Title

Reducing agriculture's groundwater pumping impact on streams: remedial action cost, resulting fish benefits, and planning tools in Scott Valley, California

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Reducing agriculture's groundwater pumping impact on streams: remedial action cost, resulting fish benefits, and planning tools in Scott Valley, California

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Abstract

In many rural areas in arid and semi-arid regions, balancing agricultural and environmental water demands is a key challenge facing resource managers, which is complicated by the interconnection of groundwater and surface water resources. In California, water management decisions are increasingly supported by hydrologic models, but these can often provide confusing or overwhelming amounts of information. The Scott River watershed (HUC8 18010208), a 2,109 km^2 undammed rural basin in northern California, was used as a case study to develop a suite of tools, informed by a groundwater-surface water model, for water managers, including: 1) a hydrologic proxy for the ecological success of a key aquatic species; 2) applying a quantitative multi-benefit framework (i.e., incorporating ecological, agricultural, and cost objectives) to an existing groundwater planning process; and 3) two locally-tailored, seasonal, quantitative predictions of fall-season watershed behavior as a complement to historically-used water year type categories.

Chapter 1 aims to quantify hydrologic conditions that support persistence of the Scott Valley coho salmon (*Oncorhynchus kisutch*) run. We applied the functional flows framework to characterize the hydrology of each water year measured at a key long-term stream gauge. Taking advantage of a nearly two-decade ecological monitoring dataset, we built linear models to predict coho salmon reproductive success using combinations of one and two hydrologic metric predictors. We used an ensemble of the three best linear models to formulate a Hydrologic Benefit function, summarizing the ecological services provided by the hydrology in different seasons into a single index value per water year.

In Chapter 2, we apply a multi-benefit framework to a portfolio of management actions, which were proposed for the Scott Valley jurisdiction during the recent development of a long-term Groundwater Sustainability Plan (GSP). We developed a summary statistic or proxy for each of the three primary policy objectives in the GSP (environmental, agricultural, and project cost). We then used them to summarize the results of 40 management scenarios developed for the Groundwater Sustainability Plan (GSP) in Scott Valley in Northern California, which were simulated using an existing integrated surface- and groundwater model. We found that a trade-off in benefits for fish and farms was evident in every category of infrastructure investment (a proxy for project cost), though greater infrastructure investment can achieve some reductions in this trade-off. Additionally, although the GSP management priorities emphasized infrastructure investments, both infrastructure-based and regulatory approaches fell within the Pareto-optimal set of management options under a strict application of these objective functions. Finally, regarding regulatory actions, management interventions targeted at low-flow periods produced a more efficient gain in environmental flow value per cost in agricultural productivity.

In Chapter 3, we propose methods to predict, approximately five months in advance, two key hydrologic metrics in the Scott River watershed. Both metrics are intended to quantify the transition from the dry to the wet season, to characterize the severity of a dry year and support seasonal adaptive management. The first metric is the minimum 30-day dry season baseflow volume, $V_{min,\ 30\ days}$, which occurs at the end of the dry season (September-October) in this Mediterranean climate. The second metric is the cumulative precipitation, starting Sept. 1st, necessary to bring the watershed to a "full" or "spilling" condition (i.e. initiate the onset of wet season storm- or baseflows) after the end of the dry season, referred to here as P_{spill}. As potential predictors of these two values, we assess maximum snowpack, cumulative precipitation, the timing of the snowpack and precipitation, spring groundwater levels, spring river flows, reference ET, and a subset of these metrics from the previous water year. We find that, though many of these predictors are correlated with the two metrics of interest, of the predictors considered here, the best prediction for both metrics is a linear combination of the maximum snowpack water content and total October-April precipitation. These two linear models could reproduce historic values of $V_{min,\ 30\ days}$ and P_{spill} with an RMSE of 1.4 Mm^3 / 30 days (19.4 cfs) and 20.7 mm (0.8 inches), respectively.

The tools developed for this case study could be of value for other local jurisdictions with similar features, including a Mediterranean and/or intermontane (snow-fed) climate, an undammed watershed, and challenges balancing agricultural and environmental water needs. The method for empirically deriving the highest-priority hydrologic functions for a threatened species could be used in other watersheds (if sufficient ecological data records are available) to evaluate trade-offs and support water management decisions in human-altered novel ecosystems. The development of basin-specific objective functions, especially ones using output from existing hydrologic models, could help quantify management decision trade-offs and improve stakeholder communication in ongoing water planning efforts throughout the region. And finally, although careful consideration of baseline conditions used as a basis for prediction is necessary, seasonal predictive indices could be used by governance entities to support adaptive management in an uncertain future climate.

Introduction

Background and Motivations

In rural water-limited regions, the hydrologic demands of agriculture and river ecosystems often resemble a zero-sum game: water that leaves a watershed as evapotranspiration through crops becomes unavailable to provide aquatic habitat. These areas often encompass surface water systems that have been heavily altered by human land uses (referred to as "novel" ecosystems; Moyle 2014), and restoration of streams to pristine natural conditions in actively farmed landscapes is rarely feasible. However, preserving specific ecological functions in an engineered landscape can be a more tractable goal (e.g., Robertson and Swinton 2005; Arthington, Bernardo, and Ilhéu 2014; Acreman et al. 2014).

Although environmental regulations are often promulgated by state or federal authorities, the mediation of these competing demands, and thus the persistence of aquatic resources, is often determined locally (Tarlock 1993). Reflecting this reality, this dissertation is composed of three separate investigations focused on a single case study watershed: Scott Valley in northern California, USA. The Scott River is a major tributary to the Klamath, and Scott Valley is an intermontane watershed with a Mediterranean climate, an alluvial aquifer, and significant agricultural land uses (Figure 1). Of relevance to this dissertation is the fact that Scott Valley is subject to the requirements the recent California water planning law, the Sustainable Groundwater Management Act (SGMA).

SGMA was passed by the California legislature in 2014, in the depths of a drought. It requires each local Groundwater Sustainability Agency (GSA) to define sustainability in the negative, by quantifying and then avoiding "undesirable results" that would be "significant and unreasonable". In addition, SGMA broke new ground in California statute by formally recognizing that groundwater and surface water are interconnected, and that extraction or diversion of one resource can affect the other. The central undesirable result in Scott Valley is streamflow depletion due to groundwater pumping. Consequently, a central challenge under SGMA was defining a "reasonable" amount of streamflow depletion reversal, accounting for environmental water demand and what degree of agricultural water security was necessary to sustain the local economy.

To comply with SGMA, the local government and public stakeholders recently spent three years developing a plan for the long-term use of groundwater (a Groundwater Sustainability Plan or GSP). During this time several themes emerged. Firstly, a key environmental goal, preserving the Scott River salmonid fishery, was somewhat underdetermined, in that the exact flows needed to support the fishery were not well constrained. This constitutes the motivation for Chapter 1. Secondly, the determination of what management scenario yielded a “reasonable” amount of stream depletion depended on a comparison to all possible other scenarios, which was challenging given the abundant information generated by each simulated scenario. This led to the motivation for Chapter 2. Finally, the concept of “water year type” was used extensively, but the categorical water year type could sometimes obscure meaningful differences in watershed behavior. This was the motivation for Chapter 3.

Objectives

Based on these motivations, the objectives of the following three studies are to:

1. Empirically identify a hydrologic regime that meets the ecological needs of a key aquatic species in the Scott River watershed, and use that information to produce a prediction formula for fish reproductive success, based only on hydrologic metrics.
2. Develop functions to quantify three planning objectives, and apply them to more than three dozen potential management actions proposed in a recent public planning process. Then, with this quantitative multi-benefit framework, summarize the hydrologic results of all proposed scenarios, thereby outlining the “solution space” of proposed management outcomes.
3. Provide locally-tailored, quantitative and predictive tools for seasonal adaptive management, which may be necessary to meet quantitative management goals, especially in a changing climate.

1 Chapter 1. A watershed-specific formula to predict coho salmon reproduction using river flow metrics

1.1 Abstract

In many rural areas in arid and semi-arid regions, balancing agricultural and environmental water demands is a key challenge facing resource managers. Although flow-ecology relationships are well-studied, the water needs of cultivated crops are generally better understood than those of aquatic ecosystems. In particular, the timing and magnitude of flow needed to sustain key ecological functions remains poorly quantified in many regions. This work aims to quantify hydrologic conditions that support persistence of the coho salmon (*Oncorhynchus kisutch*) run in Scott Valley, a 2,109 km^2 undammed rural watershed in northern California, USA. We applied the functional flows framework to characterize the hydrology of each water year measured at a key long-term stream gauge. Taking advantage of a nearly two-decade ecological monitoring dataset, we built linear models to predict coho salmon reproductive success using combinations of one and two hydrologic metric predictors. We used an ensemble of the three best linear models to formulate a Hydrologic Benefit function, summarizing the ecological services provided by the hydrology in different seasons into a single index value per water year. This method for empirically deriving the highest-priority hydrologic functions for a threatened species could be used in other watersheds (if sufficient ecological data records are available) to evaluate trade-offs and support water management decisions in human-altered novel ecosystems.

1.2 Introduction

Reconciliation ecology posits that some human-impacted ecosystems should be considered irrevocably-altered, "novel" systems (Moyle 2014), with their own specific management concerns. To implement this philosophy, rather than working to restore novel ecosystems to pre-human conditions, a natural resource manager would embrace a role as earth system engineer, and would actively manage biodiversity in human-altered landscapes as a co-equal goal with extracting and cultivating natural resources to provide for human material needs (e.g., Robertson and Swinton 2005; Arthington, Bernardo, and Ilhéu 2014; Acreman et al. 2014). But critical knowledge gaps are abundant and make this dual objective seem intractable. In many river ecosystems, though general methods to characterize environmental flows have been in wide use for at least a decade (e.g., N. L. Poff and Zimmerman 2010; Shenton et al. 2012; Solans and García de Jalón 2016), the regional-scale conditions that would maintain biodiversity are as yet unquantified or highly uncertain (N. L. Poff et al. 2010). Higher certainty in quantitative ecological targets could support more robust decision making and trade-off analysis, potentially answering questions like: how close can managers get to the desired ecological conditions, and at what cost, particularly in a changing climate?

In practice, these questions are often asked and answered locally (Tarlock 1993). The entities managing natural resources, and thus determining the regional persistence of non-human species, are typically the communities living and working with local resources. Reflecting this reality, the authors of this study have posed research questions tailored to conserving a specific endangered salmon species, coho salmon (*Oncorhynchus kisutch*), in a specific study area: the Scott River watershed in northern California, USA. In this undammed, rural watershed, the primary way to manage water use is by managing land use, and balancing the competing water needs of fish and farmers is a key challenge for local water managers (Siskiyou County 2021). Agricultural water needs are well-known and can be estimated and scheduled (Siskiyou RCD 1994; Parry 2013; DWR 2021), but, in spite of decades of investigation by local, state and federal actors (e.g., SRWC and Siskiyou RCD 2003; NMFS 2014; CDFW 2015b, CDFW 2021), the ecological water needs in this balancing act are not as well constrained.

