release more when stages 1 and 2 are volumetrically imbalanced, discussed in Chapter 3.3). All environmental flow budgets determined from B120 forecast breakdowns are included in Appendix D.

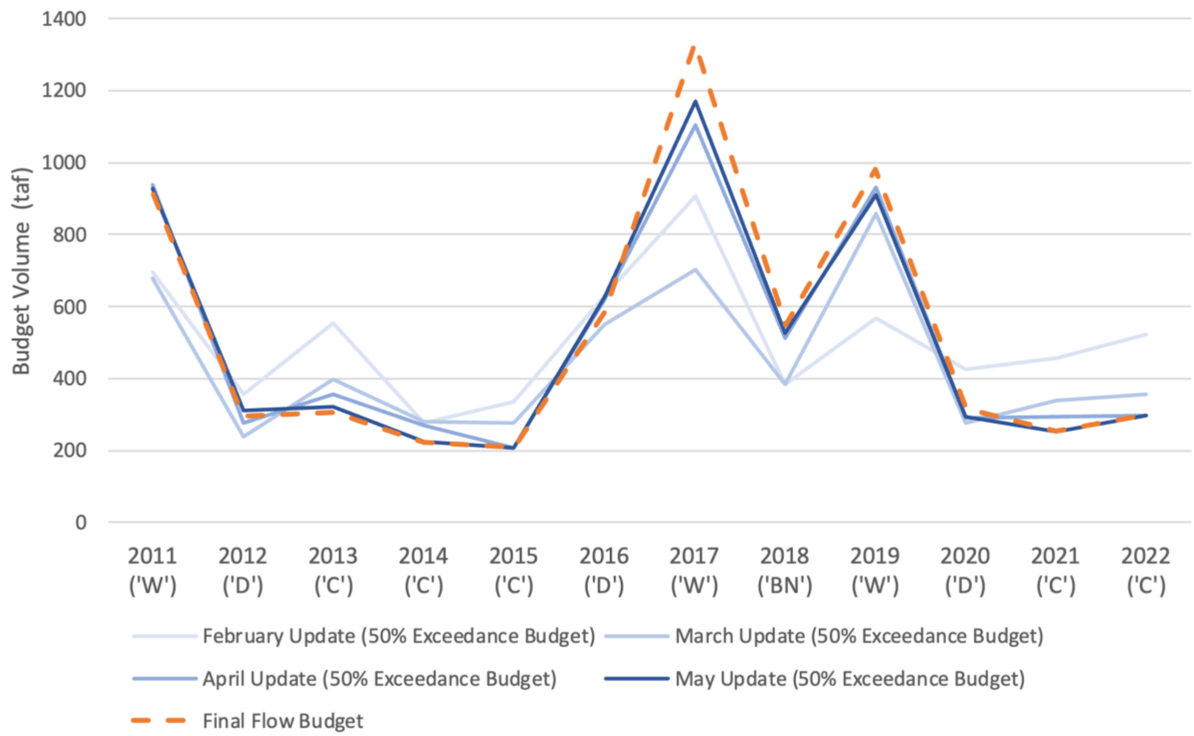


Figure 34: Annual forecasted budget volume by Bulletin 120 Update. The median forecast becomes more accurate each month.

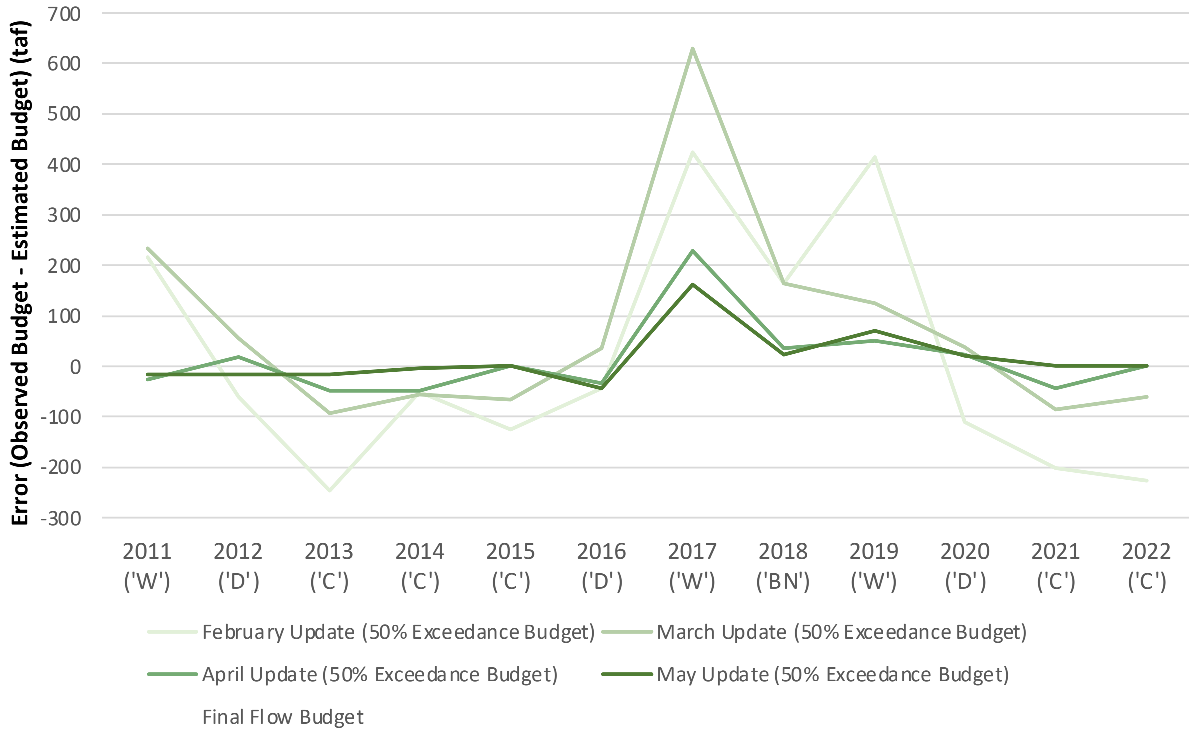


Figure 35: Median error in budget volume by Bulletin 120 Update.

Stitching together an adaptive Operating Year budget: OY 2022 Walkthrough. This section describes a simulation of monthly FFAIM recommendations over the 2022 operating year. These results show how the model responds to forecasts in a below-normal runoff year. The WY 2022 was in the 33rd percentile by annual unimpaired flow volume.

FFAIM incorporates limited predictions about future runoff to inform flow recommendations before the final environmental flow budget can be determined. FFAIM uses Bulletin 120's Forecast breakdown to estimate the flow budget. Table 10 shows the development of OY 2022 flow budget predictions input to FFAIM, which are used to simulate adaptive operations planning. Initial February flow budget predictions vary from 226 to 843 TAF, reflecting considerable early uncertainty in future precipitation. As the wet season progressed, more of that year's flow budget accumulated and forecasts tended to converge. Table 10 shows how forecasts narrowed as they approached the final flow budget of 276 TAF. The final flow budget fell on the low end of February's prediction, outside of the *80% confidence range* (i.e., between 0.90 and 0.10 exceedance probabilities), but within the middle of the range predicted in May. Monthly DWR Bulletin 120 "forecast breakdowns" are combined into a range of predicted February-June volumes to compute 40% flow budget predictions. On July 1, February-June runoff is known, giving the final flow budget.

Table 10: 2022 environmental flow budgets computed from DWR's Bulletin 120 "Forecast Breakdowns" (by update month)

	February 1 Update		March 1 Update		April 1 Update		May 1 Update		July 1
Exceedance probabilities	Predicted Feb - Jun volume (TAF)	Predicted OY flow budget* (TAF)	Predicted Feb - Jun volume (TAF)	Predicted OY flow budget (TAF)	Predicted Feb - Jun volume (TAF)	Predicted OY flow budget (TAF)	Predicted Feb - Jun volume (TAF)	Predicted OY flow budget (TAF)	Final OY flow budget (TAF)
0.10	2,108	843	1,460	584	1,063	425	883	353	276
0.25	1,650	660	1,178	471	908	363	785	314	
0.50	1,308	523	895	358	725	290	715	286	
0.75	985	394	723	289	625	250	670	268	
0.90	785	314	550	220	543	217	640	256	
0.99	565	226	363	145	430	172	610	244	
Budget range	1,543		1,097		633		273		0

*40% of February-June unimpaired flow

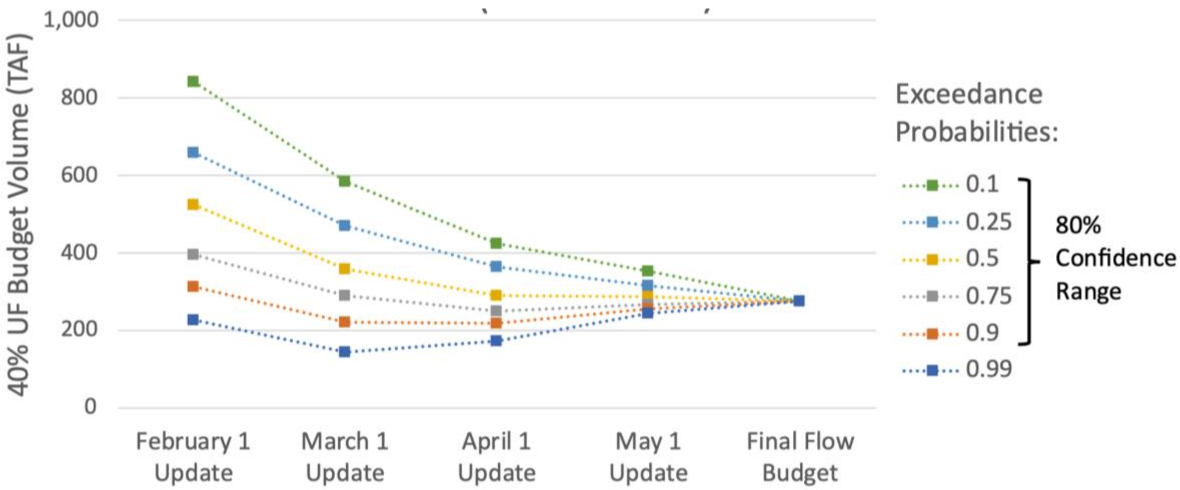


Figure 36: OY 2022 evolution of probable environmental flow budgets based on forecasted 40% of February-June UF for the Tuolumne River, updated monthly from February-May.

The first flow decision was made in early February using the February 1 Bulletin 120 Update (Figure 37). FFAIM's first decision was to release a wet season baseflow of 1,458 cfs (an FFRI of 85), requiring 123 TAF of the total flow budget. This flow decision corresponded to the 0.10 exceedance probability forecast, the highest flow suggested by the forecasts. The model allocates water into the February decision due to the certainty of achieving an exceptionally high FFRI (rather than saving this water for a slight increase later in the year). FFAIM recommended a 3-day wet season peak flow of 8,500 cfs in early February, requiring 42 TAF of the 123 TAF total. The peak flow was released for three days because the expected value of the February forecasts exceeded the 50th percentile (see step 3 text for the ruleset). Figure 37 also shows possible flow schedules corresponding to the predicted flow budgets. The highest predicted flow budget (based on the 0.10 exceedance forecast) would match the 85th water year percentile wet season baseflow magnitudes (FFRI=85). There was also a 1%-10% chance that FFAIM would have to borrow water to meet the minimum functional flow schedule, as shown by the 99th percentile schedule for March-January, which fell below the minimum FFAIM-recommended schedule. Water borrowing is permitted at no cost in this particular case study. Adding a penalty or cost for borrowing water would reduce the stage 1 FFRI.

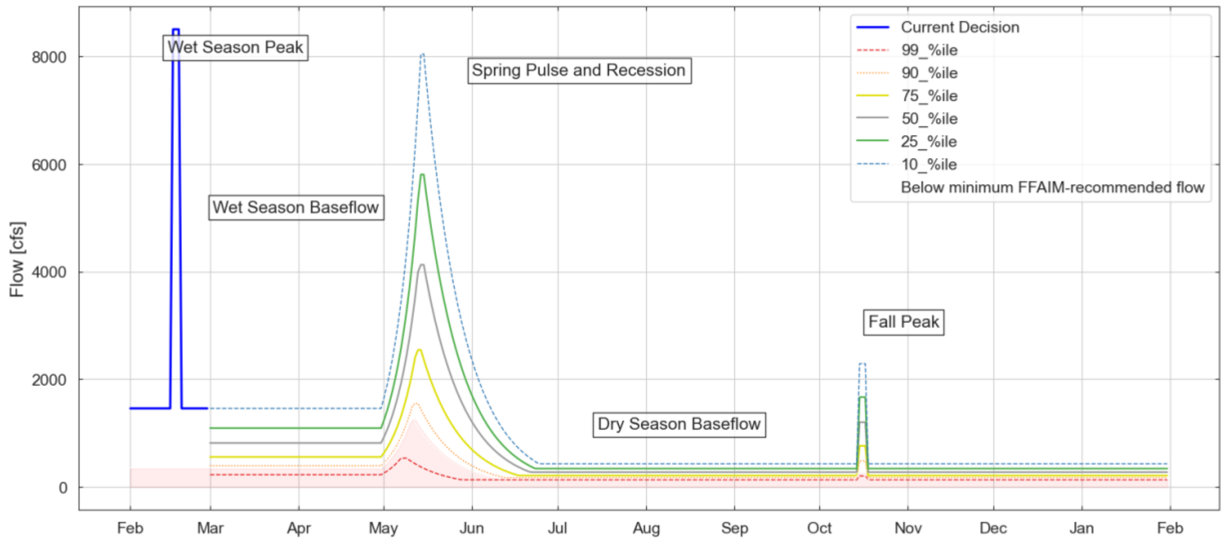


Figure 37: Hydrograph showing adaptive functional flow decisions from FFAIM in February 2022, with possible flow schedules for the remaining budget beginning March 1st.