One method for estimating ecological water needs is the functional flows framework (Poff et al. 1997; N. L. Poff and Zimmerman 2010). Functional flow metrics are used to quantify potential ecological services provided by river flow in terms of flowrate amplitude, timing, frequency, and duration in distinct seasons of a water year. Recent work has refined these metrics for California hydrology and made the metric-calculating algorithms publicly available (Yarnell et al. 2020; Patterson et al. 2020).

To learn if it is possible to empirically quantify a hydrologic regime that meets the ecological needs of coho salmon in the Scott River watershed, we examine correlations between several dozen hydrologic metrics and local salmon observations. We then use linear models to predict salmon outcomes based on potential combinations of hydrologic metric predictors. We use the best of these linear models to formulate a Hydrologic Benefit function, distilling the ecological services provided by hydrology in different seasons into a single index value per water year. This work sets the stage for a quantitative comparison of competing natural resource management alternatives (as is explored further in Chapter 2 of this dissertation).

1.3 Case study: setting and species of concern

Exploring the empirical relationship between river hydrology and an ecological response requires a study area with favorable geography and ecological monitoring data. Geographically, the ecological monitoring must be within an area that is plausibly affected by the hydrology at the point of river observation. Ecologically, in order to go beyond static snapshot analyses (Wheeler, Wenger, and Freeman 2018), the species-level observations of life stages which are facilitated by specific flow rates (such as spawning and rearing for salmonids) must cover a wide range of dry to wet water year conditions, which usually means decades of time-intensive and costly aquatic data collection.

Both of these requirements are met in Scott Valley, where daily river flow monitoring has been ongoing since the 1940s at the USGS stream gauge downstream of the town of Fort Jones (Station ID #11519500, or the Fort Jones Gauge or FJ Gauge; Figure 1). The flow at this gauge is correlated with flow in tributary streams (Foglia et al. 2013), and though a single monitoring location may not be able represent flow status in the full stream system at all times, it has been used in recent water planning documents as an indicator of overall hydrologic conditions (Siskiyou County 2021). Because most water use in Scott Valley occurs upgradient of this gauge, its measurements are used to inform water management decisions in the populated areas of the valley.

Routine monitoring of spawning anadromous fish in this watershed and the broader Klamath basin has been ongoing since at least 1978 (Knechtle and Chesney 2012). More in-depth monitoring of multiple salmonid life stages in the Scott River watershed has occurred since 2003 (e.g., Maurer 2003; Knechtle and Giudice 2021). Local fish monitoring has included observations of Chinook salmon and steelhead, but for purposes of this study we will focus on the most threatened species, the coho salmon. In this study we will take advantage of this nearly two-decade record of adult spawner and juvenile coho salmon abundance observations to draw preliminary conclusions regarding this hydrology-ecology relationship.

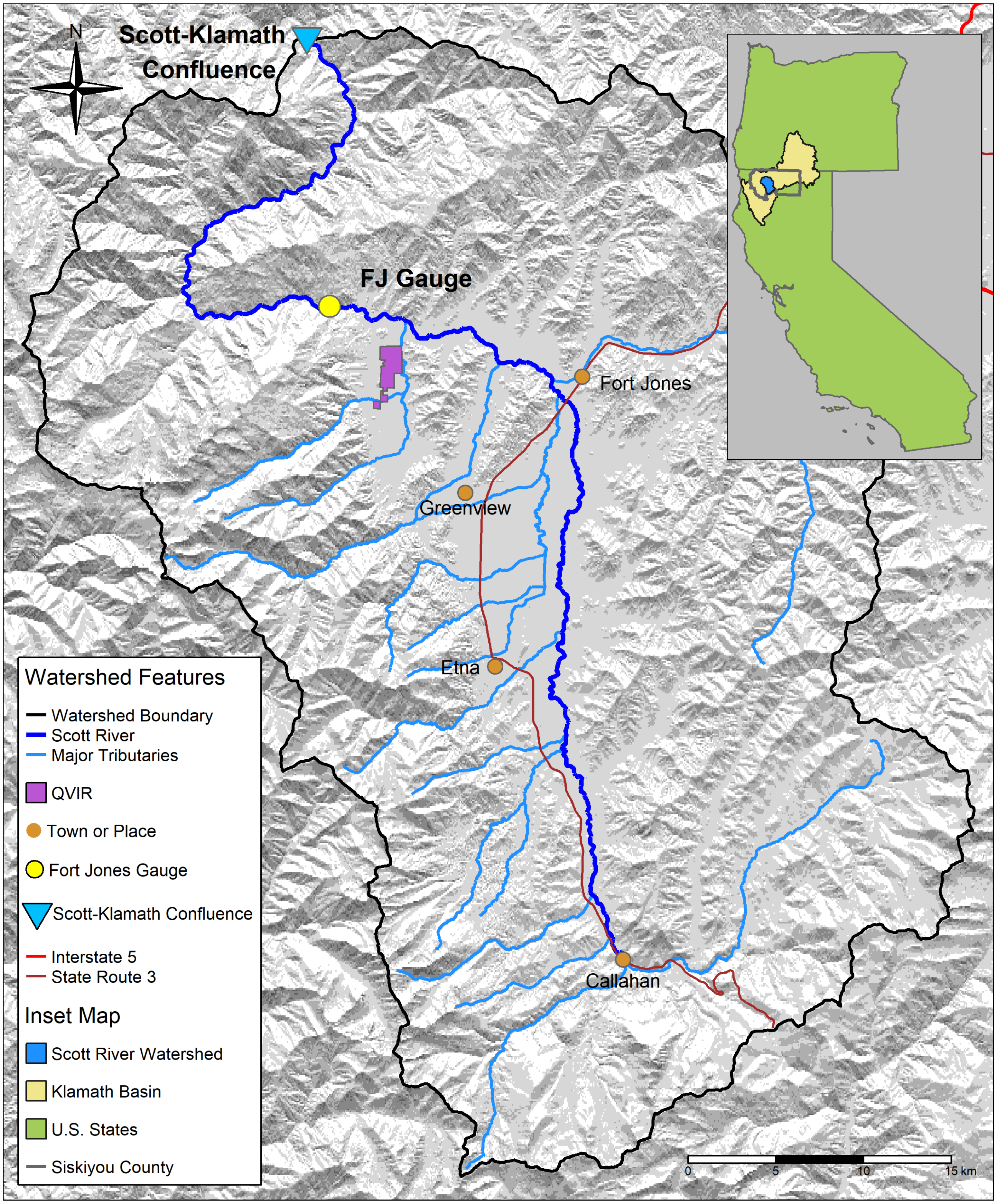


Figure 1: The Scott River watershed, with regional geographic context (see inset) and local features. Scott River flows generally from south to north and joins the Klamath after flowing through a steep canyon.

1.3.1 Scott River watershed setting and water use

Geography, climate and hydrology

The Scott River drains a 2,109 km^2 (814 square mile) watershed known as Scott Valley, and is a major tributary to the Klamath River, which drains an area spanning sections of Northern California and Southern Oregon (Figure 1). Scott Valley has a Mediterranean climate with distinctive seasons of cool, wet winters and warm, dry summers. This seasonality in water input creates highly seasonal flow in the Scott River and tributary streams (Figure 2). To accommodate this precipitation and runoff schedule, water years in California conventionally begin on Oct. 1; they are named for the year in which they end (e.g., water year 2021 begins Oct. 1, 2020 and runs through Sep. 30, 2021).

In most dry-to-average water years, sections of the Scott River become seasonally dewatered (NCRWQCB 2005; Figure 5 in Tolley, Foglia, and Harter 2019). This occurs when the elevation of the water table drops below the bottom of the river channel, because streams and groundwater are highly interconnected in the Scott River watershed. Tributary streams, particularly along their alluvial fan apeces, and the Scott River are a source of recharge to the aquifer, and groundwater discharge sustains streamflow in some areas, especially during the dry season of August-October or November (Tolley, Foglia, and Harter 2019).

Human population

Two incorporated communities, the towns of Fort Jones and Etna, are located within the boundary of the watershed (Figure 1). The estimate of their population size in 2020 was 695 and 678, respectively (U.S. Census Bureau 2021). Other communities in the watershed include the unincorporated communities of Callahan, Greenview, and the Quartz Valley Indian Reservation on tribal trust lands.

The region is largely rural, and many watershed residents live outside the incorporated community boundaries. Scott Valley is not a census-designated place and therefore does not have an official population estimate; however, census block-level population data, area-weighted according to the fraction of each block that overlaps with the watershed, indicate that in 2020 the population of the Scott River watershed was approximately 5,186 (U.S. Census Bureau 2021), including the populations of the two incorporated towns.

Water uses and management objectives

Water in Scott Valley is used for agricultural, domestic, and municipal supply. It also facilitates recreation and provides Native American cultural services, among other designated beneficial uses (NCRWQCB 2006). Because the watershed is undammed, managers and water users influence Scott River flow primarily via

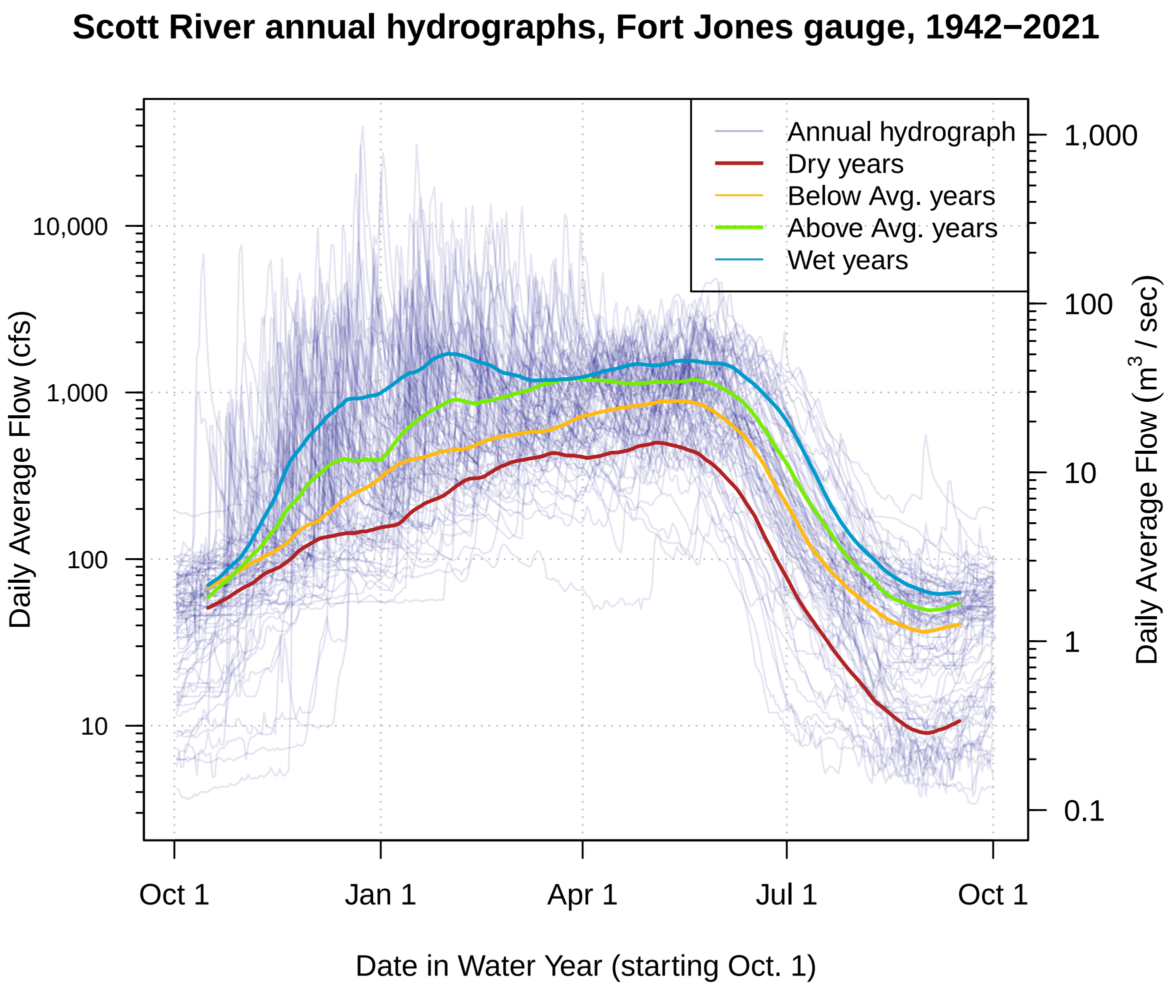


Figure 2: The Mediterranean climate produces highly seasonal flows in the Scott River. Each translucent line traces one annual hydrograph measured at the Fort Jones gauge, and the darker lines illustrate the 30-day smoothed median daily flow in Dry, Below Average, Above Average, and Wet water year types, for water years 1942-2021. The water year type is defined by quartiles of the distribution of total annual flow.