In March and April 2022, new Bulletin 120 Updates provided new forecast distributions for FFAIM. Figure 38 and Figure 39 show FFAIM's updated flow decisions for March and April. As forecast expectations narrowed and trended drier in March, the chance of needing to borrow water grew to 25-50%. The immediate flow decision decreased dramatically to 711 cfs (an FFRI of 35), consuming 44 TAF of the environmental flow budget. In April, there was again a 25-50% likelihood of needing to borrow water to meet the minimum FFRI. The optimal wet season baseflow in April decreased again from 711 cfs to 462 cfs (an FFRI of 18), consuming an additional 28 TAF of the flow budget.

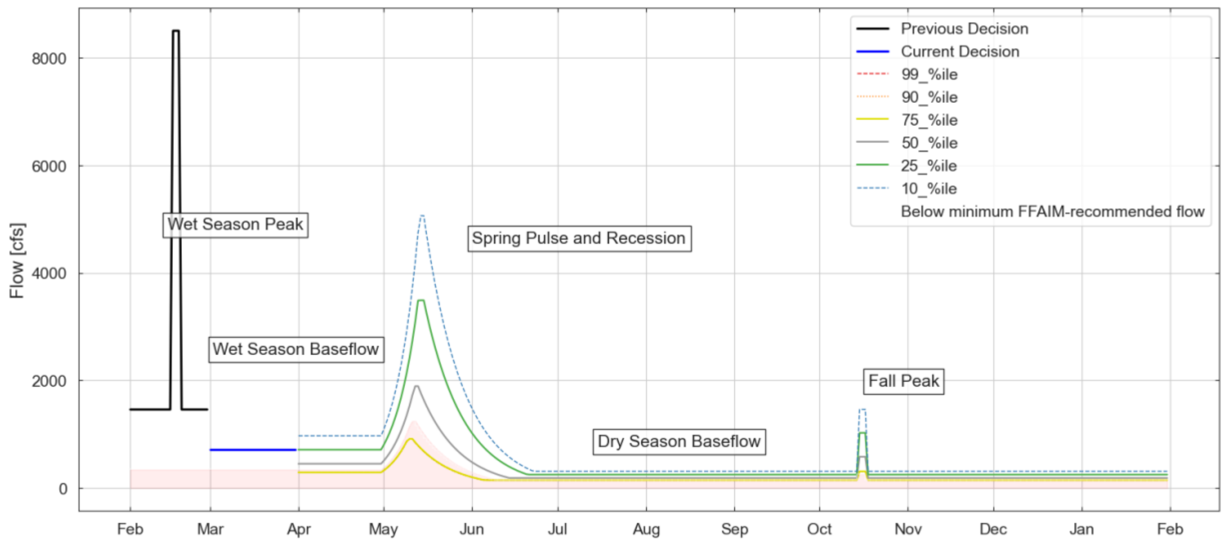


Figure 38: Hydrograph showing adaptive functional flow decisions from FFAIM in March 2022, with possible flow schedules for the remaining budget beginning April 1st.

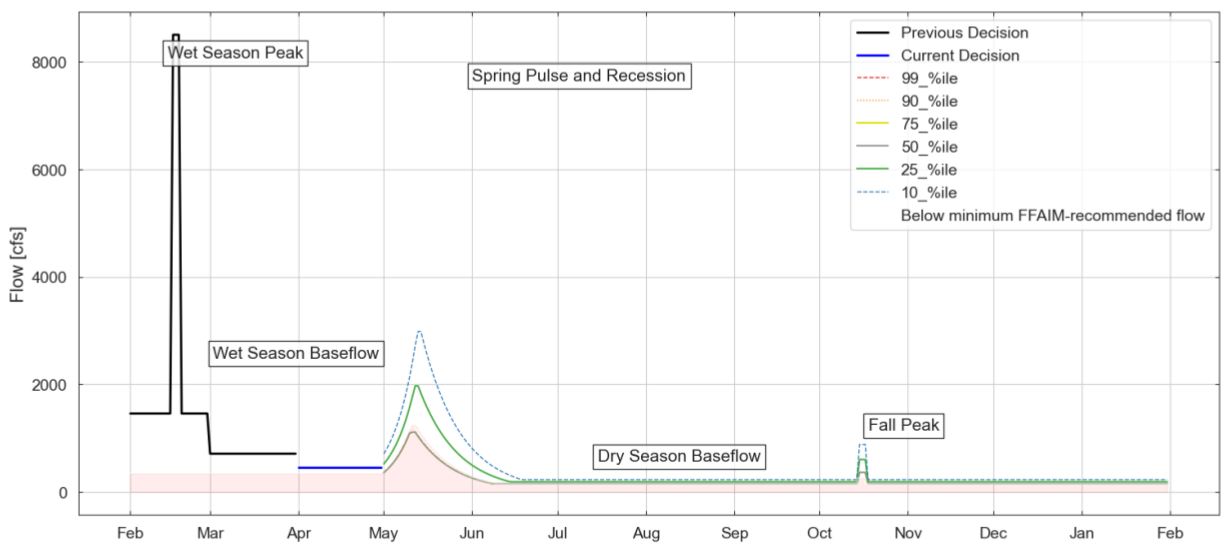


Figure 39: Hydrograph showing adaptive functional flow decisions from FFAIM in April 2022, with possible flow schedules for the remaining budget beginning May 1st.

The May 1, 2022 Bulletin 120 is the final DWR forecast before July 1 and, importantly, decides the peak magnitude of the Spring Pulse/Recession. Figure 40 shows flow decisions for May and June, which became drier in response to the still drier forecast. The flow schedule increased to the spring pulse peak at 13% per day, peaked on May 19th at 1,220 cfs (the minimum FFRI of

10), and ramped down for the spring recession at 7% per day to a July 2nd dry season start date. The May-June decision consumed 56 TAF of the environmental flow budget.

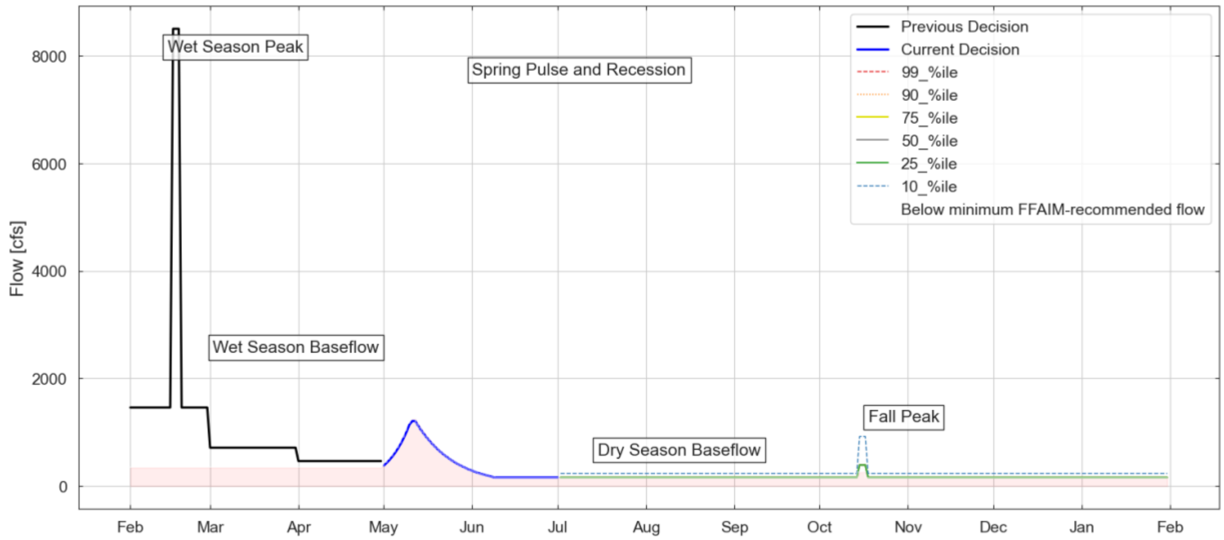


Figure 40: Hydrograph showing adaptive functional flow decisions from FFAIM beginning in May 2022, with possible flow schedules for the remaining budget beginning in July.

On July 1, the final environmental flow budget becomes known and flow recommendations can be made with near certainty for the rest of the operating year. Figure 41 shows the combined flow schedule for the entire operating year. The remaining flow recommendations included a 161 cfs dry season baseflow and a 268 cfs fall pulse, corresponding to an FFRI of 10, borrowing 42 TAF to meet the remaining 70 TAF of the final flow budget (297 TAF). This composite adaptive flow schedule is shown alongside the (dashed) perfect foresight schedule, which provides the most efficient distribution of flows across the five flow components, given the final flow budget.

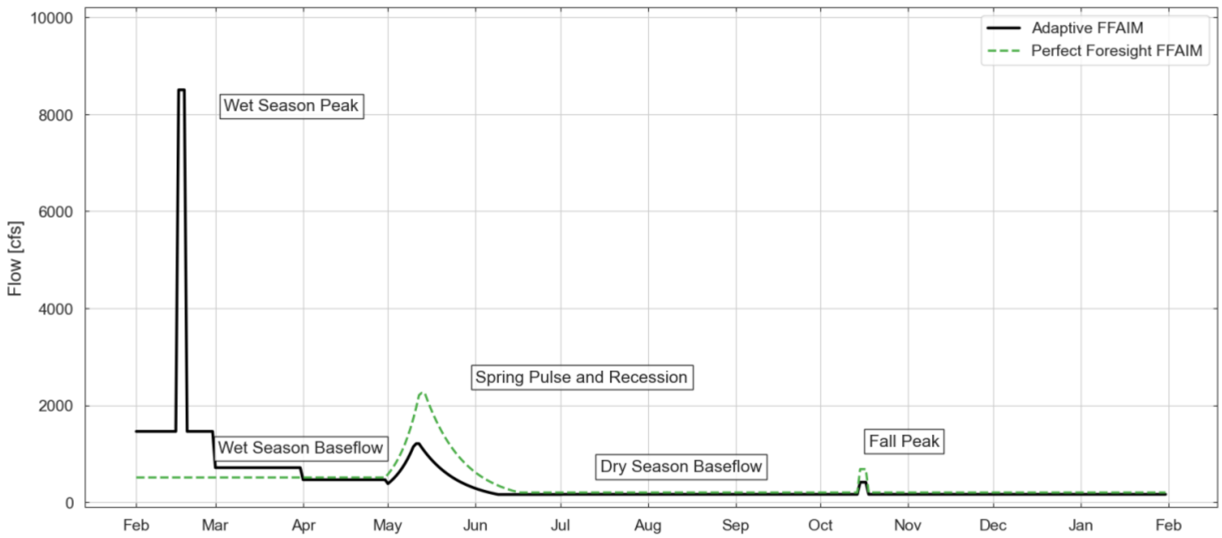


Figure 41: Hydrograph showing adaptive functional flow decisions made in July 2022 for the dry season when the adaptive flow budget was known.

Table 11 shows the predicted and final borrowed water volumes needed to achieve the minimum FFRI. With each Bulletin 120 Update, the model can borrow water to meet the 10th water year percentile functional flow schedule at no cost. In July, when the February-June decisions have been made and the OY environmental flow budget volume is known, the water borrowing is no longer hypothetical. In OY 2022, 42 TAF of additional water was needed to release the minimum functional flow (which has an FFRI of 10) from July through January. Table 12 shows how the model's decision-making evolves across updates, ultimately requiring water-borrowing.

Table 11: Predicted borrowed water volumes required to meet minimum functional flow regime for February-May FFAIM updates. In July, when the February-June decisions have been made and the budget is known, the final borrowed water volume is 42 TAF.

	Predicted borrowed water volume (TAF)				Borrowed volume (TAF)
Exceedance probabilities	February 1 Update	March 1 Update	April 1 Update	May 1 Update	July 1 (Final Decision)
0.10	-	-	-	-	42
0.25	-	-	-	3	
0.50	-	-	21	31	
0.75	-	-	60	50	

0.90	-	68	93	61	
0.99	6	143	139	73	

Table 12: Annual Minimum (AF) and Remaining (RF) FFRIs values (from Equation 6-9) for each updated FFAIM rerun. Stage 1 FFRIs are boxed within the AF columns, showing decisions made along the 0.25 exceedance forecast or wetter. RF values that might require borrowed water are noted in parentheses. At the bottom, the likelihood of water borrowing for the remainder of the year is shown, increasing with each update.

	Annual Minimum and Remaining FFRIs AF_k is the minimum of stage 1 and stage 2 FFRIs for each exceedance forecast, k RF_k is the stage 2 FFRI for each exceedance forecast, k									
	February 1 Update		March 1 Update		April 1 Update		May 1 Update		July 1 (Final Decision)	
Exceedance probabilities (k)	AF_k	RF_k	AF_k	RF_k	AF_k	RF_k	AF_k	RF_k	AF_k	RF_k
0.10	85	85	35	52	18	29	10	31	(10)	-
0.25	60	60	35	35	18	18	10	(10)		-
0.50	42	42	17	17	8	(8)	10	(10)		-
0.75	24	24	6	(6)	8	(8)	10	(10)		-
0.90	13	13	6	(6)	8	(8)	10	(10)		-
0.99	2	(2)	6	(6)	8	(8)	10	(10)		-
Likelihood of water-borrowing	1-10%		25-50%		50-75%		75-90%		100%	

OY 2022 is a near-worst-case scenario, where early budgets over-estimate the true budget, causing FFAIM to release larger flows early in the season. This problem is exacerbated by FFAIM's unweighted objective function and lack of penalty for borrowing water if the budget is over-spent, which causes FFAIM to increase FFRI in the stage where this can be achieved most cheaply (usually in the stage with a shorter duration).

There is a need not only to maximize the annual minimum FFRI but also to hedge and save water for future periods, but there remains a possibility of being caught short. Early in the year, a mismatch in the response of FFRI to additional volume across stages leads to excessively high FFRIs. This exacerbates the already low margin of error for early decisions to release wet season peak flows in February, using the least accurate forecasts of the operating year. Furthermore, the ability of the model to borrow water at no cost to meet minimum required flows encourages the model to make increasingly riskier decisions across the operating year. The monthly decision, composite adaptive, and perfect foresight hydrographs are included in Appendix E.

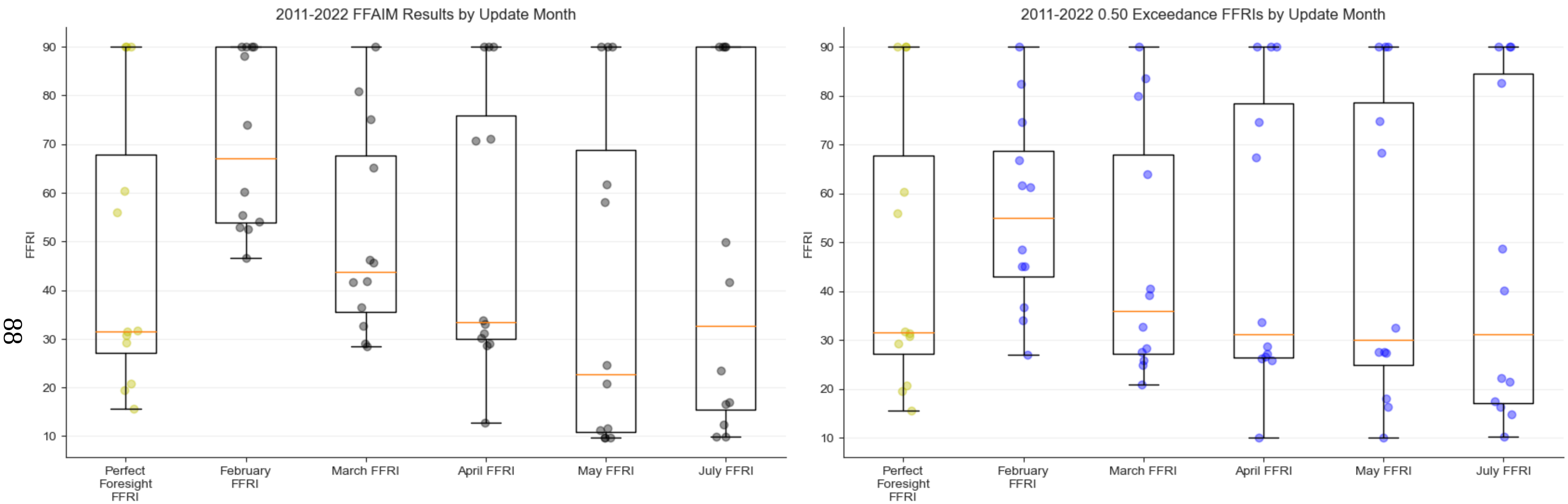
4.5 Discussion: Opportunities to Improve Forecast-informed Operations

An important measure of FFAIM's success in providing adaptive functional flows is the model's ability to recommend flows that reflect the full range of flows expressed in the natural flow regime. Section 4.2 shows how FFAIM's functional flow regime meets (or has capacity to meet) interannual variability of flow component magnitude metrics. This section examines how well an unweighted FFAIM model using the objective function described in Section 3.2 enables us to achieve desired interannual variability in a real-time operational context complete with forecast uncertainties. Here, we compare adaptive and perfect foresight results and consider how well FFAIM embodies natural interannual variability of flow components in an operational context.

Figure 42 shows the FFRIs of the adaptive flow schedules by update month for the 12 years simulated. Because adaptive flow schedules consist of multiple decisions, they can have different FFRIs over the operating year, particularly given evolving water budget uncertainty over the operating year. Therefore, it is useful to consider how well each decision period embodies the range of water year percentiles over the period of interest, approximated by the perfect foresight FFRIs.

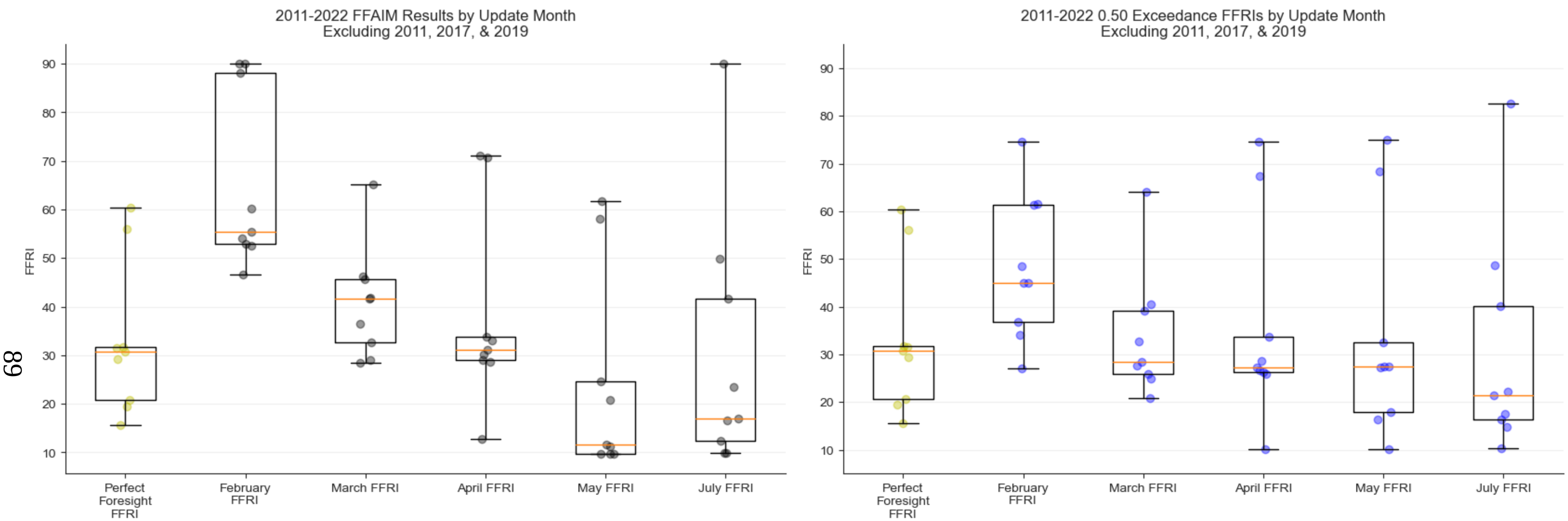
Figure 42a shows a downward trend in average FFRIs over the operating year, with a notable tendency to recommend wetter-than-ideal environmental flows in February. In 12 years, not a single February would have been drier than an FFRI 45, nor drier than an FFRI 25 in March. A significant proportion of 2011-2022 were drought years. Because flow forecasts in dry years tend to overestimate flows (Figure 35), it is tempting to dismiss February releases due to inherent forecast inaccuracies. Figure 42b highlights the hypothetical distribution of FFRIs if FFAIM were forced to only release according to the 0.50 exceedance probability (i.e., the median) flow budget, the median estimate of the final flow budget in each forecast update. The 0.50 exceedance results remove the influence of the objective function and consider only the variability in FFRIs presented by forecast inaccuracies. These results show that forecasts account for some, but not all, of the variability in the fall forecast.

Boxplots in Figure 42 are strongly influenced by three wet years (where carryover was produced). These wet years are also when FFAIM's adaptive flow schedules are most likely to be supplanted by flood operations. Figure 43 shows these same boxplots excluding the wettest three years, each with an FFRI of 90: 2011, 2017, and 2019. In these plots, it is easier to visualize the tradeoff between elevated releases early in the operating season and their consequences on later decisions. Functional flows in later months are reduced, often to the minimum functional flow schedule. Figure 44 shows the average error of the adaptive FFAIM at estimating the most efficient distribution of flows for the final flow budget. This is another tool to visualize the inaccuracy of the unweighted FFAIM model in early model runs.



(a) (b)

Figure 42: Boxplots of FFRIs by Bulletin 120 Update Month. Perfect foresight FFRIs (yellow) represent the ideal distribution of FFRIs, if forecasts were perfect. On the left (a), the spread of FFAIM results are shown using default weighting of six Bulletin 120 exceedance probabilities. On the right (b), only the median forecasts are used to inform flow decisions, ignoring the tails of the forecast distribution. In the FFAIM results (a), early model runs are likely to overestimate the perfect foresight distribution, resulting in higher than expected low FFRIs in May and July.



(a) (b)

Figure 43: Boxplots of FFRIs by Bulletin 120 Update Month, excluding the three wettest years (2011, 2017, and 2019) and limiting analysis to years when the budgets were over-estimated by forecasts. Perfect foresight FFRIs (yellow) represent the ideal distribution of FFRIs, if forecasts were perfectly accurate. On the left (a), the spread of FFAIM results are shown using default weighting of six Bulletin 120 exceedance probabilities. On the right (b), only the median forecasts are used to inform flow decisions, ignoring the tails of the forecast distribution. Similarly to Figure 42 but more exaggerated, early FFAIM runs (a) are likely to overestimate the perfect foresight distribution, resulting in low FFRIs in May and July.

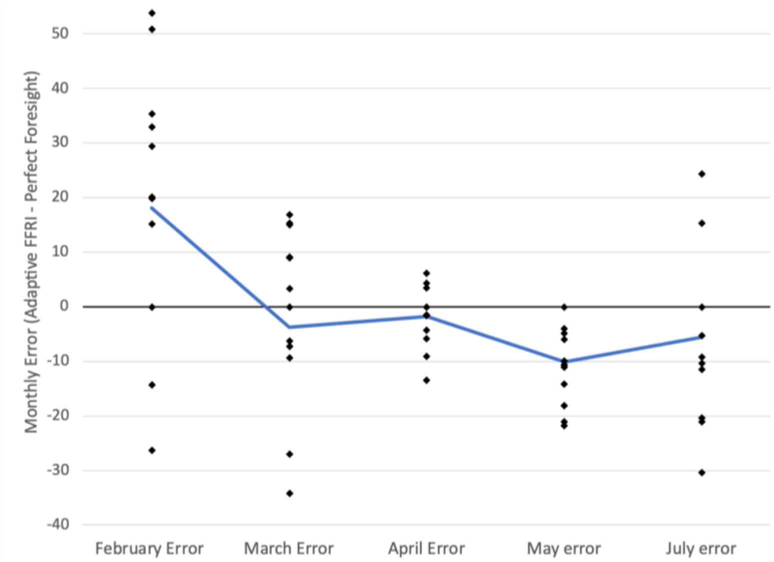


Figure 44: Monthly error of adaptive FFAIM FFRIs by forecast update, compared to the perfect foresight ideal.

Differences between monthly results produce water year percentile inconsistencies among seasonal flow components, seen in their FFRIs. The wet season baseflow magnitude, which is the minimum of the three flows decided in February-April, is reasonably representative of the distribution of perfect foresight (usually, April is the limiting month in determining wet season baseflow FFRI). The spring recession magnitude is frequently set to the minimum allowable magnitude and tends closer to the extremes than perfect foresight. The dry season baseflow and fall pulse are determined once the flow budget is known on July 1st. Over-allocating water early in the operating year creates higher wet season baseflows at the expense of spring peak magnitudes and dry season baseflows. This imbalance hampers FFAIM's ability to express each flow component's full interannual range and frequency.

The imbalanced response of FFRI to changes in volume across stages upstages the hedging of flows for later in the operating year. These patterns mirror the patterns of the stage-related volume sensitivity discussed in Section 3.4. Similarly, calibrated w_k values may help promote hedging without abandoning the straightforward objective—to maximize the minimum annual FFRI. This method will require the calibration of w_k values to match adaptive results more closely (Bellido-Leiva 2024).

The case study presented here shows the unweighted adaptive FFAIM results on the Tuolumne, which remain preliminary, but clearly show that environmental water budgets can be operated adaptively with great promise, relative to perfect foresight results. FFAIM results using calibrated w_k values are featured in Yarnell et al. 2024 and resolve some issues raised in this study. Future explorations will revisit this hedging issue. Because the optimization tends to converge at discrete corner points, multiple sets of w_k weights will produce similar results, making it challenging to identify a single set of appropriate values. There also may be a way to derive an approximate empirical formula to establish w_k values as a function of the sensitivity of stage-FFRI to changes in volume ($\frac{\Delta\, FFRI}{\Delta Volume}$). Other potential objective functions also might effectively promote hedging without calibration or weights. Tradeoffs for other objectives also should eventually be considered.

5. Conclusions

5.1 Future Work

This thesis develops scalable functional flow regimes that vary continuously by water year percentiles as a foundation for modeled adaptive environmental flow operations. There are many ways to further explore these FFAIM and its operation, particularly in several key areas:

Method Improvements and Applications. Initial results are quite promising, this thesis presents many opportunities for further refining budget-based environmental flow operations. Future work can:

- expand seasonal flow variability,
- experiment with non-linear FFRI-metric relationships,
- consider FFRIs for non-magnitude metrics (such as timing and rate of change metrics),
- incorporate and tune weights to reflect cost of water borrowing for dry scenarios,
- investigate w_k calibration,
- employ alternative objective function formulations, and
- explore use of this modeling approach in larger institutional operations decision-making.