diversion of surface waters and pumping of groundwater. Consequently the most powerful tool available to manage Scott River water flow is regulation of land use and thus water demand (Siskiyou County 2021).

Historically, local regulation of land use has focused on maintaining the rural and agricultural character of Scott Valley (Scott Valley Area Plan Committee 1980). Regulating land use to improve ecological outcomes would entail significant economic, political and social risks, because much of the economic activity in this area is related to agriculture. The primary crops grown in Scott Valley are pasture for cattle feed and alfalfa (Siskiyou County 2021). In addition to local economic impact, Scott River conditions influence fish population dynamics both within the watershed and in the broader Klamath system. The health of the Klamath salmon run has implications for commercial fishing, recreational activities, and cultural practices of Native American tribes in the region, including the Quartz Valley Indian Community and the Karuk and Yurok Tribes (Graham 2012).

All of the regulatory and management programs in this region, including recommended instream flows (CDFW 2017) and legal rights governing surface water diversion (Superior Court of Siskiyou County 1980), are tabulated in units of cubic feet per second (cfs). For consistency, this document will also use primarily cfs units.

1.3.2 Species of concern: coho salmon, *Oncorhynchus kisutch*

Coho salmon in the Scott Valley are listed as threatened under the federal and California Endangered Species Acts (ESAs). They belong to the Southern Oregon / Northern California Coast (SONCC) Evolutionarily Significant Unit (ESU), which was listed as threatened under the federal and state ESAs in 1997 and 2005, respectively. State-wide, coho populations have declined more than 90% since the 1940s (Brown, Moyle, and Yoshiyama 1994). Of course, factors influencing the population size of anadromous fish include ocean conditions and freshwater conditions; in this study, because we are interested only in the conditions in their natal streams, we have focused on fish population metrics that are influenced by the freshwater system, such as number of coho smolt produced per female spawner.

Coho salmon life cycle

Returning adult coho spawn in natal streams between November and January (Moyle 2002; McMahon 1983), and juvenile coho spend approximately one full year in freshwater streams before migrating to the ocean as smolts. Their habitat needs are somewhat different during summer and winter: in summer, coho are found most commonly in cool pools, more than 1 meter deep, with abundant cover (e.g., woody debris or undercut banks) (Moyle 2002; Giannico and Hinch 2007; Nickelson et al. 1992). In winter, coho are most abundant in areas with flow refugia, such as alcoves and beaver ponds (Nickelson et al. 1992) or riverine ponds (Peterson 1982), and complex cover such as low velocities, shade, and complex woody debris (McMahon and Hartman 1989; Bustard and Narver 1975). In winter, without such refugia, juvenile coho risk being swept downstream or out to sea by storm flows before they are physiologically ready to live in ocean conditions (McMahon 1983).

Coho salmon can be harmed by acute or chronic thermal stress, by exposure to suspended solids, and (at a population level) by hatchery effects. Critical thermal maxima of coho (the temperature at which acute exposure is fatal) has been measured between 28.21 and 29.23 ºC (Konecki, Woody, and Quinn 1995). Below critical thermal maxima, chronic exposure to elevated temperatures (above a threshold of approximately 16º-18ºC) can increase prevalence of disease and reduce survival rates (Miller et al. 2014); however, if sufficient food resources are available to sustain the faster growth that takes place at higher temperatures, chronic thermal stresses may be mitigated (Lusardi et al. 2020). Similarly, juvenile coho exposed to high levels (2-3 g/L) of suspended solids have exhibited higher stress levels, lower feeding rates, and lower resistances to disease (Redding, Schreck, and Everest 1987). Additionally, hatchery fish tend to have lower fitness than wild-reared fish, and releasing them into wild populations can negatively impact wild coho salmon populations (Quiñones, Johnson, and Moyle 2014); one proposed cause is that the lack of sexual selection in hatchery fish populations leads to a higher number of less fit individuals competing for resources (Thériault et al. 2011).

In previous studies, the strongest predictor of juvenile coho abundance in a stream system was spatial habitat (Bradford et al. 2016; Nickelson et al. 1992; Bustard and Narver 1975), although adequate food and cover were also important (McMahon 1983). The primary mechanism for spatial constraints on abundance appears to be that juvenile coho become more territorial as they grow, and those that cannot hold a territory typically emigrate downstream or all the way to the ocean in their first summer or spring. These early migrators are not well suited to ocean conditions and are much less likely to return as spawning adults (McMahon 1983), though there is evidence that some of these fish may be able to rear in non-natal habitats (Gorman 2016).

An average coho life cycle is illustrated in Figure 3. Some coho salmon return to spawn at age 2 as grilse, but the majority (e.g., 92.4% in 2020) return after more than one year in the ocean, giving the Scott coho salmon run its characteristic 3-year cohort return interval (Knechtle and Giudice 2021).

Coho salmon management and monitoring in the Scott River watershed

Over the past three decades, several organizations and agencies have conducted extensive monitoring and

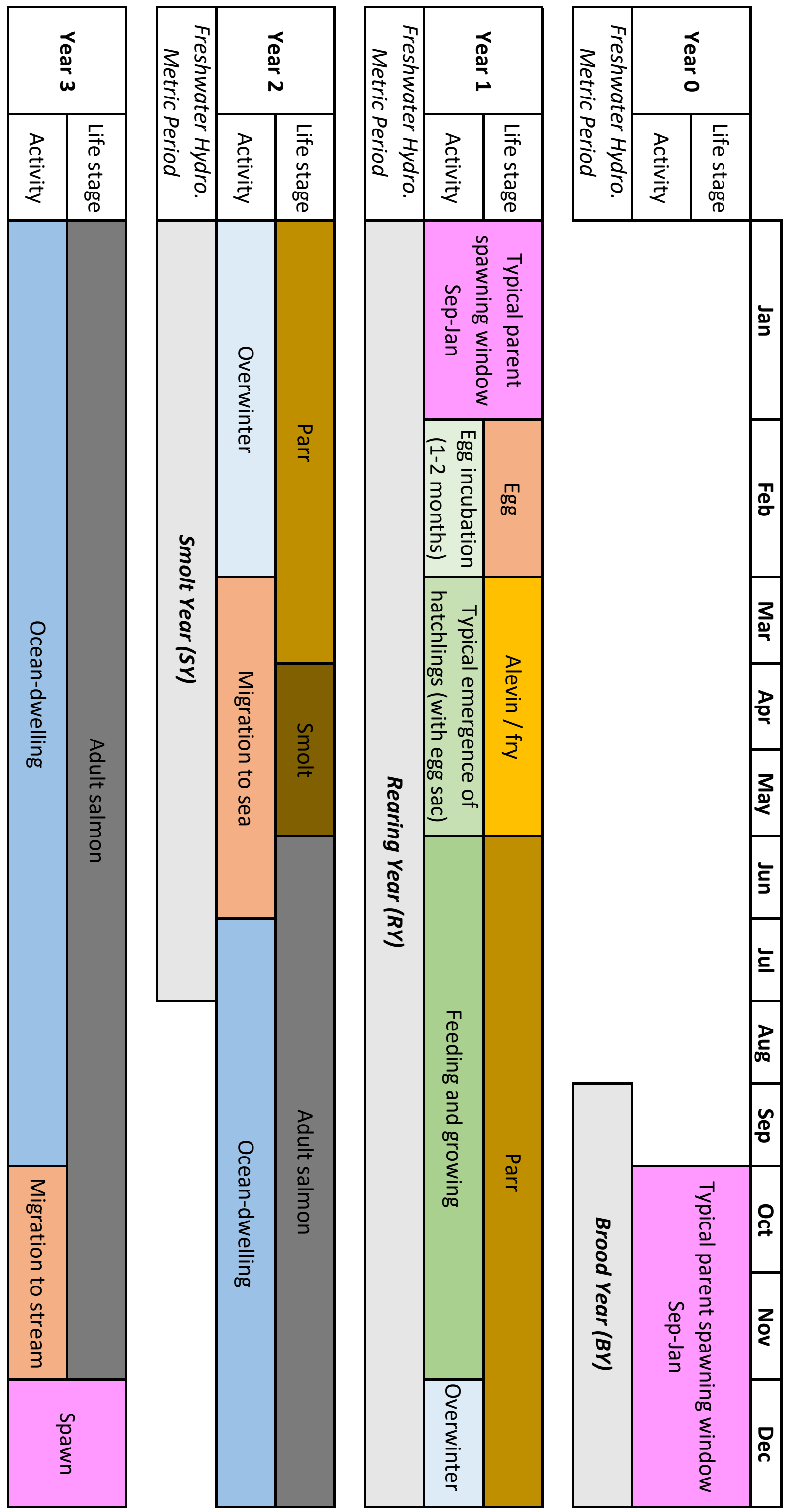


Figure 3: Typical life stage progression of coho salmon in the Scott River watershed.

published a series of reports and plans regarding the salmon fisheries in the Scott River watershed. In the 1990s, fall flows in the Scott River were reported to be too low in some years to allow for Chinook spawning in September-November (CRMP and SRWC 2000), but in the mid-2000s it was reported that low fall flows rarely affected the later (November-January) spawning runs of steelhead and coho salmon (SRWC 2005). More recently, fall flows have affected coho salmon as well as Chinook, as the late onset of winter storms has delayed coho spawning in some water years (e.g., CDFW 2015a). In the mid-2000s, a local conservation organization identified the lack of suitable summer and winter rearing habitat as a probable limitation on Scott River smolt production (SRWC and Siskiyou RCD 2005). Several years later, in a NOAA Fisheries Coho Recovery Plan, NMFS identified the juvenile life stage as the most limited in the population (NMFS 2014).

Monitoring activity in the past 20 years has included population estimates from a video counting flume and a rotary screw trap operated by CDFW (CDFW 2015b; Massie and Morrow 2020), and spawning surveys for Chinook (Siskiyou RCD 2015b, 2017b, 2018) and coho (Maurer 2003; Siskiyou RCD 2005, 2006, 2010, 2011, 2012, 2013, 2014, 2015a, 2017a; Quigley 2007). Recent management activity has included the leasing of surface water rights from landowners to enhance summer flows (e.g., SRWT 2018), the prioritization of stream reaches for habitat restoration (SRWC 2018), several pilot projects to construct and assess the impact of beaver dam analogs (BDAs) on aquatic habitat and fish populations (Yokel 2018), a coordinated rescue effort to relocate juvenile salmon that were cut off from outmigrating by disconnected river reaches (CDFW 2015a), and the development of long-term groundwater management plan by Siskiyou County and local stakeholders (Siskiyou County 2021).

The key ecological observations used in this study are:

1. Number of adults migrating from the ocean to freshwater natal streams to spawn. This quantity, the "escapement", is measured at a CDFW counting facility, using a resistance board weir and video counting flume in the Scott River (e.g., Knechtle and Giudice 2021).
2. Number of salmon gravel nests, or redds, observed during spawning window (e.g., Siskiyou RCD 2017a).
3. Number of juvenile yearling, or smolt, coho salmon. Smolt are counted as outmigrants, often from rotary screw trap observations (e.g., Massie and Morrow 2020).

In addition to these three metrics, it is possible to calculate a combined metric, the number of coho smolt produced per spawning female, after monitoring for multiple years to capture both the spawning and out-migrating events for the relevant cohort.

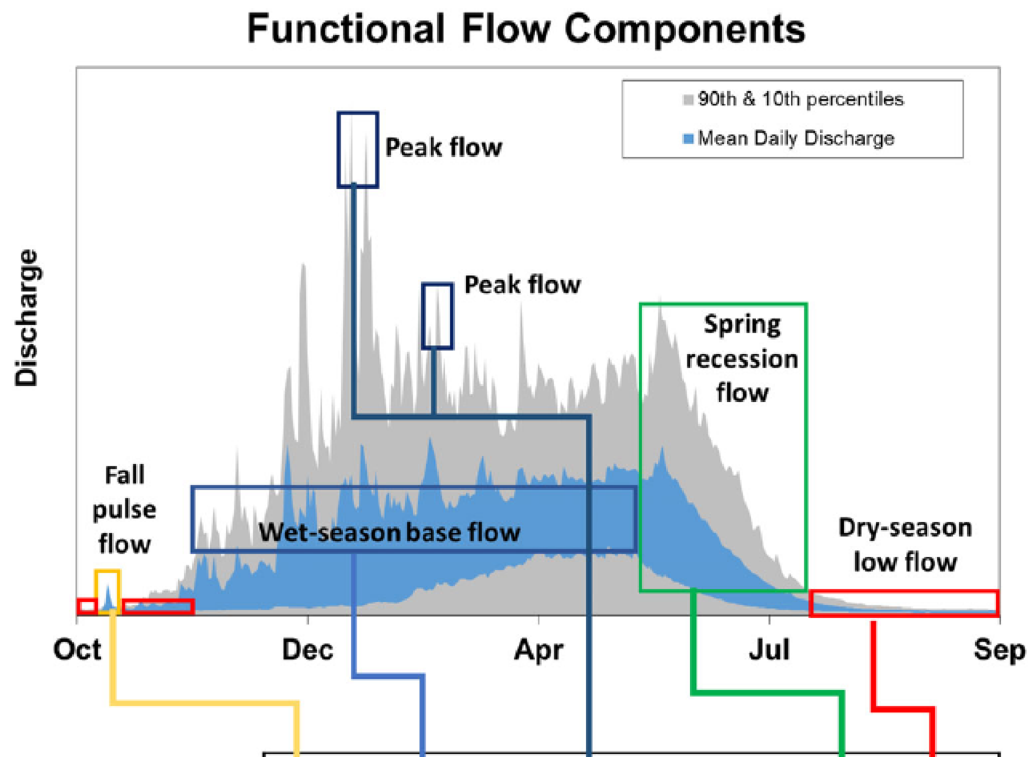
1.4 Methods

Hydrologic metric predictors of fish response variables were screened in two passes: first, using correlation coefficients on a large number of potential predictors, and then using linear models to assess combinations of a refined set of potential predictors. The objectives of the linear model selection exercise were to 1) empirically determine which hydrologic flows were related to coho reproductive outcomes and 2) assign weights of relative importance for a Hydrologic Benefit formula, using slopes in the linear models.

1.4.1 Flow metrics to describe Scott River flow regime

A series of metrics from the catalog of California-specific functional flows (as illustrated in Figure 4; Yarnell et al. 2020; Patterson et al. 2020) were selected to highlight the history and salient characteristics of the Scott River flow regime over the past eight decades. Abbreviations and descriptions are listed in Table 1, and additional information is available in Patterson et al. (2020) and supporting documentation. Total annual flow is used to evaluate water year type. Fall metrics, such as fall pulse magnitude and fall pulse timing, provide olfactory migration signals and spawning access to anadromous fish; however, a discrete fall pulse does not occur in every water year. Wet season metrics, such as wet season onset timing and baseflow magnitude, can be used to gauge conditions during egg incubation or the overwintering period for juvenile salmon. Spring metrics, such as spring flow recession rate of change, occur during the transition from wet to dry season, and indicate conditions during early juvenile salmon rearing as well as the flow available for outmigration from Scott Valley to the ocean. Finally, metrics like the duration and median flow of the dry season indicate the timing and severity of low-flow conditions in which spatial habitat is constrained and connectivity between reaches may be limited.

In addition to the metrics discussed above, we devised two metrics for this study area related to timing of anadromous fish access to preferred spawning habitat (illustrated in Figure 5). These metrics are referred to as "reconnection" and "disconnection" dates. They assume a flow threshold, defined at the Fort Jones gauge, that corresponds to a certain degree of "connectivity" in the Scott River stream system. The date on which this connectivity is lost in the spring/summer or gained in the fall has implications for whether salmon passage exists during the preferred migrating time window. While these metrics can be somewhat correlated with some of the California-specific functional flows, they add value to this analysis because of their direct relation to fish passage in the watershed.



	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 4: Figure 2 from Yarnell et al., 2020. Illustration of five functional flow categories identified for a mixed rain-snowmelt runoff river in California.

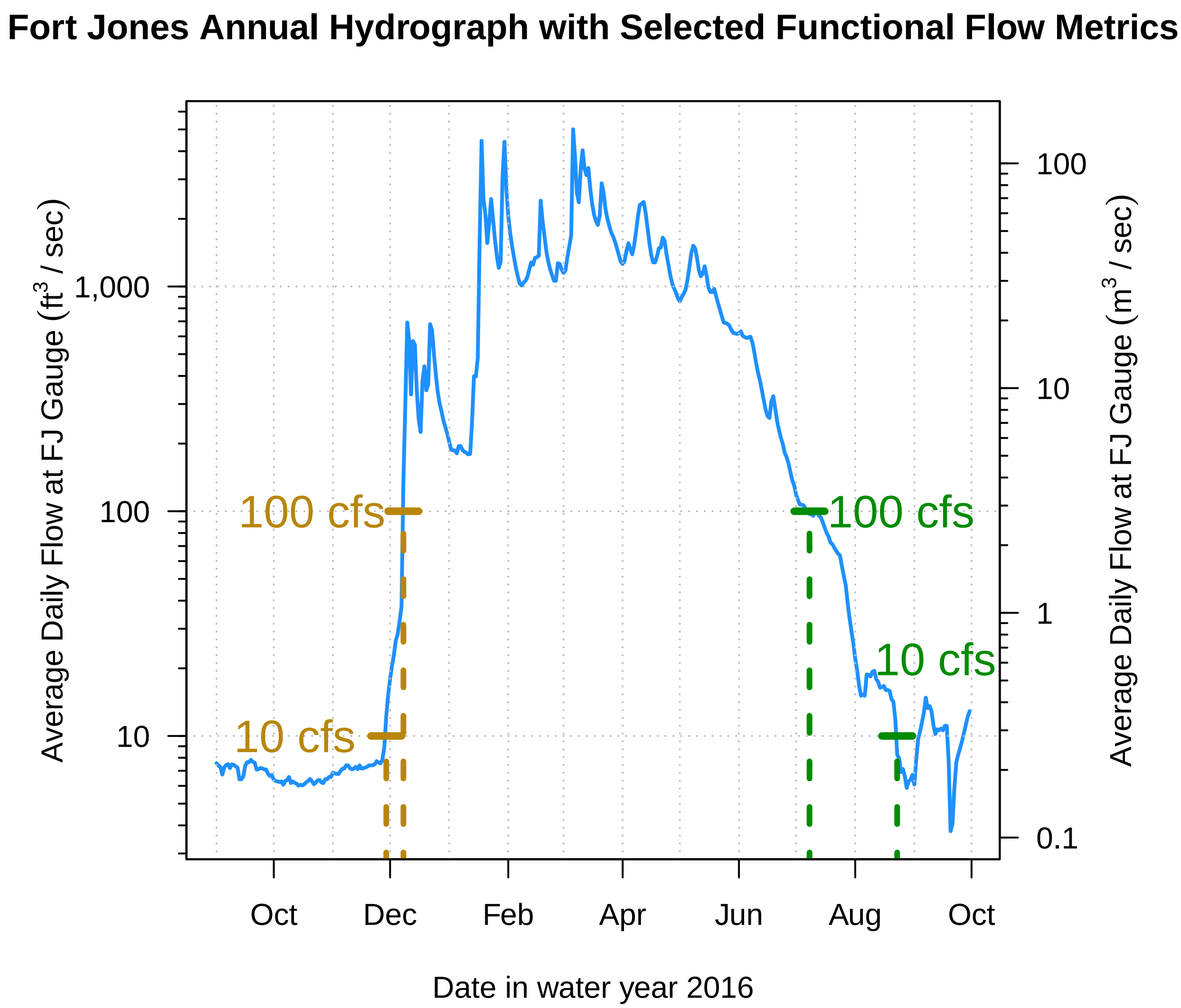


Figure 5: Reconnection and disconnection dates are highlighted for one water year. Two example thresholds, 10 and 100 cfs (0.28 and 2.8 cms, respectively) are highlighted, which correspond to distinct river connectivity (and salmon habitat access) conditions in the Scott River watershed as observed at the Fort Jones gauge (see Results for more detail on selection of flow thresholds).