Additional improvements can align the model with other regulatory flow, ecological, and implementation requirements, such as:

- temperature and water quality requirements,
- reservoir storage, and
- combined flow requirements beyond the confluence with the Lower San Joaquin River,

and explore the expansion of regulatory tools, such as:

- over-year water banking of surplus water,
- water trading, and
- flow adjustment tradeoffs.

FFAIM also could integrate other forecasting information to expand the possibilities for adaptive operations updates (i.e., CNRFC unimpaired flow forecast breakdowns that are updated daily and short-term weather forecasts for deciding the timing of wet season peak events).

Approach and Exploration. A significant challenge in implementing environmental flows is demonstrating the comparative desirability of different approaches and implementations. Future work will compare environmental flow strategies and develop tradeoff curves to help decision-makers balance tradeoffs among approaches. In early phases, FFAIM is a desktop-based method that helps design flow regimes using limited, readily available daily unimpaired flow estimates. Further work should involve a multidisciplinary, expert panel to test the initial functional flow regime, make refinements, and conduct field flow experiments. In convening these experts, there will be opportunities to add mechanistic criteria to fill gaps in the empirically-based model.

Climate considerations. Climate change will affect the seasonal and interannual distribution of %UF flow budgets and flows. Budget-based environmental flow approaches will face more frequent extreme years and fewer years within the "normal" range. Because FFAIM aims to uphold the natural interannual frequency of flow components, future work will consider the feasibility of modeling multi-year operation and interannual storage capabilities to redistribute flows from wet to dry years. This will likely conflict with other reservoir operating priorities, but the possibility remains worth exploring.

Policy Implementations and Exploration. The benefits of holistic environmental flows are theoretical until they are tested in the field. Effective functional flow operation warrants adaptive management to ensure flows produce the expected results. Monitoring programs must be designed to assess the return of flow-driven functions to the system and not focus exclusively on species-specific responses (which are sensitive to various non-flow-mediated factors) (Whipple & Viers 2019). Additional work will also involve outreach and education to inform practitioners about the objectives and rationale for holistic environmental flows and how FFAIM could be used and adapted in an operational context.

5.2 Conclusions

We cannot fully reproduce the benefits of natural flows with only a portion of the natural volume. Still, the Functional Flows approach provides a framework to distribute a limited and varying environmental flow budget in an ecologically responsible way—maintaining signatures of both seasonality and interannual variability. The continuously scaling functional flow regimes explored in this paper improve on coarse water year type designations used today for environmental flows. This scaling enhances the diversity of flow magnitude and timing and ties environmental flows more directly to current and evolving environmental science and management. FFAIM operationalizes functional flows using a flow budget based on a percentage of unimpaired flow. These quantitative methods are rooted in natural flows and provide a promising method for dealing with seasonal hydrologic uncertainty.

This thesis shows how one might adapt a Functional Flows approach to a budget-based environmental flow policy. Further, it explores one way to explicitly employ probabilistic optimization to incorporate hydrologic uncertainty. To clarify adaptive operation under FFAIM, model results (without cautionary weights or costs to borrow water) were presented for 2011-2021 on the Tuolumne River. FFAIM efficiently maximizes the annual minimum FFRI (i.e., water year percentile as represented by functional flows) across two stages in each run by allocating water to the stage where it can achieve greater water year percentiles for its investment. In practice, this results in FFAIM allocating more water to the shorter first stage, the limited duration of which increases FFRI at a relatively low cost, boosting the annual minimum. The desirability of ensuring wet year flows in short periods at the expense of flows later in the operating year is debatable.

This thesis demonstrates how FFAIM allocates water in the absence of additional features to promote hedging. There is promise that challenges explored here will be alleviated by weighting dry scenarios for model runs with an imbalance in incremental response to volume between stages 1 and 2. Furthermore, discouraging water borrowing using a cost function will improve the model's ability to exert extra caution in years like OY 2022, when there is a significant chance that the budget is insufficient to meet remaining flow needs.

Transitioning from theory to implementation is a significant challenge for any environmental flow strategy. Uncertainty and knowledge gaps must not become roadblocks to urgent ecosystem crises but challenges to overcome technically and institutionally. Managing environmental flows will require changes in technical methods and institutional arrangements. FFAIM and the Functional Flows approach have the flexibility and adaptability to set the foundation for effective budget-based environmental flow policies and operations. With proper maintenance and adjustments, this method provides a framework for timely environmental flow operations, trade-off analyses, and negotiations for California's major rivers, which can be adjusted for scientific advances and changes in landscapes, hydrology, policy, and understanding over time.

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Appendix A. Ecosystem functions provided by Functional Flow components (Table 2.1 from CEFWG 2021)

Table 1.2. Descriptions of the ecosystem functions that are supported by each of the five components of functional flows and the corresponding references in the scientific literature. References listed specifically link the associated flow characteristic with the ecosystem function.

Functional Flow Component	Type of Ecosystem Function	Supported Ecosystem Function	Associated Flow Characteristic	References
Fall Pulse Flow	Physical	Flush fine sediment and organic material from substrate	magnitude	Postel and Richter 2003; Kemp et al. 2011
		Increase longitudinal connectivity	magnitude, duration	Grantham 2013
		Increase riparian soil moisture	magnitude, duration	Stubbington 2012
	Biogeochemical	Flush organic material downstream and increase nutrient cycling	magnitude, duration	Ahearn et al. 2006
		Modify salinity conditions in estuaries	magnitude, duration	Postel and Richter 2003
		Reactivate exchanges/connectivity with hyporheic zone	magnitude, duration	Stubbington 2012
		Decrease water temperature and increase dissolved oxygen	magnitude, duration	Yarnell et al. 2015
	Biological	Support fish migration to spawning areas	magnitude, timing, rate of change	Sommer et al. 2011; Kiernan et al. 2012
Wet-season Baseflow	Physical	Increase longitudinal connectivity	magnitude, duration	Grantham 2013; Yarnell et al. 2020
		Increase shallow groundwater (riparian)	magnitude, duration	Vidon et al. 2010
	Biogeochemical	Support hyporheic exchange	magnitude, duration	Stubbington 2012
	Biological	Support migration, spawning, and residency of aquatic organisms	magnitude	Grantham 2013
		Support channel margin riparian habitat	magnitude	Vidon et al. 2010
Wet-season Peak Flows	Physical	Scour and deposit sediments and large wood in channel and floodplains and overbank areas.	magnitude, duration, frequency	Ward 1998; Florsheim and Mount 2002; Escobar-Arias and

		Encompasses maintenance and rejuvenation of physical habitat.		Pasternack 2010; Wheaton et al. 2010; Senter et al. 2017
		Increase lateral connectivity	magnitude, duration	Ward 1998, Cienciala and Pasternack 2017
		Recharge groundwater (floodplains)	magnitude, duration	Opperman et al. 2017
	Biogeochemical	Increase nutrient cycling on floodplains	magnitude, duration	Ahearn et al. 2006
		Increase exchange of nutrients and organic matter between floodplains and channel	magnitude, duration	Ahearn et al. 2006
	Biological	Support fish spawning and rearing in floodplains and overbank areas	magnitude, duration, timing	Jeffres et al. 2008; Opperman et al. 2017
		Support plant biodiversity via disturbance, riparian succession, and extended inundation in floodplains and overbank areas	magnitude, duration, frequency	Ward 1998; Shafroth et al. 1998; Opperman et al. 2017
		Limit vegetation encroachment and non-native aquatic species via disturbance	magnitude, frequency	Petts and Gurnell 2013; Kiernan and Moyle 2012; Poole and Berman 2001
Spring Recession Flow	Physical	Sorting of sediments via increased sediment transport and size selective deposition	magnitude, rate of change	Hassan et al. 2006; Ashworth 1996; Madej 1999
		Recharge groundwater (floodplains)	magnitude, duration	Opperman et al. 2017
		Increase lateral and longitudinal connectivity	magnitude, duration	Ward and Stanford 1995
	Biogeochemical	Decrease water temperatures and increase turbidity	duration, rate of change	Leland 2003
		Increase export of nutrients and primary producers from floodplain to channel	magnitude, duration, rate of change	Bowen et al. 2003; Ward and Stanford 1995

		spawning; support juvenile fish rearing	change	Shirey 2013; Yarnell et al. 2010
	Biological	Increase hydraulic habitat diversity and habitat availability resulting in increased algal productivity, macroinvertebrate diversity, arthropod diversity, fish diversity, and general biodiversity	magnitude, timing, rate of change, duration	Lambeets et al. 2008, Pastuchova et al. 2008; Peterson et al. 2001; Propst and Gido 2004
		Provide hydrologic conditions for riparian species recruitment (e.g. cottonwood)	magnitude, timing, rate of change, duration	Shafroth et al. 1998; Rood et al. 2005; Stella et al. 2006; Mahoney and Rood 1998
		Limit riparian vegetation encroachment into channel	magnitude, rate of change	Lind et al. 1996; Shafroth et al. 2002
Dry-season Baseflow	Physical	Maintain riparian soil moisture	magnitude, duration	Postel and Richter 2003
		Limit longitudinal connectivity in ephemeral streams; limit lateral connectivity to disconnect floodplains	magnitude, duration, timing	Lee and Suen 2012; Beller et al. 2011
		Maintain longitudinal connectivity in perennial streams	magnitude	Kiernan and Moyle 2012
	Biogeochemical	Maintain water temperature and dissolved oxygen	magnitude, duration	Yarnell et al. 2015
	Biological	Maintain habitat availability for native aquatic species (broadly)	magnitude, timing, duration	Postel and Richter 2003; Yarnell et al. 2016; Kupferberg et al. 2012
		Condense aquatic habitat to limit non-native species and support native predators	magnitude, duration	Lee and Suen 2012; Kiernan and Moyle 2012; Postel and Richter 2003
		Support primary and secondary producers	magnitude	Power et al. 2008; Yarnell et al. 2015

Appendix B. FFRI Functions: Relating Functional Flow Metrics to Water Year Percentile

All FFRI Functions are in the following format:

$$FFRI = m\ (Functional\ Flow\ Metric\ value) + b$$

Wet season Base Flow Magnitude:

WetBFL_mag_cfs, m:0.06722689075630253 b:-13.126050420168083

Spring Base Flow Magnitude:

SP_mag_cfs, m:0.011034482758620689 b:-3.7931034482758594

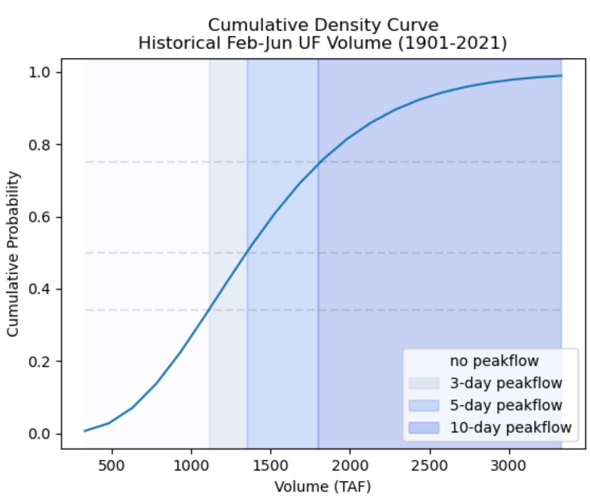
Dry Season Base Flow Magnitude:

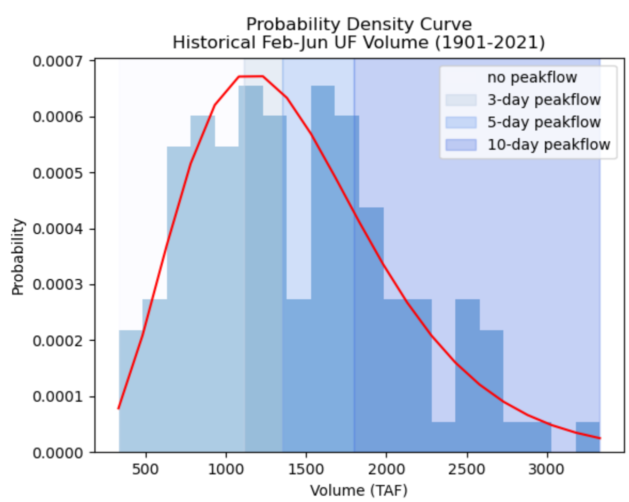
DS_mag_cfs, m:0.2787456445993031 b:-34.59930313588847

Fall Pulse Magnitude:

FA_mag_cfs, m:0.04597701149425285 b:-1.954022988505714

Peak flow duration computed in February based on expected budget volume:





Appendix C. Tuolumne River 1987-2021 Functional Flows Calculator API Output (Abridged)