Abbreviation	Full Name	Description
BY	Brood Year	September-December window in which spawning occurs (by the parents of the designated cohort).
RY	Rearing Year	January-December window during which a cohort hatches and rears in freshwater.
SY	Smolt Year	January-July window during which a cohort grows in freshwater and outmigrates to the ocean.
Recon. Day	River Reconnection Day	The day, usually in the fall, on which the Scott River gains a certain degree of connectivity. Defined as the first day on which FJ Gauge flow rises above a designated threshold (e.g., 10 or 100 cfs) (units of days after Aug. 31).
Discon. Day	River Disconnection Day	The day, usually in the spring or early summer, on which the Scott River loses a certain degree of connectivity. Defined as the first day on which FJ Gauge flow drops below a designated threshold (e.g., 10 or 100 cfs) (units of days after Aug. 31).
Min. Flow	Minimum Flow	Minimum average daily flowrate recorded in the relevant period.
CFLP	Coho Freshwater Life Period	The (conservatively wide) 21-month window, September through July, in which members of a cohort or the cohort's spawning parents are present in the freshwater system.
Tot. Flow	Total Flow	Sum of all daily flow volumes recorded in the relevant period.
FA_Mag	Fall Pulse Magnitude	Peak magnitude of fall pulse event (maximum daily peak flow during event) (cfs)
Wet_Tim	Wet Season Onset Timing	Start date of wet-season in water year days
Wet_BFL_Dur	Wet Season Baseflow Duration	Wet-season baseflow duration (# of days from start of wet-season to start of spring season)
SP_ROC	Spring Recession Rate of Change	Spring flow recession rate (median daily rate of change over decreasing periods during the recession)
DS_Mag_50	Dry Season Flow Magnitude (50th percentile)	50th percentile of daily flow within dry season
DS_Mag_90	Dry Season Flow Magnitude (90th percentile)	90th percentile of daily flow within dry season

Table 1: Explanation of hydrologic metrics and other terms used in this analysis.

1.4.2 Data alignment and correlation coefficients between flow metrics and ecological observations

In the first pass of flow metric predictor selection, potential predictor variables were screened using correlation coefficients. Before the coefficients could be calculated the data was manipulated to assign each cohort's ecological observations to the metrics of flow phenomena occurring at each life stage.

Water managers think of flow in terms of water years, making it the relevant unit for decision-support tools. However, a cohort of coho salmon experiences conditions during multiple water years. The relevant unit of time for identifying the impacts of freshwater hydrology on a salmon cohort is defined here as a

Coho Freshwater Life Period (CFLP), a duration of 21 months beginning the September of the year their parents spawned and ending the July of their outmigration from the watershed as smolts. This time period is conservatively wide; most spawning occurs in October or later, and most outmigration occurs in June or earlier (Moyle 2002), but the September-July duration was chosen to capture critical life stages even in extreme water years.

For convenience in referring to hydrologic metrics in different water years, this Coho Freshwater Life Period has been broken up into three subperiods (as shown in Figure 3 and described in Table 1):

- Brood Year (BY), September-December of the year of the cohort's parents' spawning
- Rearing Year (RY), January-December of the full year the cohort spends in the watershed
- Smolt Year (SY), January-July of the year of the cohort's smolt outmigration

Coho Freshwater Life Periods overlap, e.g., the fall pulse flows in water year i take place during one cohort's Brood Year, and the same fall flows occur during the end of the Rearing Year for the cohort born in water year $i-1$. In some rare cases, flow metrics may fall outside their designated subperiods (e.g., the extreme dry water year of 2014, in which the "fall reconnection" of flows in Brood Year 2013 did not occur until February of the cohort's Rearing Year), but they will be nevertheless be referred to by these designations for consistency.

To build empirical relationships between hydrology and biology, we tabulated the flow metrics by Brood Year of the affected cohort *(Supplemental Table 1)*. In each record (or row) of this table, multiple "fish outcome" observations are assigned to each brood year, including number of spawners observed and the estimated number of smolt observed at the end of their CFLP. Hydrologic metrics are assigned to each Brood Year in terms of which flow metrics affected the salmon cohort as eggs, as rearing juveniles, and as yearlings/outmigrating smolt.

After this exercise to align the hydrologic metric data with the appropriate salmon cohort, we assessed the potential for hydrologic metrics to predict biological outcomes by calculating Pearson correlation coefficients. Correlation coefficients were calculated between all hydrologic metrics under consideration and each of four biological measurements (e.g., number of spawners observed and estimated number of outmigrating smolt; see Results). This set of correlations was used to refine the set of predictors evaluated in the second step of predictor selection. The refined set consisted of the following:

- Reconnection dates, for Brood Year and Rearing Year, for 10, 15, 20, and 100 cfs
- Disconnection dates, for the Rearing Year, for 10, 15, 20 and 100 cfs, and for 100 cfs in the Smolt Year

- Total flow (i.e., the sum of volumetric flow on all days) in the Brood Year, Rearing Year, Smolt Year, and CFLP periods
- Wet season onset timing and baseflow duration, Rearing Year and Smolt Year
- Spring recession rate of change, Rearing Year and Smolt Year
- Dry season flow magnitude in the Rearing Year (50th and 90th percentiles)

1.4.3 Selection of ecological response variable and critical flow thresholds for reconnection predictors

Of the ecological response variables that were evaluated, one variable clearly showed a higher degree of correlatedness with hydrologic metrics: the number of coho smolt produced (i.e., that were estimated as outmigrating from the watershed) divided by the estimate of spawning females migrating upstream almost two years prior (i.e., the cohort's parents). One reason for this strong degree of correlatedness may be that the normalization to the number of spawners makes the three cohorts more comparable. This metric has also been identified by state agency analysts as indicative of freshwater ecosystem conditions at coho salmon populations below carrying capacity (CDFW 2021). Consequently, all further hydro-ecological modeling uses this coho smolt per female (coho spf) metric as the response variable.

To avoid introducing redundant information into the prediction analysis (Olden and Poff 2003), we examined relationships between reconnection dates and biological monitoring data to find the flow thresholds with the highest predictive power. Two critical flow thresholds (10 cfs and 100 cfs) were selected, based on the ability for the flow threshold reconnection dates to predict the observed biological data (based on R^2 values), as well as professional judgment and previous work done on salmon passage in the watershed (e.g., SRWC 2018).

1.4.4 Linear model selection

In the second pass of flow metric predictor selection, a refined set of potential predictor variables was used to make one- and two-predictor linear models of the coho spf response variable.

With a dataset this small, the risk of overfitting is relatively high (James et al. 2013). Consequently linear models with a maximum of two predictors were evaluated. The four best one-predictor models and six of the best two-predictor models are shown in Table 2. Criteria used to make the selection included degree of variability explained by the predictors (R^2 and adjusted R^2), statistical significance (p-value and F-statistic), the amount of total non-correlated information contained in the set of predictors (corrected AIC, or AIC_c, a statistic used for small sample sizes). Because the predictor BY_recon_10 (Brood Year reconnection date, 10 cfs) performed so much better than all other metrics in the one-predictor model set, all two-predictor models evaluated included that predictor.

For each of these models, we calculated the estimated average model error using leave-one-out cross-validation (LOOCV; Table 3). In the LOOCV method, for a dataset with n observations, the LOOCV error of a predictive model is obtained by recalculating the model coefficients n times, each time leaving out one observation, and comparing the resulting prediction to the single left-out observation. The root mean square of these n errors is the LOOCV error used to evaluate model performance in Results.

Finally, minimum performance criteria were established to select the models which were incorporated into the ultimate HB function. These criteria were: adjusted R^2 value of >0.6, a p-value of <0.2, an F-statistic of more than 10, and a LOOCV value of less than 747 (i.e., the LOOCV value of the best one-predictor model). The predictors and slopes of the three models which met these criteria (lm2a, lm2b, and lm2c) are shown in Table 4.

These criteria were selected using professional judgment based on the features of the available models, and the diversity of predictors in the resulting ensemble model. For example, the selection of a p-value criteria of <0.2 allowed the inclusion of lm2c (Table 2), with a p-value of 0.18, but excluded lm2d, with a p-value of 0.64. The authors felt that this was a reasonable cutoff in statistical significance for such a small sample size of observed response variable. Additionally, the three models that met these criteria incorporate information from the end of a dry season (BY_recon_10 and 100), the onset of the wet season (RY_Wet_Tim), and the wet season duration (Wet_BFL_Dur), which supports the professional judgment of the authors that the degree of hydro-ecological services provided each water year should be evaluated using information from multiple seasons.

1.4.5 Proposed formulation of a water year-based Hydrologic Benefit function

To avoid over-interpreting the results of this small dataset, the coefficients of the three best selected models were averaged into the coefficients of an ensemble model (Table 4). The ensemble model coefficients provide the formulation of the Hydrologic Benefit function. Consequently the Hydrologic Benefit values can be interpreted as predictions of coho spf-equivalents for a given water year. The values of the predictors – the four hydrologic metrics for each water year in the Fort Jones gauge record (water years 1942-2021) – are included in *Supplemental Table 2*.

The combined formulation is as follows:

$$HB_{wy} = b + m_1 * metric_{1,\ wy} + ... + m_4 * metric_{4,\ wy}$$

Where:

$HB_{wy} = Hydrologic\ Benefit\ value\ for\ a\ given\ water\ year\ (coho\ spf\ equiv.)$

$b = 93.4\ spf\ equiv.$

$m_1 = -1.15\ spf\ equiv./(day\ of\ reconnection\ after\ Aug.\ 31,\ 10\ cfs)$

$m_2 = -0.17\ spf\ equiv./(day\ of\ reconnection\ after\ Aug.\ 31,\ 100\ cfs)$

$m_3 = -0.20\ spf\ equiv./(day\ of\ wet\ season\ onset\ after\ Sep.\ 30)$

$m_4 = 0.12\ spf\ equiv./(day\ of\ wet\ season\ baseflow\ duration)$

Model	Predictor(s)	F-stat.	P-value	R squared	Adj. R squared	AICc
lm1a	BY_recon_10	10.8	0.00003	0.546	0.496	108.4
lm1b	BY_recon_100	6.9	0.00056	0.434	0.371	110.8
lm1c	RY_Wet_Tim	4.1	0.00336	0.316	0.239	112.9
lm1d	RY_Wet_BFL_Dur	6.7	0.83792	0.427	0.363	110.9
lm2a	BY_recon_10, BY_recon_100	12.9	0.00004	0.764	0.705	105.1
lm2b	BY_recon_10, RY_Wet_Tim	11.7	0.00017	0.745	0.681	106.0
lm2c	BY_recon_10, RY_Wet_BFL_Dur	11.4	0.18325	0.740	0.675	106.2
lm2d	BY_recon_10, SY_SP_ROC	10.2	0.64086	0.718	0.648	107.0
lm2e	BY_recon_10, SY_Wet_Tim	7.6	0.06299	0.654	0.568	109.3
lm2f	BY_recon_10, RY_discon_10	6.9	0.47116	0.634	0.542	109.9

Table 2: Summary statistics of an example set of linear models predicting the number of coho smolt produced per female in a given water year. Because the Brood Year reconnection date for 10 cfs was by far the best single-predictor model, it is included in all two-predictor models under consideration.

1.4.6 HB function sensitivity to one additional observation

To further explore the uncertainty associated with such a small dataset, the sensitivity of the predictive model was estimated by adding one additional data point. Specifically, a hypothetical value of “observed” coho spf was assigned to brood year 2015 (influenced by conditions in water year 2016). This is a missing value in the existing observational dataset. Furthermore, flow conditions in and just before water year 2016 were very dry, and the hydrologic predictors for water year 2016 generated the lowest predicted coho spf

Model	LOOCV value	Average error (coho spf-equiv.)
lm1a	747	27.3
lm1b	940	30.7
lm1c	1,165	34.1
lm1d	938	30.6
lm2a	579	24.1
lm2b	587	24.2
lm2c	703	26.5
lm2d	952	30.9
lm2e	706	26.6
lm2f	1,086	33.0

Table 3: Average model prediction error, based on leave-one-out cross-validation (James et al., 2013).

	Intercept	BY_recon_10	BY_recon_100	RY_Wet_Tim	RY_Wet_BFL_Dur
lm2a	118.1	-1.12	-0.50		
lm2b	128.6	-1.24		-0.61	
lm2c	33.5	-1.10			0.35
Ensemble Avg.	93.4	-1.15	-0.17	-0.20	0.12

Table 4: Summary of slope values (coho smolt per female per relevant unit) for predictors included in the three best linear models. The ensemble average values are used as weights in the Hydrologic Benefit function.

value of the entire Fort Jones gauge flow record (-35.9; see Figure 11). The significance of predicted negative coho spf values is described further in Results.

This missing value for brood year 2015 was replaced by 0, as well as the minimum, mean and maximum values of observed coho spf (5.8, 60.0, and 101.8 coho spf, respectively). The ensemble average coefficients in the HB function were recalculated based on each revised dataset.

1.5 Results

1.5.1 Flow history of the Scott River, described in functional flow metrics

Diagnostic metrics of Scott River flow have demonstrated clear trends over the past 8 decades. Between 1942 and 2021, total annual flow measured at the Fort Jones gauge has dropped from an average of approximately 600 to 400 thousand acre-feet (TAF, or from >800 to <600 million m^3) (Figure 6, panel A). Ecosystem functional flow metrics, calculated with signal-processing techniques (Patterson et al. 2020 and illustrated in Figure 4), also show clear trends over time (Figure 6, panels B-H). The fall pulse onset date has trended slightly later (though a distinct fall pulse flow does not occur every year), and the magnitude of the fall pulse flows has decreased. The onset of the wet season has trended slightly later, though wet season median baseflows (i.e., flows not occurring during storm pulses) have remained stable on average (with a very slight downward trend). The rate of flow reduction during the spring has increased over time (i.e., the spring recession curve has grown steeper). The median dry season flow has dropped by approximately 50%, the onset of the dry season is earlier, and the duration of the dry season has increased (Figure 6).

The reconnection and disconnection dates also show trends over time, illustrating that since 1942 the wet season has narrowed, in that its (approximate) onset has trended later and the spring flow recession has trended earlier (Figure 7).

In aggregate, these metrics show an increased prevalence over the past 80 years of unfavorable hydrologic conditions for salmonids, in terms of the flows needed during critical life stages. The primary causes of this reduced ecological functionality are a changing climate (especially a reduced snowpack and earlier snowmelt) and long-term changes in local consumptive water uses (Van Kirk and Naman 2008; Drake, Tate, and Carlson 2000).

1.5.2 Correlation of hydrologic metrics with coho salmon metrics

The information in *Supplemental Table 1* was used to calculate Pearson correlation coefficients between flow metrics and four observed quantities in coho ecological monitoring (the number of spawners, number of redds, number of smolt, and the number of smolts produced per female spawner) (Figure 8). These correlations were used to refine the set of variables considered in the linear modeling exercise. A larger number of predictors was evaluated than the set depicted here; the predictors included in Figure 8 are selected because of a high correlation coefficient or an unexpected result. A full correlation matrix is shown in *Supplemental Figure 1.*

As mentioned in Methods, the coho salmon indicator that is most correlated with hydrologic metrics is the number of coho smolt produced per spawning female (Figure 8). One reason for this may be that normalizing the observed number of smolt to the number of spawners eliminates the independent influence of cohort strength. Because of the already small number of water years for which smolt and spawner counts are available, explicit consideration of each 3-year cohort of coho salmon was deemed statistically impossible for this study. Notably, data limitations for the coho spf metric reduce the sample size to only 11 years of observations.

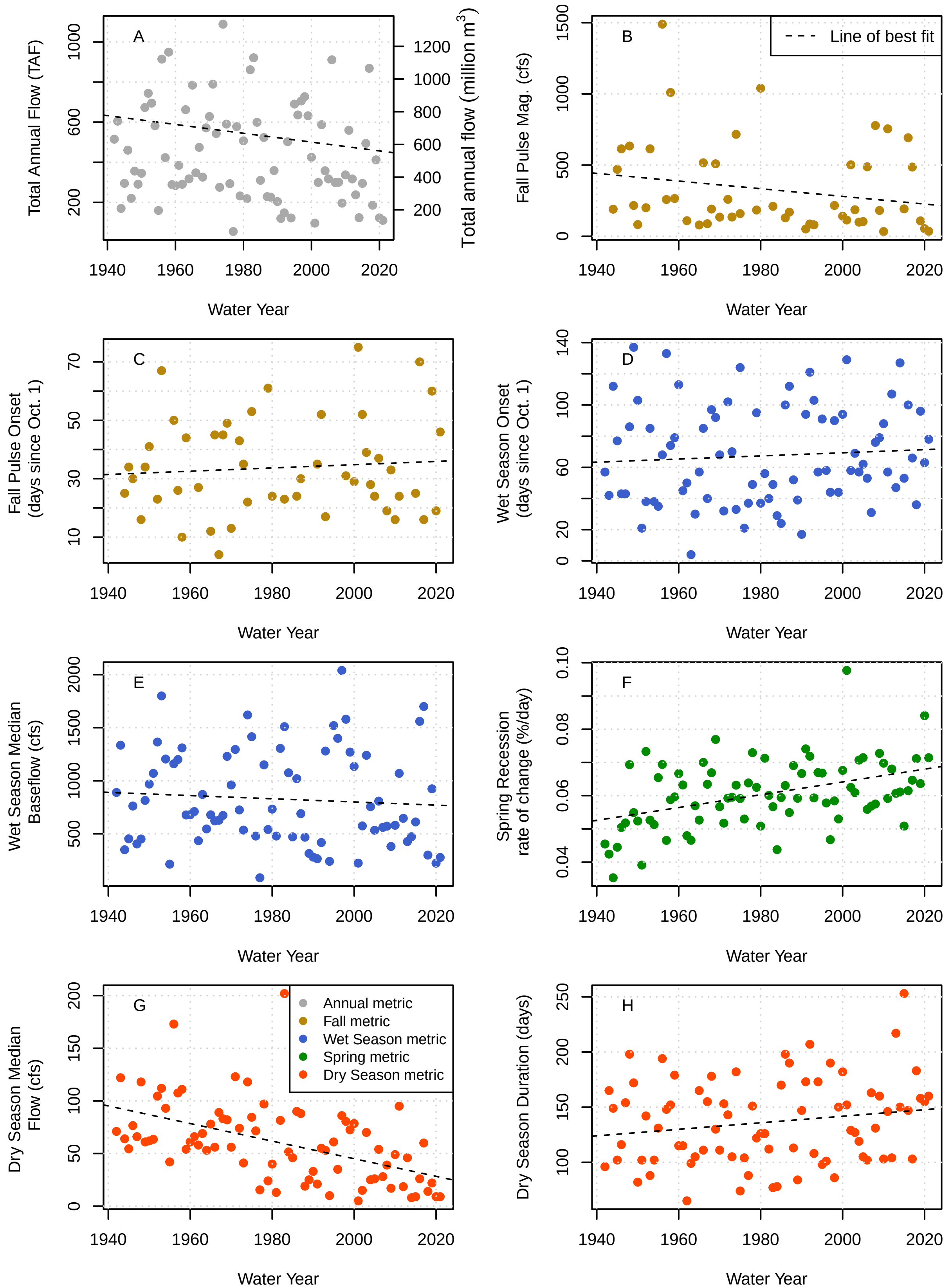


Figure 6: Total annual flow volume (panel A) and functional flow metrics (panels B-H; Patterson et al. 2020), derived from daily average flow measurements at the Fort Jones USGS flow gauge (ID 11519500) for water years 1942-2021.

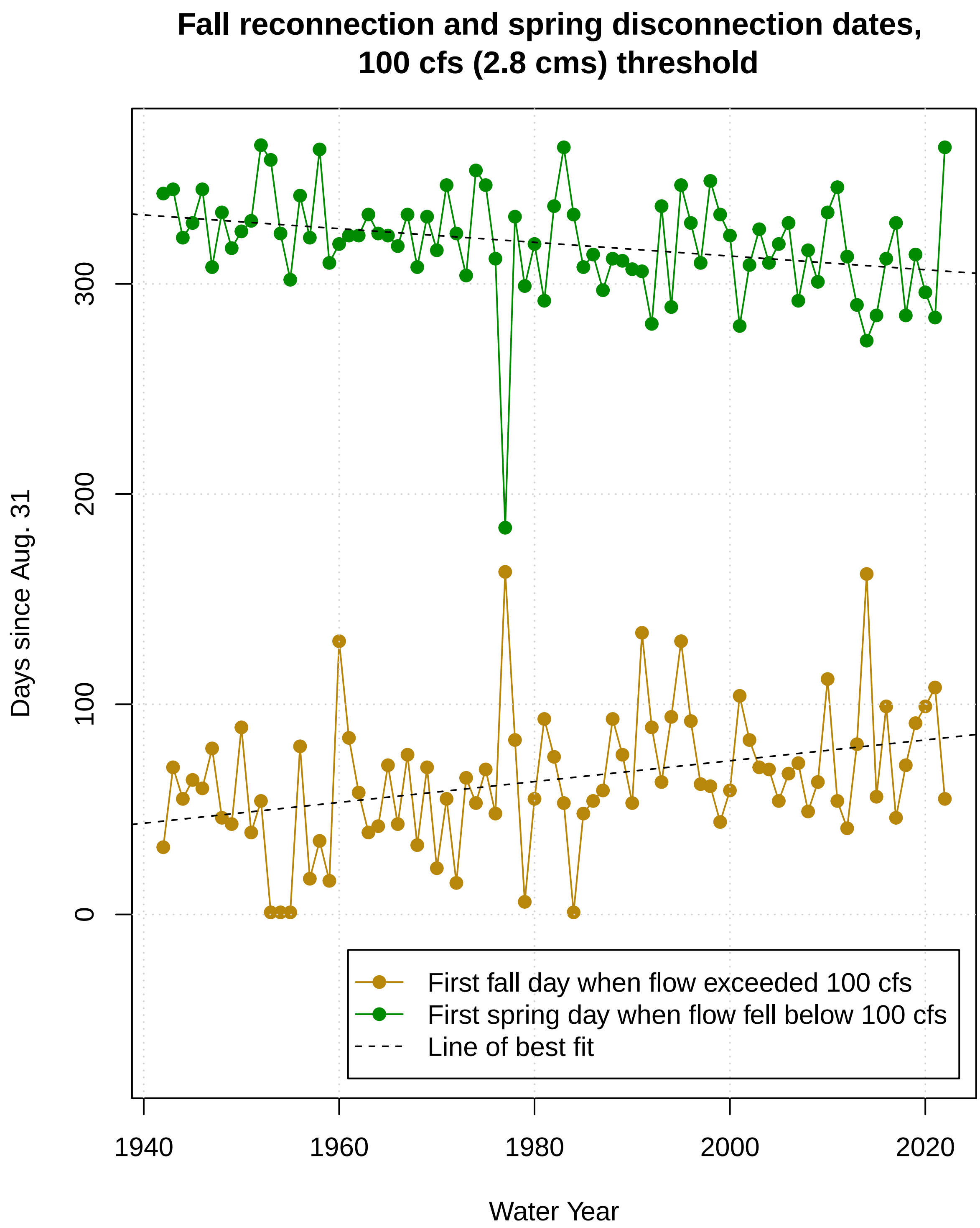


Figure 7: Disconnection and reconnection dates for the 100 cfs (2.8 cms) flow threshold, water years 1942-2021. The disconnection date refers to the first day in the spring on which flow drops below the designated threshold (100 cfs); the reconnection date refers to the first date in the fall on which flow rises above the designated threshold. Trends over the past 80 years suggest that the spring flow recession is trending earlier, and the fall river reconnection is trending later.