Table C1: Calculator API Metric results by metric percentile

	p10	p25	p50	p75	p90
DS_Dur_WS	101	122	164	182	196
DS_Tim	285	293	302	314	329
DS_Mag_50	172	262	356	393	466
DS_Mag_90	461	667	864	1126	1532
FA_Dur	2	2	2	4	4
FA_Mag	437	572	885	1318	2729
FA_Tim	1	3	7	18	36
SP_ROC	0.11	0.14	0.18	0.25	0.29
SP_Dur	43	52	61	69	75
SP_Mag	4743	5909	9433	16049	20416
SP_Tim	224	232	244	254	265
Wet_BFL_Dur	92	110	138	183	210
Wet_BFL_Mag_10	413	635	955	1251	1559
Wet_BFL_Mag_50	1484	2310	3196	4497	5588
Wet_Tim	45	76	95	131	139
Peak_Tim_10	91	92	104	127	147
Peak_Tim_2	118	171	213	236	249
Peak_Tim_5	80	117	149	186	227
Peak_Dur_10	1.0	1.0	1.5	2.3	2.7
Peak_Dur_2	1.0	2.5	5.0	17.3	23.4
Peak_Dur_5	1.0	1.0	1.5	2.5	5.2
Peak_10	42849	42849	42849	42849	42849
Peak_2	14749	14749	14749	14749	14749
Peak_5	29668	29668	29668	29668	29668
Peak_Fre_10	1.0	1.0	1.0	1.3	1.7
Peak_Fre_2	1.0	2.0	3.5	5.8	9.0
Peak_Fre_5	1.0	1.0	1.0	2.0	2.6

Year	DS_Dur	DS_Tim	DS_Mag_50	DS_Mag_90	FA_Dur	FA_Mag	FA_Tim	SP_ROC	SP_Dur	SP_Mag	SP_Tim	Wet_BFL_Dur	Wet_BFL_Mag_10	Wet_BFL_Mag_50	Wet_Tim
1987	165	281	308	822	2	711	1	0.29	55	5718	226	90	555	2114	136
1988	175	310	276	668	2	455	23	0.29	72	4484	238	158	718	1501	80
1989	197	301	397	1070	4	425	3	0.22	65	5924	236	117	799	3782	119
1990	195	305	233	543	2	1134	0	0.34	62	5002	243	111	1054	2554	132
1991	181	302	354	664	2	490	0	0.15	52	9168	250	116	243	3101	134
1992	117	329	219	672	5	2850	25	0.25	105	5822	224	107	489	2325	117
1993	184	320	392	855	2	529	0	0.18	58	11102	262	182	1455	5085	80
1994	157	288	375	1035	3	1118	4	0.28	42	6316	246	108	1182	2318	138
1995	114	345	325	1178	3	774	4	0.11	60	17980	285	206	1985	6851	79
1996	88	309	363	717	2	625	1	0.10	77	37270	232	139	1270	4491	93
1997	136	314	405	913	3	638	7	0.22	68	11059	246	215	1091	4374	31
1998	130	328	642	1421	1	6000	6	0.07	61	15740	267	183	1645	5635	84
1999	156	302	358	689	2	1289	37	0.18	42	10061	260	168	1197	3586	92
2000	186	300	407	834	4	561	15	0.20	37	6876	263	171	1091	4515	92
2001	168	270	365	910	3	885	15	0.16	46	10379	224	104	746	2340	120
2002	223	293	443	1570	2	547	17	0.22	47	9698	246	174	903	2300	72
2003	198	288	494	1611	1	1347	36	0.17	44	16889	244	94	1116	3379	150
2004	146	297	446	1377	2	1003	36	0.26	52	7171	245	125	1050	3930	120
2005	122	313	364	873	4	3017	18	0.11	72	22172	241	164	1578	4627	77
2006	163	315	390	757	2	931	26	0.11	62	15883	253	184	1512	5542	69
2007	190	283	295	607	2	1818	44	0.25	56	6034	227	115	474	2313	112
2008	158	304	253	935	2	1151	1	0.19	71	11210	233	126	945	2140	107
2009	189	308	337	1667	1	400	2	0.18	75	13322	233	137	965	3002	96
2010	98	314	332	1354	4	1426	11	0.16	59	16546	255	124	1527	3941	131

Year	DS_Dur_WS	DS_Tim	DS_Mag_50	DS_Mag_90	FA_Dur	FA_Mag	FA_Tim	SP_ROC	SP_Dur	SP_Mag	SP_Tim	Wet_BFL_Dur	Wet_BFL_Mag_10	Wet_BFL_Mag_50	Wet_Tim
2011	174	337	391	964	2	1154	4	0.14	62	20682	275	229	1758	5367	46
2012	121	278	169	380	3	1603	5	0.10	60	8084	218	73	699	2167	145
2013	173	299	173	372	4	406	12	0.25	70	6969	229	196	567	1467	33
2014	117	292	91	230	2	268	5	0.13	60	4221	232	126	299	1424	106
2015	128	299	171	600	4	639	2	0.20	60	3744	239	196	240	932	43
2016	103	316	153	1849	6	584	17	0.14	68	8977	248	187	849	3360	61
2017	164	341	530	1494	8	14942	16	0.15	75	20149	266	213	1540	7598	53
2018	168	286	378	929	3	2548	45	0.15	93	29237	193	54	486	3291	139
2019	181	321	485	1108	2	608	3	0.12	62	17784	259	171	1244	5737	88
2020	222	293	265	745	2	973	8	0.44	49	5498	244	108	752	2964	136
2021	79	289	213	402	2	716	4	0.24	68	5862	221	72	657	2442	149

Additional Functional Flows Calculator API Documentation is available at https://eflows.ucdavis.edu and on GitHub https://github.com/ceff-tech/ffc_api_client

Appendix D. Forecasted environmental flow budgets for the Tuolumne River for February, March, April, and May B120 updates, by year

Year	Final Environmental Flow Budget
2011	912
2012	295
2013	306
2014	223
2015	209
2016	585
2017	1332
2018	547
2019	982
2020	315
2021	253
2022	297

	February B120 Volumes (TAF)						
year	10% Exc.	25% Exc.	50% Exc.	75% Exc.	90% Exc.	99% Exc.	Expected Value
2011	972	821	696	601	516	446	666
2012	656	509	356	272	194	194	347
2013	813	666	552	426	328	241	499
2014	598	435	275	198	193	193	291
2015	668	500	335	231	193	193	331
2016	911	770	628	526	425	350	594
2017	1185	1031	908	806	697	526	859
2018	503	445	383	349	314	276	375
2019	698	638	568	518	455	382	544
2020	554	489	424	383	343	314	413
2021	654	552	455	394	334	240	435
2022	843	660	523	394	314	226	482

	March B120 Volumes						
year	10% Exc.	25% Exc.	50% Exc.	75% Exc.	90% Exc.	99% Exc.	Expected Value
2011	865	759	678	612	573	502	659
2012	452	314	239	202	202	202	253

2013	628	504	398	334	285	285	393
2014	510	399	279	228	193	193	286
2015	482	370	276	215	199	199	276
2016	762	640	550	480	428	354	529
2017	861	779	703	663	625	559	694
2018	333	298	383	227	210	210	283
2019	1068	964	858	766	672	596	817
2020	338	308	276	240	216	216	263
2021	490	416	339	290	237	221	326
2022	584	471	358	289	288	288	363

	March B120 Volumes (TAF)						
year	10% Exc.	25% Exc.	50% Exc.	75% Exc.	90% Exc.	99% Exc.	Expected Value
2011	865	759	678	612	573	502	659
2012	452	314	239	202	202	202	253
2013	628	504	398	334	285	285	393
2014	510	399	279	228	193	193	286
2015	482	370	276	215	199	199	276
2016	762	640	550	480	428	354	529
2017	861	779	703	663	625	559	694
2018	333	298	383	227	210	210	283
2019	1068	964	858	766	672	596	817
2020	338	308	276	240	216	216	263
2021	490	416	339	290	237	221	326
2022	584	471	358	289	288	288	363

	April B120 Volumes (TAF)						
year	10% Exc.	25% Exc.	50% Exc.	75% Exc.	90% Exc.	99% Exc.	Expected Value
2011	1082	1005	937	906	879	820	933
2012	412	346	276	246	217	207	277
2013	482	419	354	322	299	299	355
2014	390	325	270	232	206	204	265
2015	255	217	209	209	209	209	214
2016	740	677	618	588	560	530	614
2017	1199	1151	1103	1077	1051	1013	1097
2018	580	546	512	482	448	418	498
2019	1052	994	932	882	830	764	908
2020	328	310	290	272	252	224	280
2021	395	347	295	261	245	245	292

2022	425	363	296	296	296	296	319

	May B120 Volumes						
year	10% Exc.	25% Exc.	50% Exc.	75% Exc.	90% Exc.	99% Exc.	Expected Value
2011	977	951	927	911	895	863	920
2012	372	342	312	296	285	268	310
2013	377	350	321	307	307	307	324
2014	286	255	226	213	213	213	230
2015	209	209	209	209	209	209	209
2016	681	653	628	612	594	560	621
2017	1254	1212	1170	1142	1114	1084	1160
2018	573	549	525	501	477	454	513
2019	1004	958	912	878	844	814	899
2020	327	312	295	285	268	234	288
2021	294	270	252	252	252	252	259
2022	353	314	296	296	296	296	305

Appendix E. Results from FFAIM for all modeled years (2011-2022)