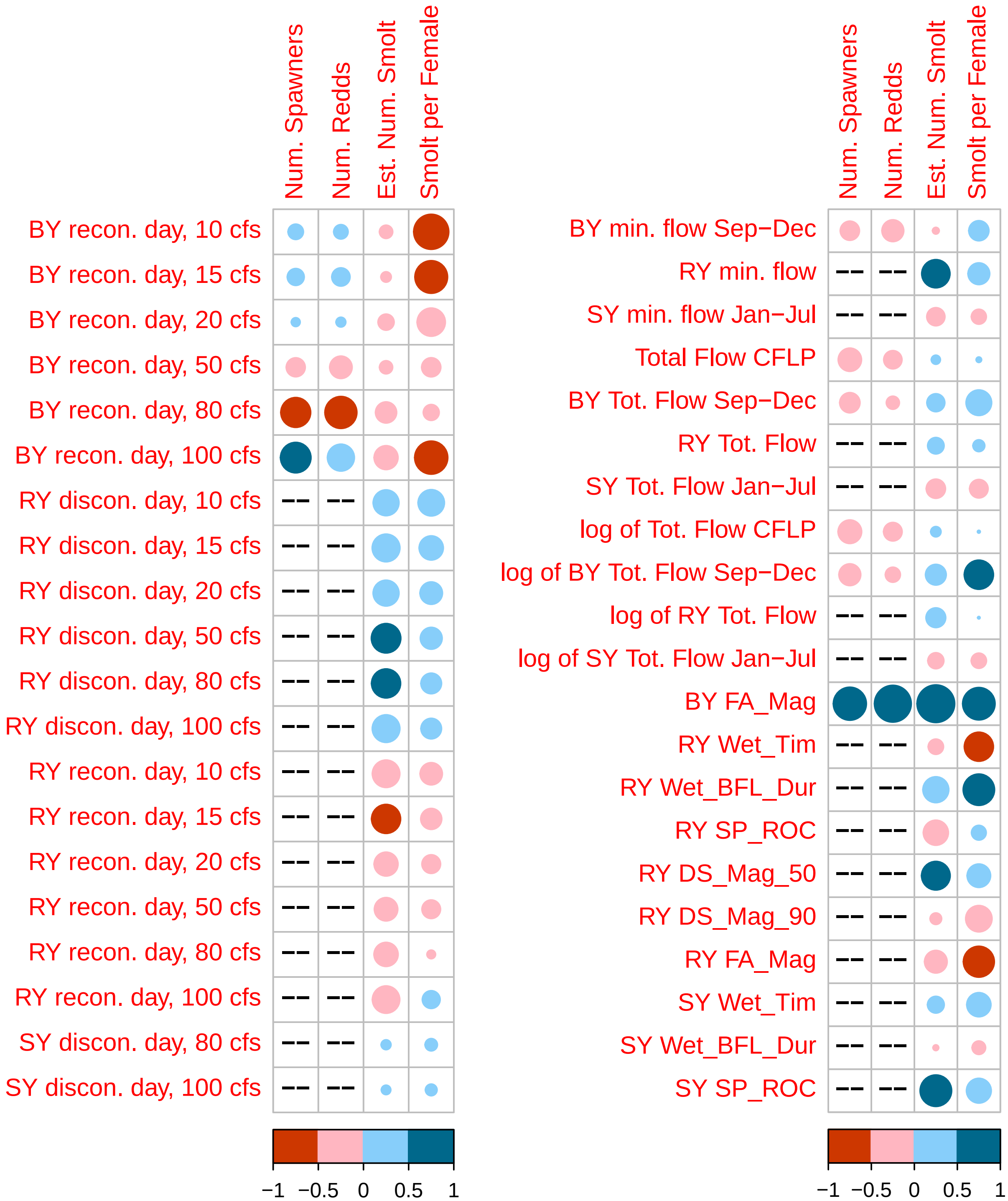


Figure 8: Correlations between 41 predictors and 4 coho monitoring metrics. Red colors indicate a negative correlation and blue colors indicate a positive correlation; the size and color of the circle in each box are both scaled to the value of the correlation coefficient. Large blue circles indicate that the quantity (such as the Brood Year fall pulse magnitude, or BY FA_Mag) is positively correlated with observed fish metrics; for dates, a blue dot indicates that a later date is correlated with higher fish values, while a red dot indicates that an earlier dot is correlated with higher fish values.

1.5.3 Selection of 10 and 100 cfs thresholds for fall disconnection dates

Fall reconnection dates in a cohort's Brood Year appear strongly correlated with coho spf (Figure 8), and previous work in the region has documented that fall flows are critical for salmon spawning (SRWC and RCD 2003). However, some flow thresholds may be less relevant to coho life stages than others, and the reconnection timing of proximate flow thresholds is somewhat correlated. It was therefore necessary to reduce the number of flow thresholds under consideration in the linear model selection process, in order to a) identify flow thresholds with the greatest impact on coho reproduction (to the extent possible with such a small dataset), and b) avoid the inclusion of redundant hydrologic information.

Relationships between the Brood Year reconnection dates for six flow thresholds and coho spf are shown in Figure 9. The trends in slope value and R^2 suggest that the date of crossing lower flow thresholds such as 10 and 15 cfs has greater biological significance than the date of crossing thresholds like 40 cfs, with 20 cfs being somewhat intermediate. In the context of this watershed, it suggests that a Fort Jones gauge flowrate of 10 cfs is a critical threshold for coho passage into the mainstem Scott River.

At reconnection dates for 100 cfs, the R^2 of the relationship is higher than at 40 cfs. In previous monitoring, a Fort Jones gauge flowrate of 100 cfs has corresponded with the reconnection of a key river reach impacted by mine tailings, allowing coho passage to favorable tributary stream habitat upstream of this reach (*pers. comm.*, Sommarstrom 2020). The relatively high R^2 value between the 100 cfs Brood Year reconnection date and coho spf (0.434) suggests that earlier access to this additional habitat improves watershed-wide reproductive outcomes.

It should be noted that for this metric, at very low flows like 8 and 10 cfs, a data censoring problem emerges, as there are some years where the flow never drops below the threshold, so "reconnection" as flows rise above that threshold cannot occur. For these water years, the date of September 1st was selected as the "threshold crossing day". This is considered to represent the earliest date that a spawning coho salmon would require spawning flows measurable at the Fort Jones gauge. Thus, in average and wet years (and, in the mid-20th century, most years) the distribution of values for this threshold-exceeding date for low flowrates would be heavily skewed to September 1st. This data processing method retains the information that the flow in a high-baseflow year may have served the spawning needs of the salmon, but conveys no other information about flow timing.

Based on the trends shown in Figure 9, we narrowed the reconnection and disconnection date flow thresholds under consideration to 10 cfs and 100 cfs. This decision could be revisited if additional years of data become available.

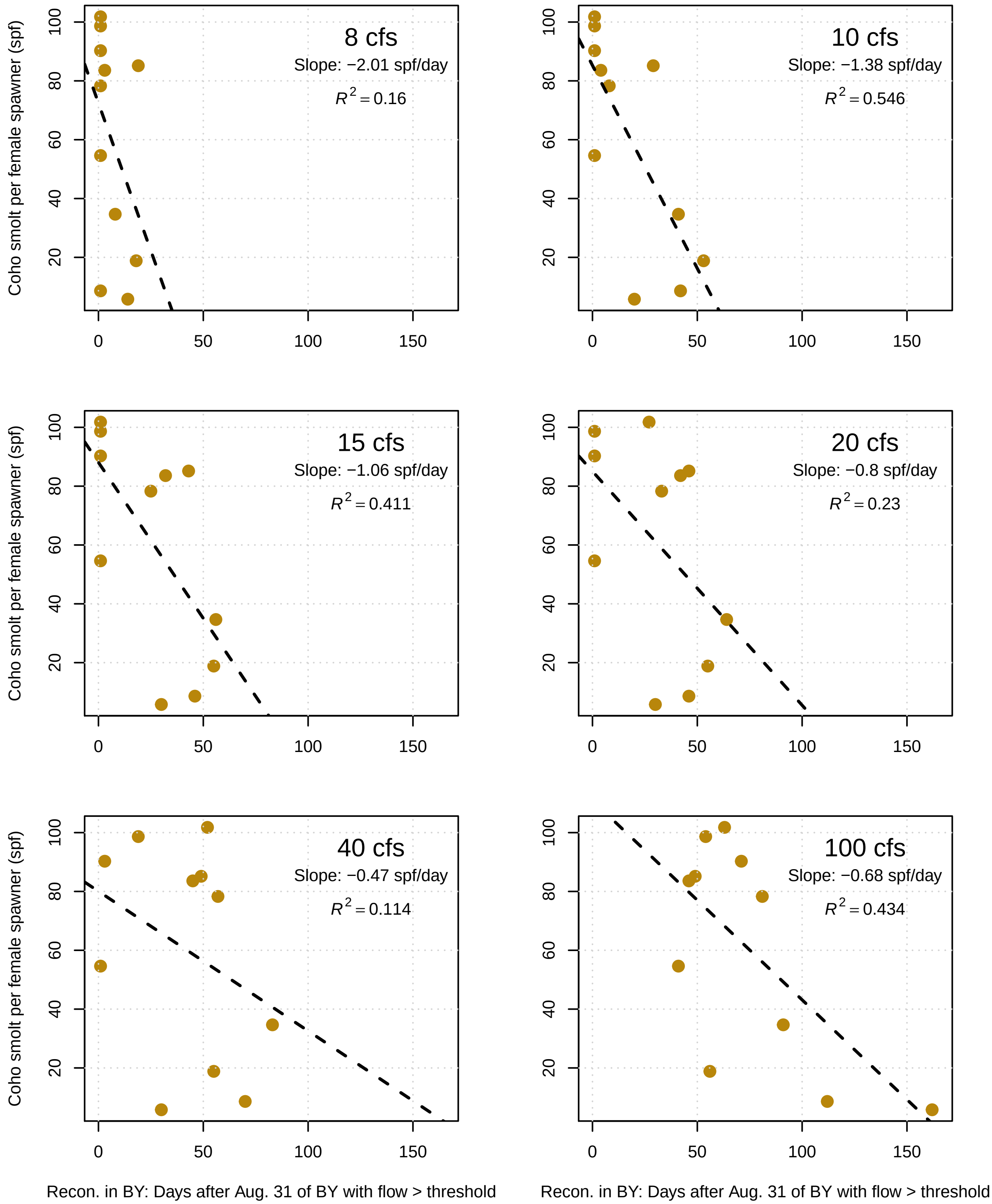


Figure 9: Correlations between the 'reconnection' dates, or dates of fall flow rising above the designated flow threshold, for six flowrates. X-axis units are days after Aug. 31 of the salmon cohort Birth Year.