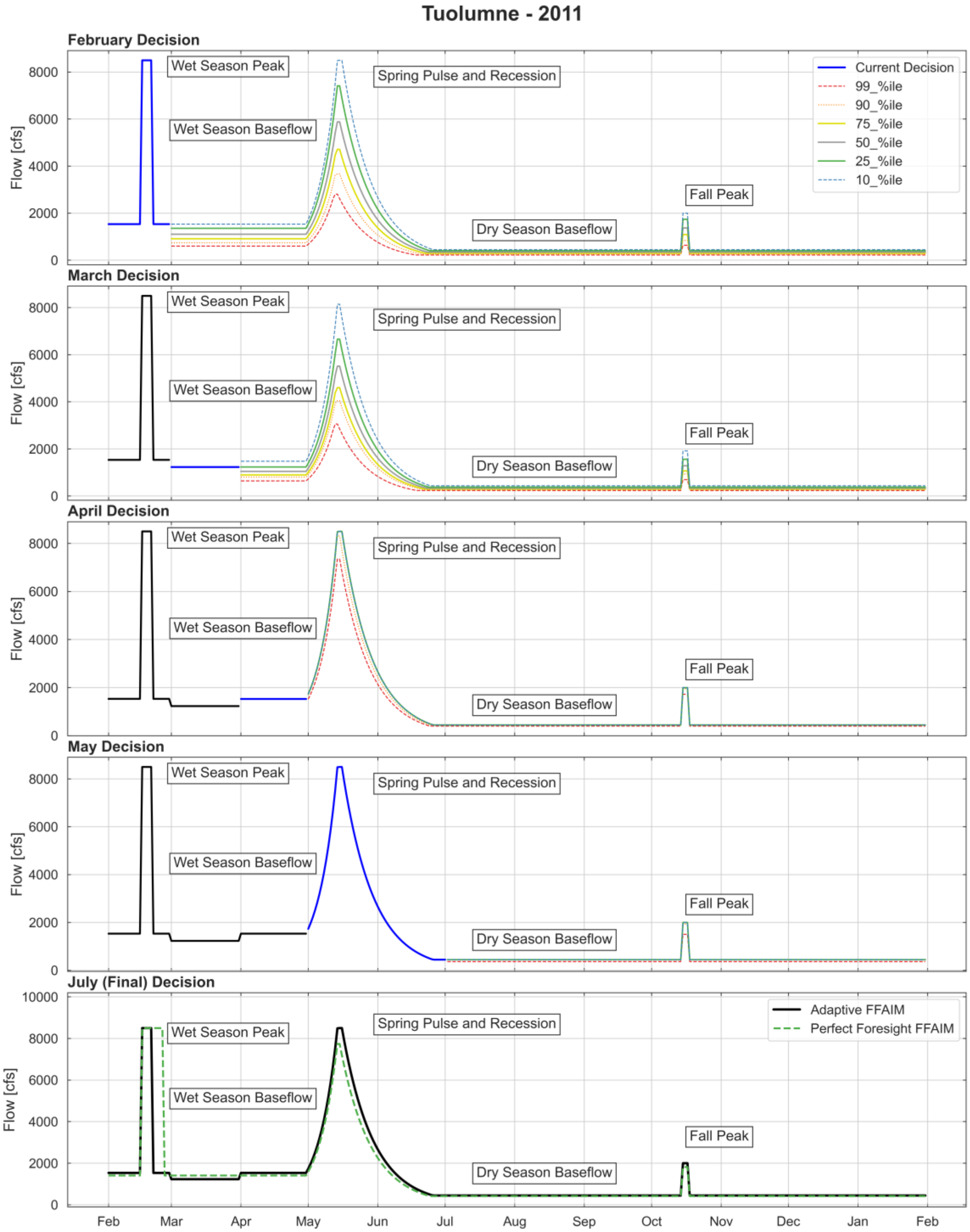


Figure 1: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

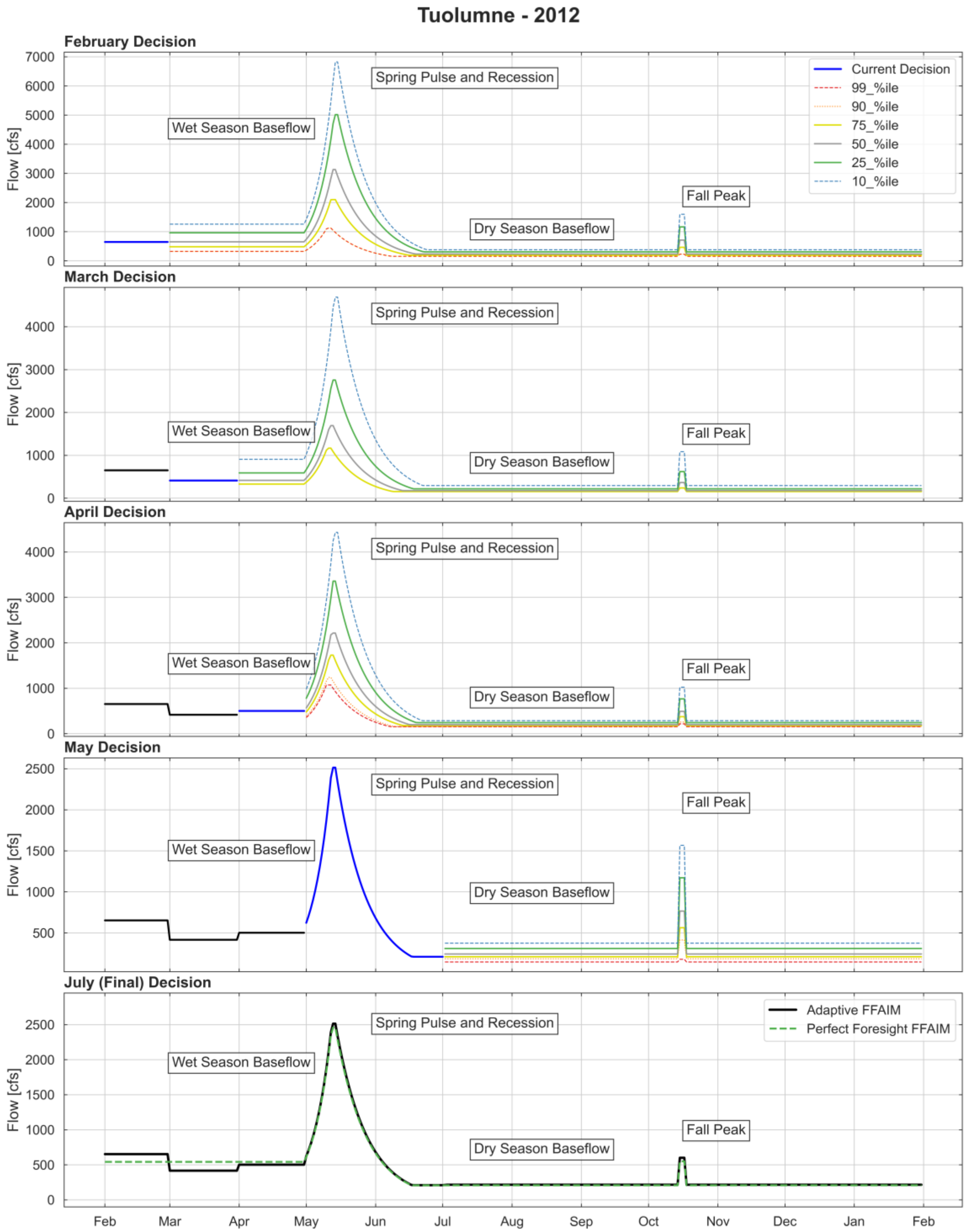


Figure 2: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

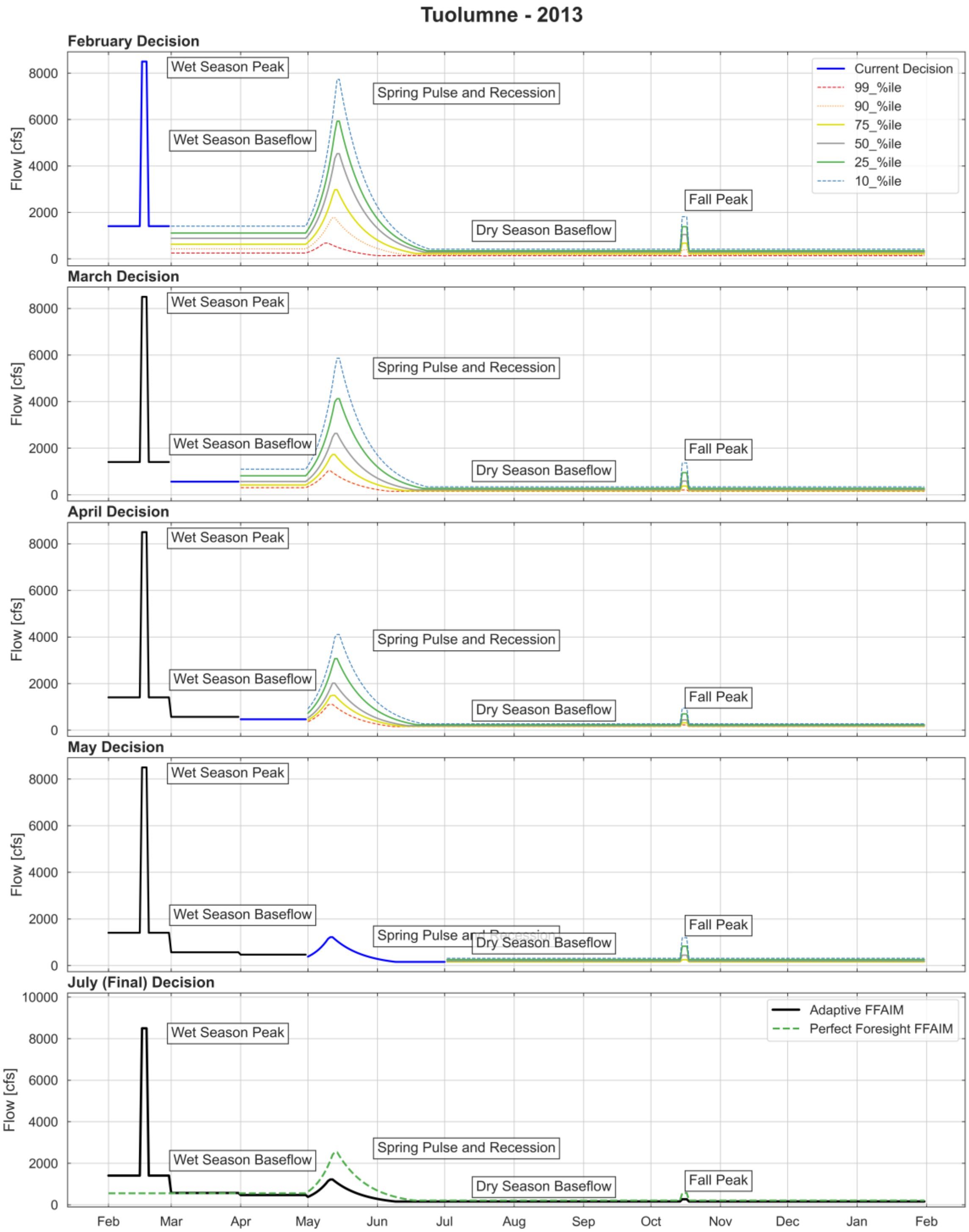


Figure 3: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

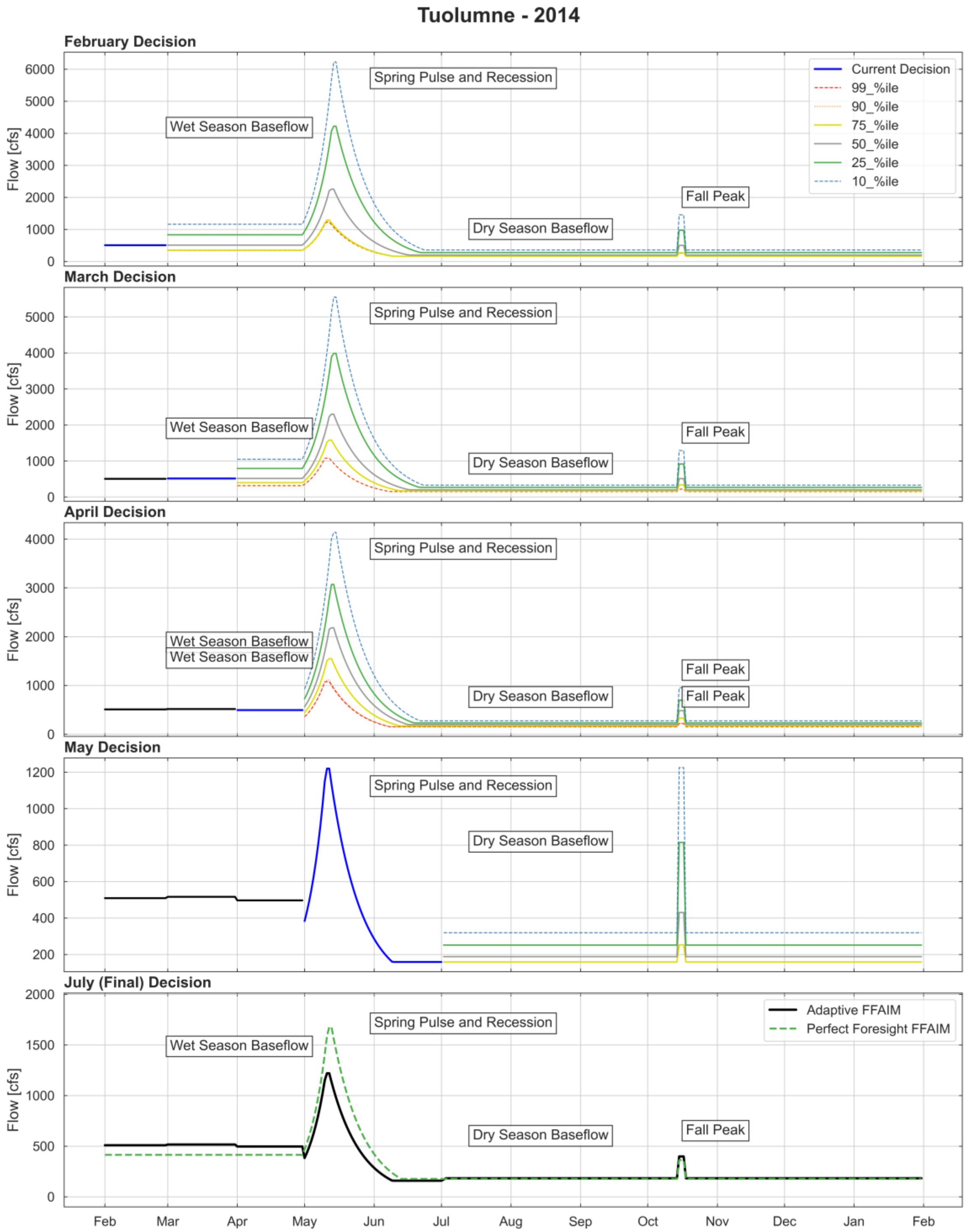


Figure 4: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

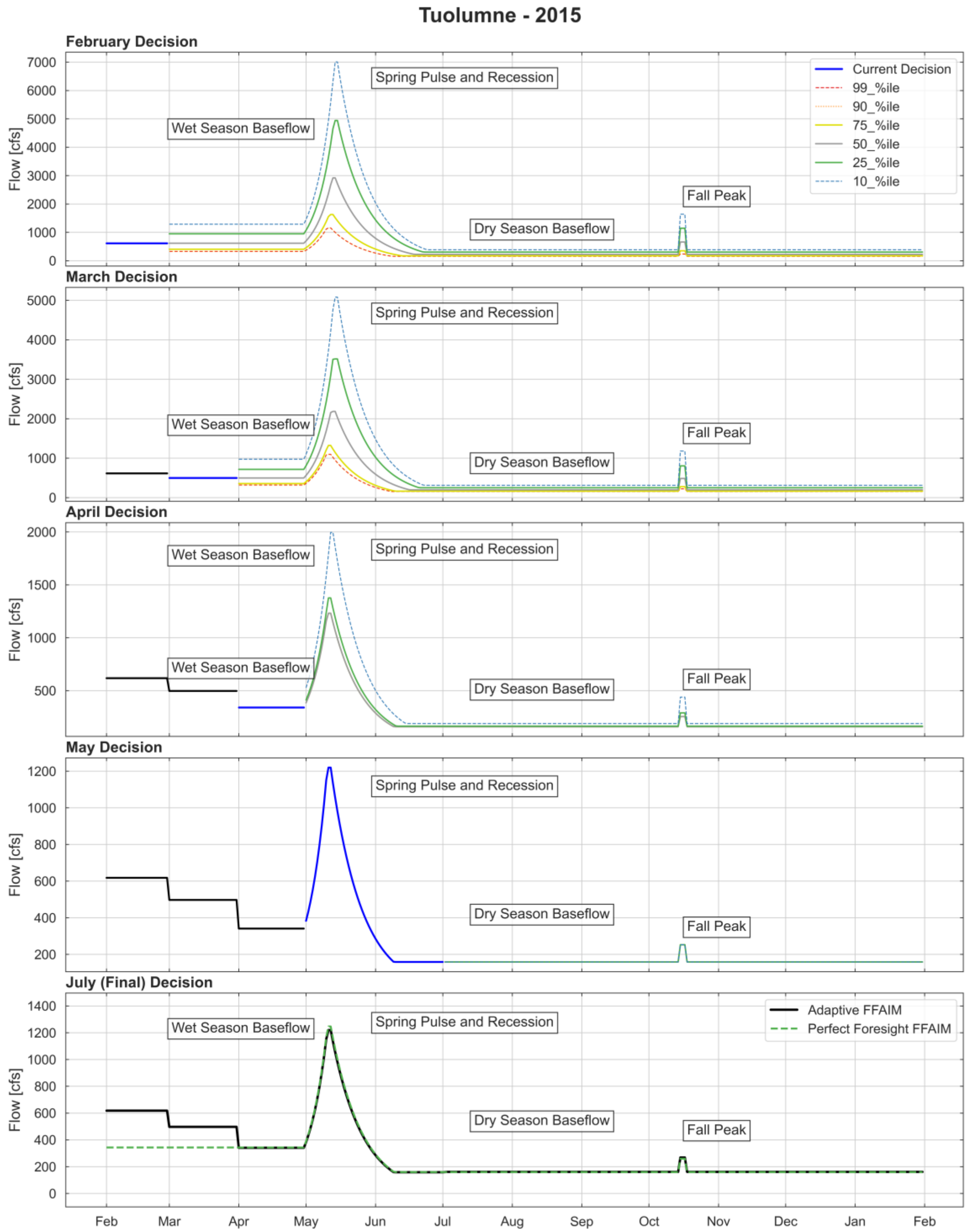


Figure 5: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

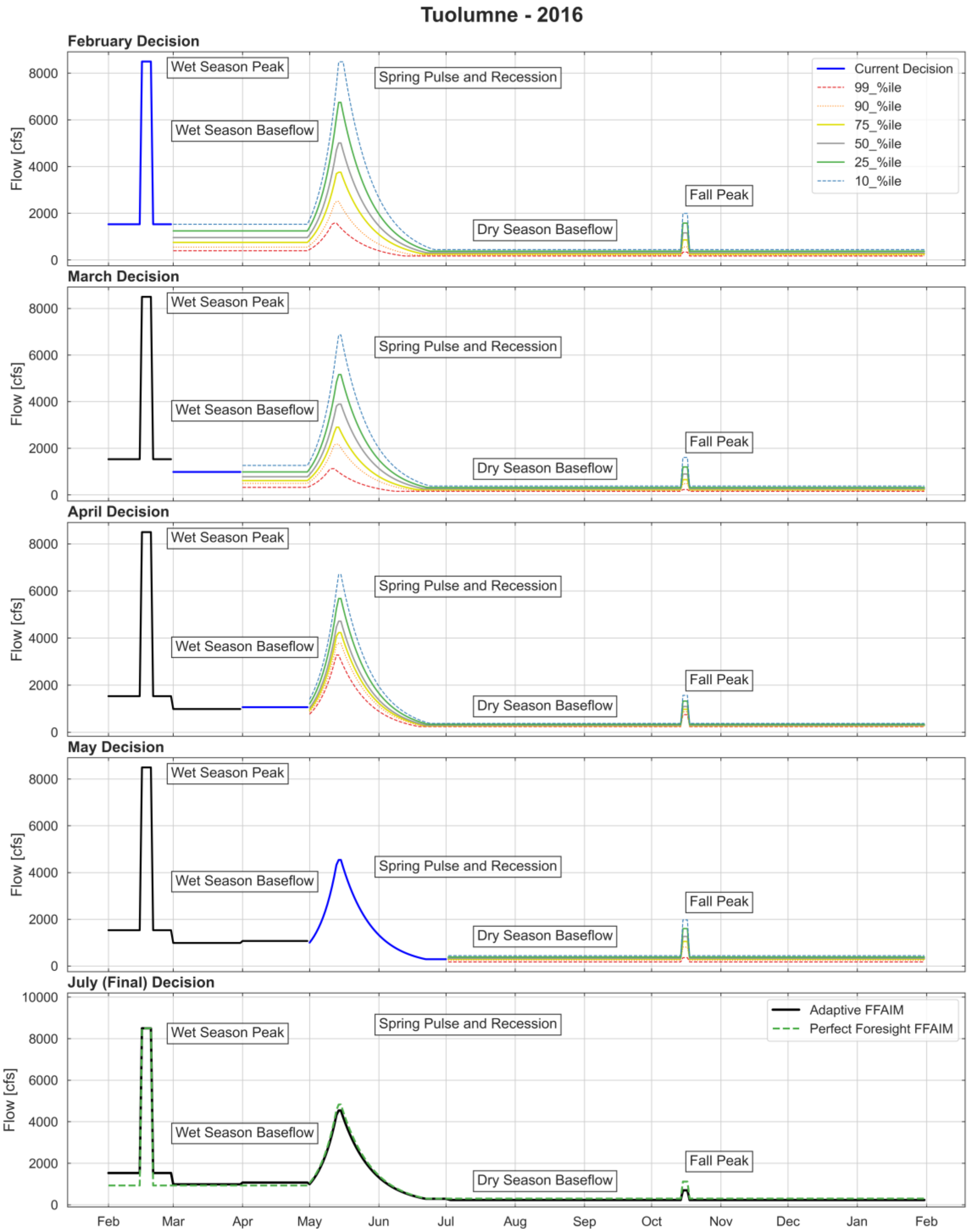


Figure 6: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

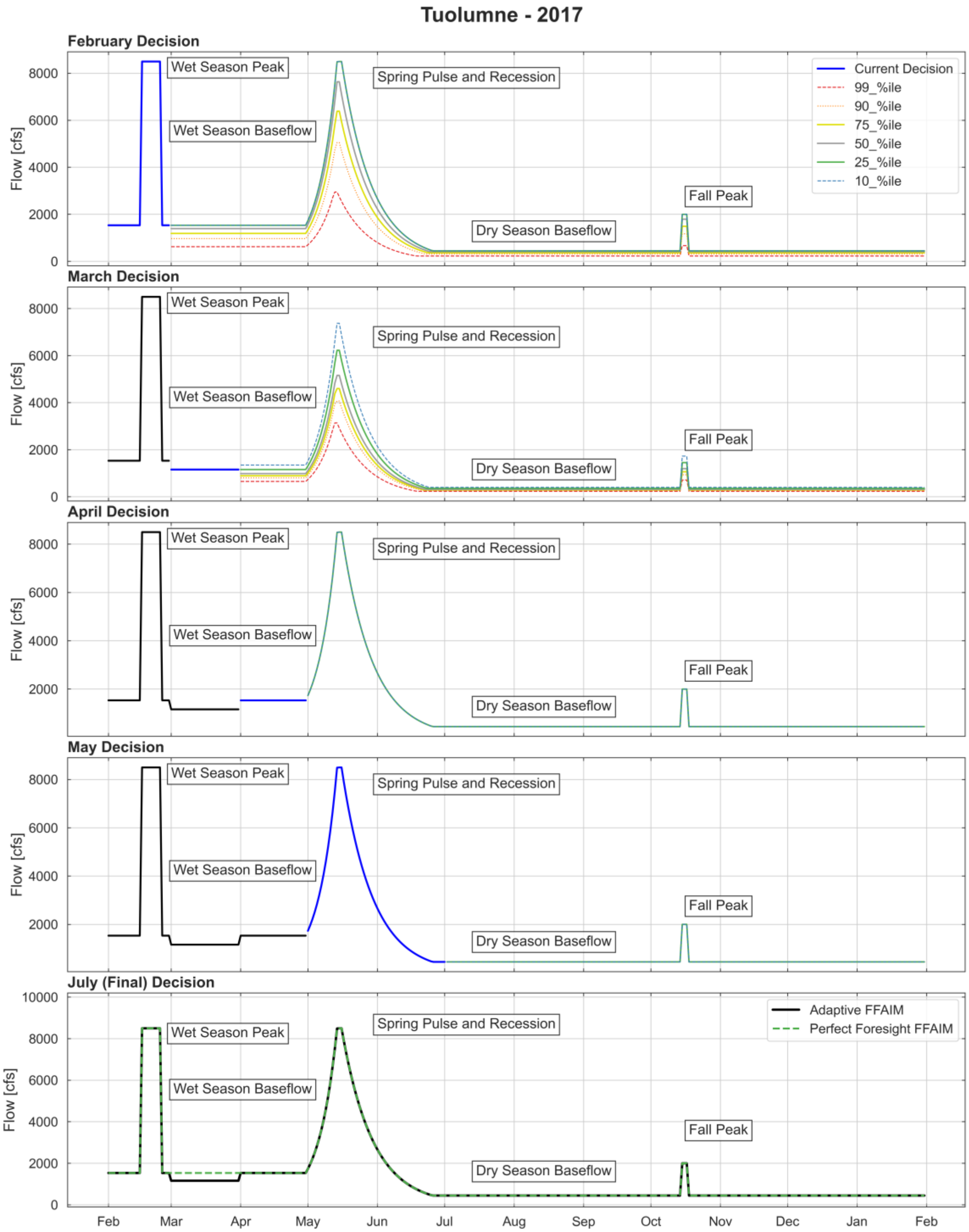


Figure 7: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

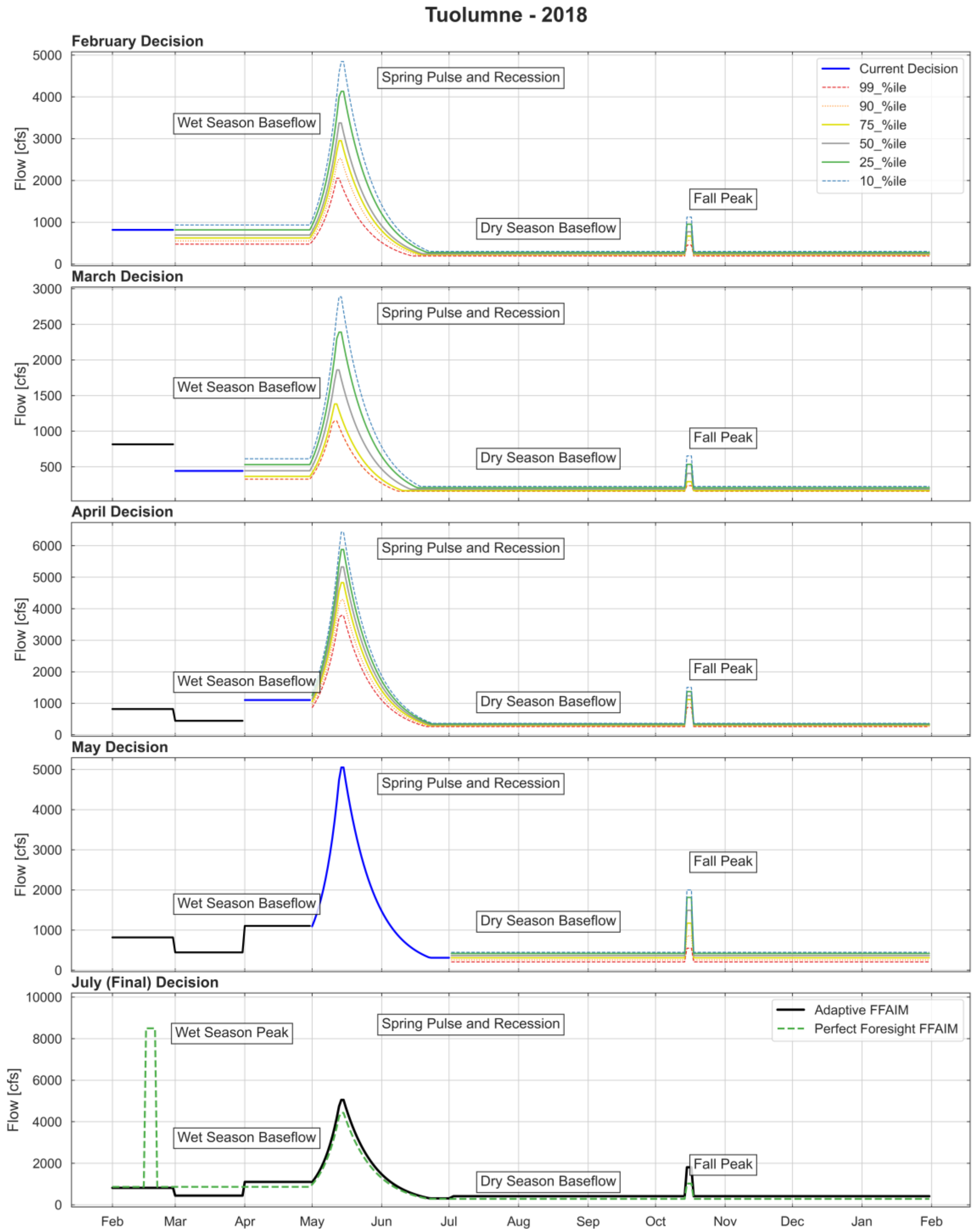


Figure 8: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

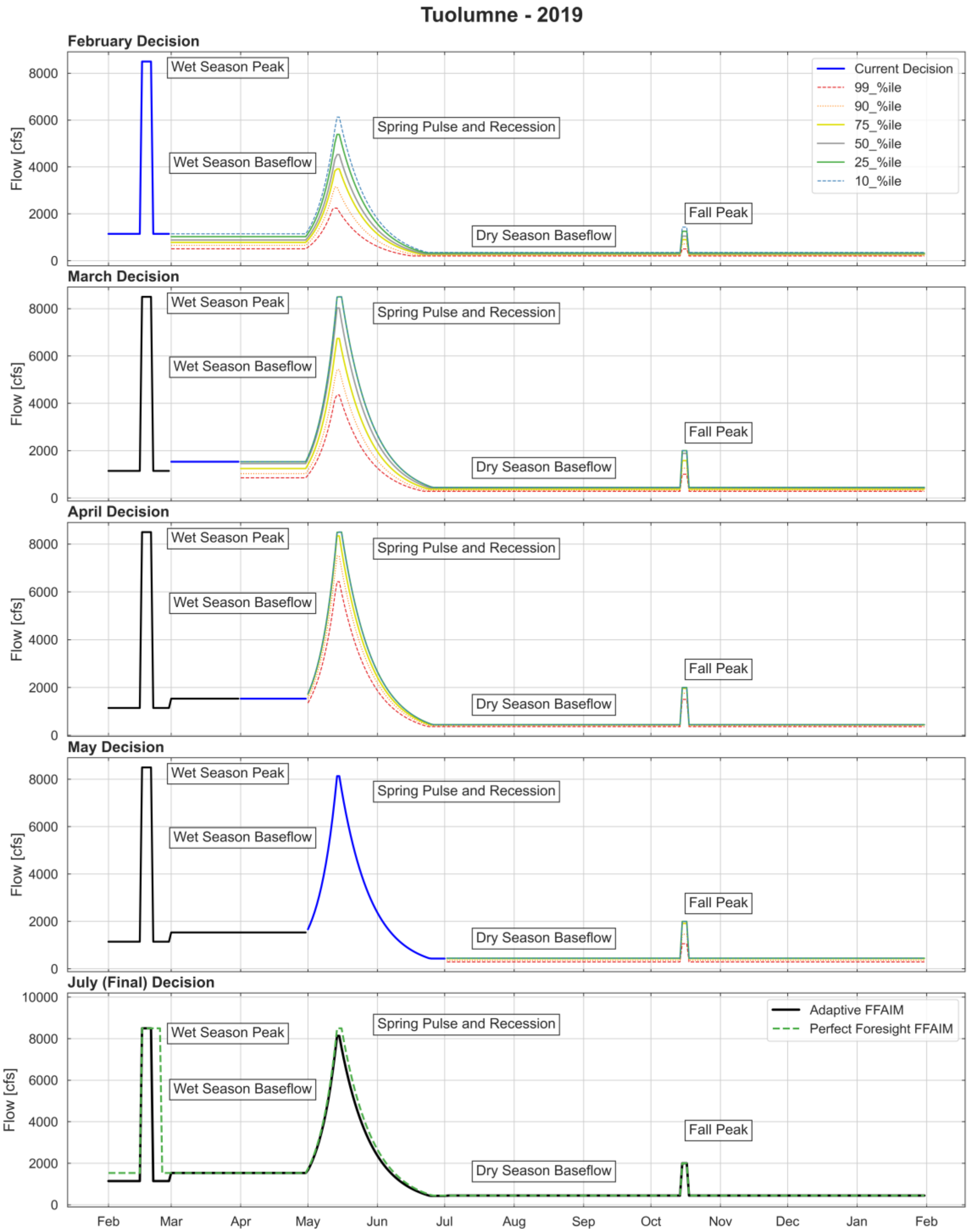


Figure 9: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

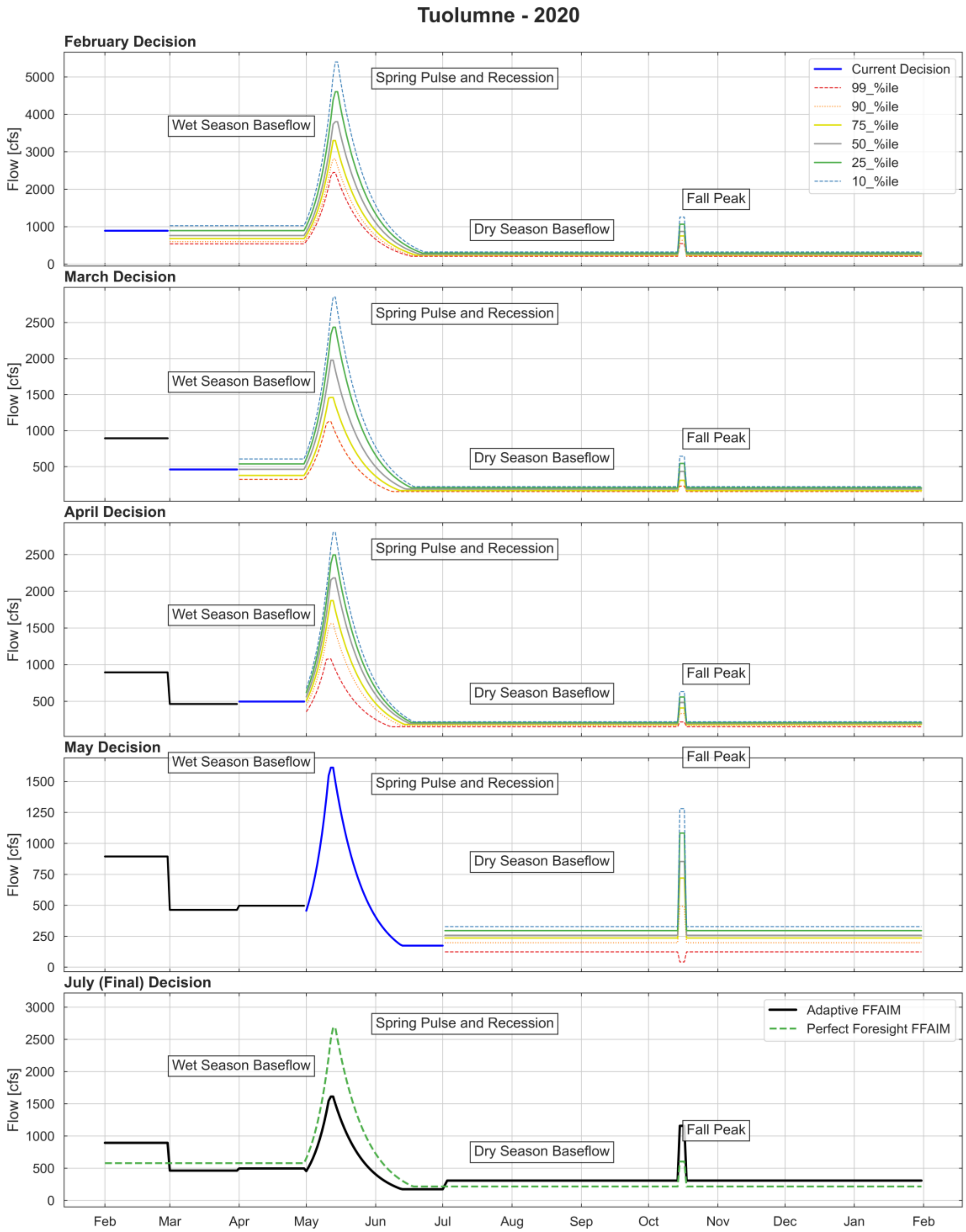


Figure 10: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

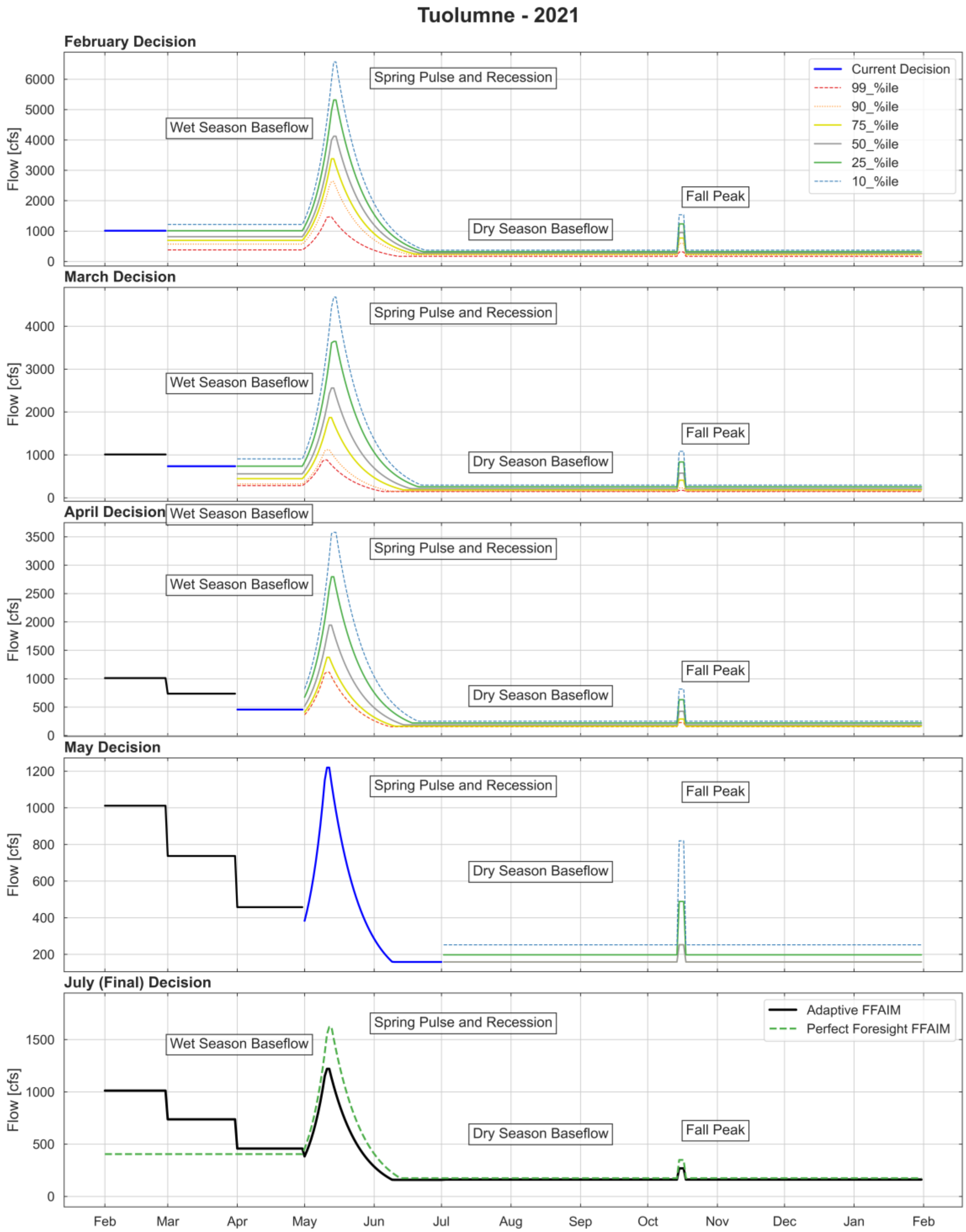


Figure 11: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.

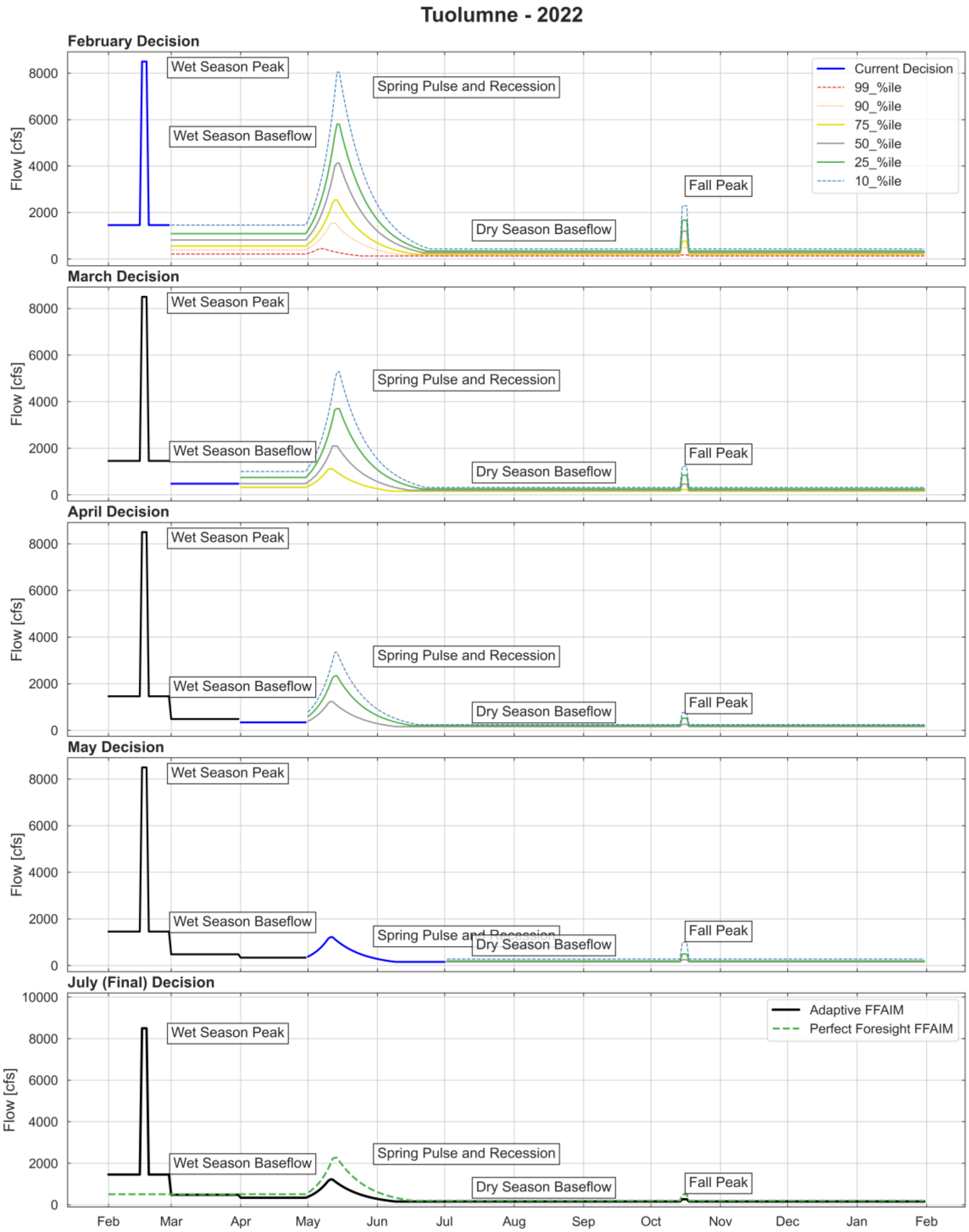


Figure 12: FFAIM recommended flows at each decision period, February to May, with expected releases for each forecasted scenario (10-99th percentiles). The last decision period also includes Perfect Foresight as the final flow-budget is known.