1.5.4 Linear model predictions

Coho reproduction rates appear to be correlated with some hydrologic metrics, based on the hydrologic conditions and coho observations in water years 2007-2020 (though these linear models should not be over-interpreted, given the small sample size). The best single-predictor models (Brood Year reconnection dates for 10 and 100 cfs, or BY_recon_10 and BY_recon_100) are both related to the timing of rising fall flows in the Brood Year of each salmon cohort (Table 2).

The predictor BY_FA_Mag, or the magnitude of the Brood Year fall pulse, was also highly correlated with coho spf (Figure 8). However, because a distinct fall pulse does not occur every year, including it would reduced the sample size to an unacceptable level (i.e., a total of six water years with a complete set of predictors and response observations). Because of this sample size limitation, and because some of the information about this pulse was carried in the reconnection date metric, FA_Mag was excluded from the set of potential predictors.

The addition of a second predictor clearly improves model performance in terms of predictive power and test error, given the increased R^2 values, reduced AIC_c values, and reduced average error when comparing models lm2a and lm2b versus lm1a and lm1b (Tabulated in Tables 2 and 3; with observed and predicted values shown in Figure 10). The three best two-predictor models included the Brood Year reconnection date for 10 cfs (BY_recon_10) and an indication of the onset or duration of the following wet season: Brood Year reconnection date for 100 cfs (BY_recon_100), wet season onset or duration for the Rearing Year (RY_Wet_Tim and RY_Wet_BFL_Dur). (Though they both occur as the Brood Year transitions to the Rearing Year, the two metrics BY_recon_100 and RY_Wet_Tim are not highly correlated, due to the more complex criteria needed for a flow event to qualify as the wet season onset.)

1.5.5 Hydrologic Benefit value over time and component contributions

Matching the historical flow trends discussed above, the predicted value of coho spf-equivalent produced by a given water year has trended downward over time (Figure 11). The hydrology of a severe drought in water years 2012-2016 is reflected in three consecutive years (2014-2016) of lower-than-40 predicted coho spf.

Since 1990, the low predicted coho spf values in dry water years have become progressively lower, culminating in three years, all occurring after water year 2000, in which < 0 coho spf are predicted. Though a negative value for coho reproduction is obviously not possible, we chose to retain these impossible values to visually represent uncertainty associated with this modeling exercise (see Discussion for more information).

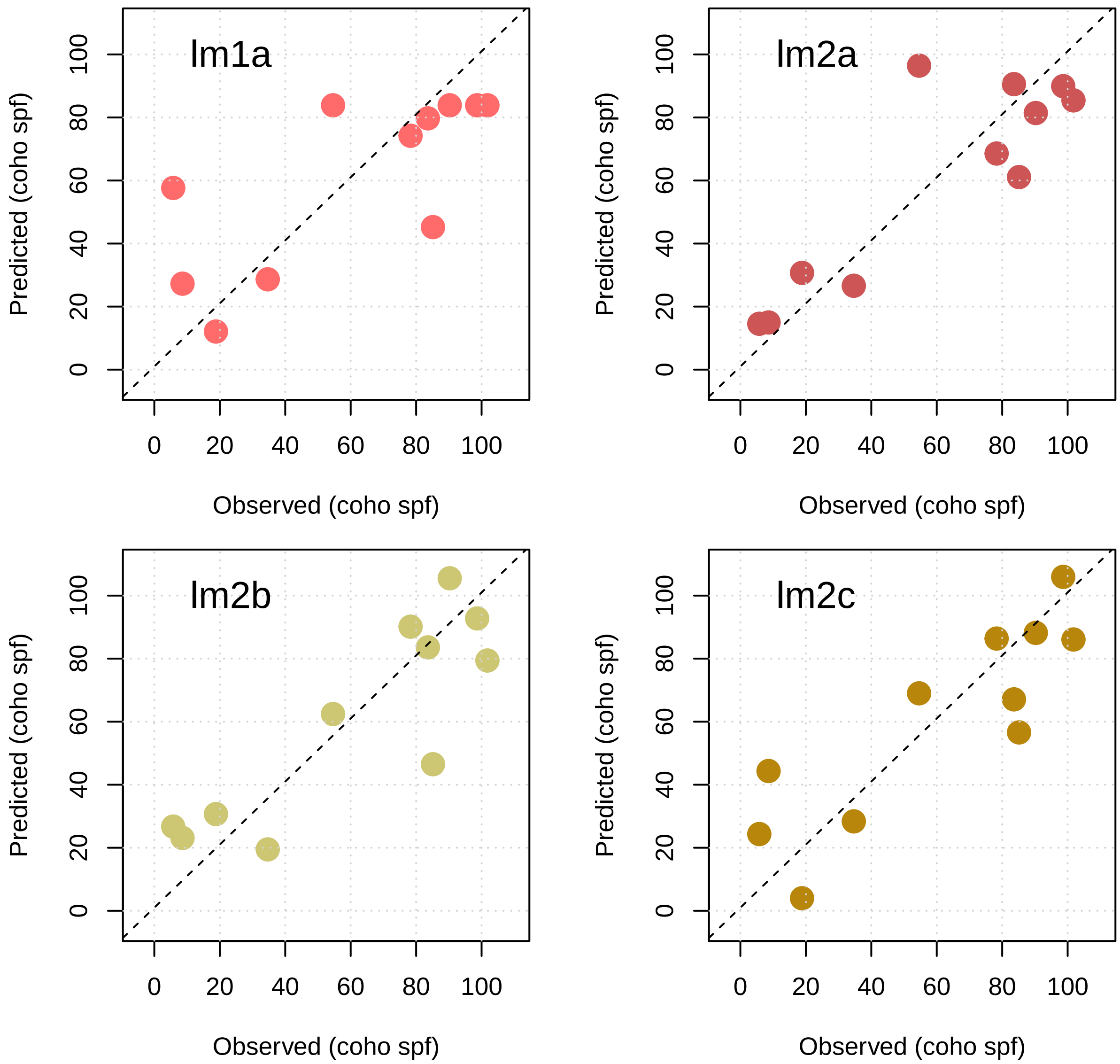


Figure 10: Predicted vs observed values for coho smolt production per female in the linear models with one through four hydrologic predictors. A dashed 1:1 line is included for reference.

The relative contributions of each hydrologic metric to predicted Hydrologic Benefit values (except the intercept term, which is excluded for ease of visualization) is shown in Figure 12.

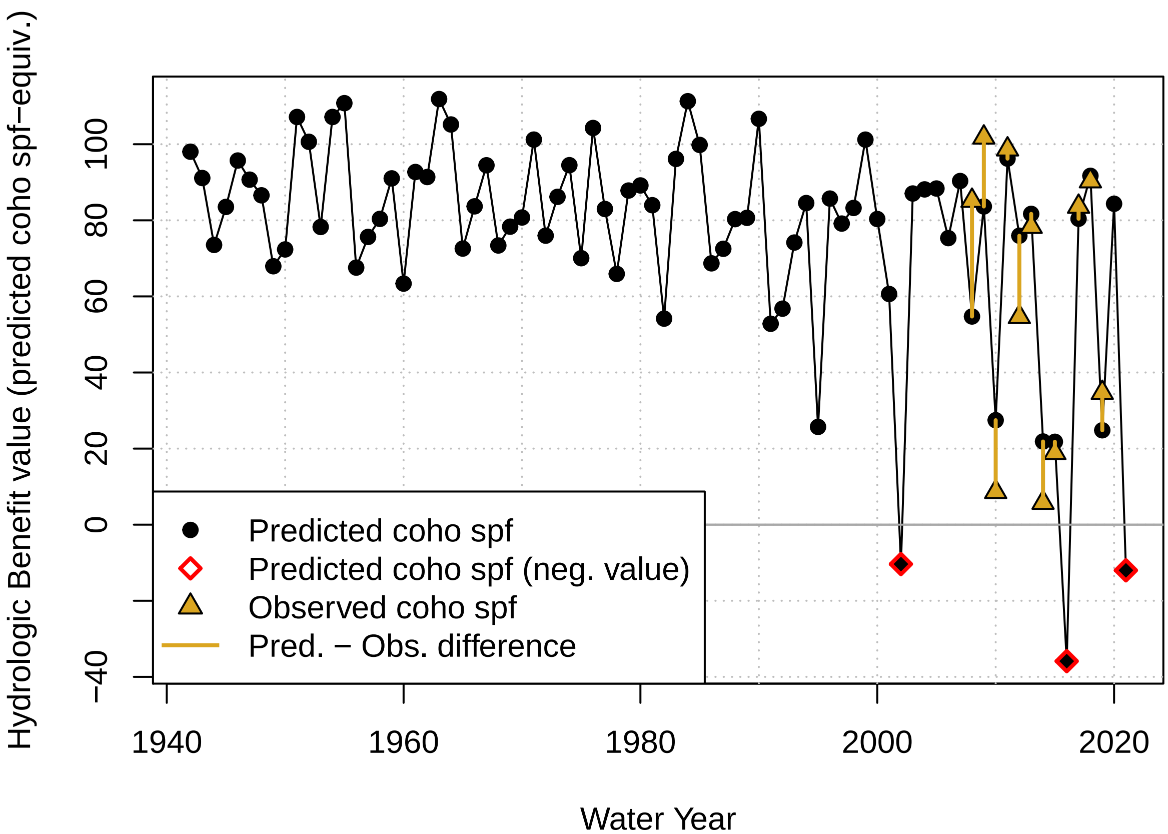


Figure 11: Annual observed and predicted values of coho smolt produced per female spawner (coho spf). Predicted coho spf quantities are shown as Hydrologic Benefit (HB) function values. The coho spf values are plotted in the water year spanning each cohort's Brood and Rearing Year. Negative prediction values (considered physically impossible) are flagged but are retained to visually demonstrate the uncertainty in the exercise of predicting fish outcomes from hydrologic metrics alone, based on a small sample size.

1.5.6 Sensitivity of the Hydrologic Benefit function to one additional data point

The best-fit HB function weights are relatively sensitive to the addition of one new data point, as can be expected for a small dataset. Assigning a coho spf value of 0 to the missing 2016 observation (brood year 2015) changes the coefficient (or conceptual weight) of the predictor BY_recon_10 from -1.15 to -0.88 (a difference of 24%). Replacing it with higher numbers produces less and less negative coefficient values. Specifically, a 1-coho spf increase in the missing value makes the coefficient less negative by 0.007 coho spf per day of 10-cfs reconnection delay, such that if it is replaced with the maximum observed coho spf value

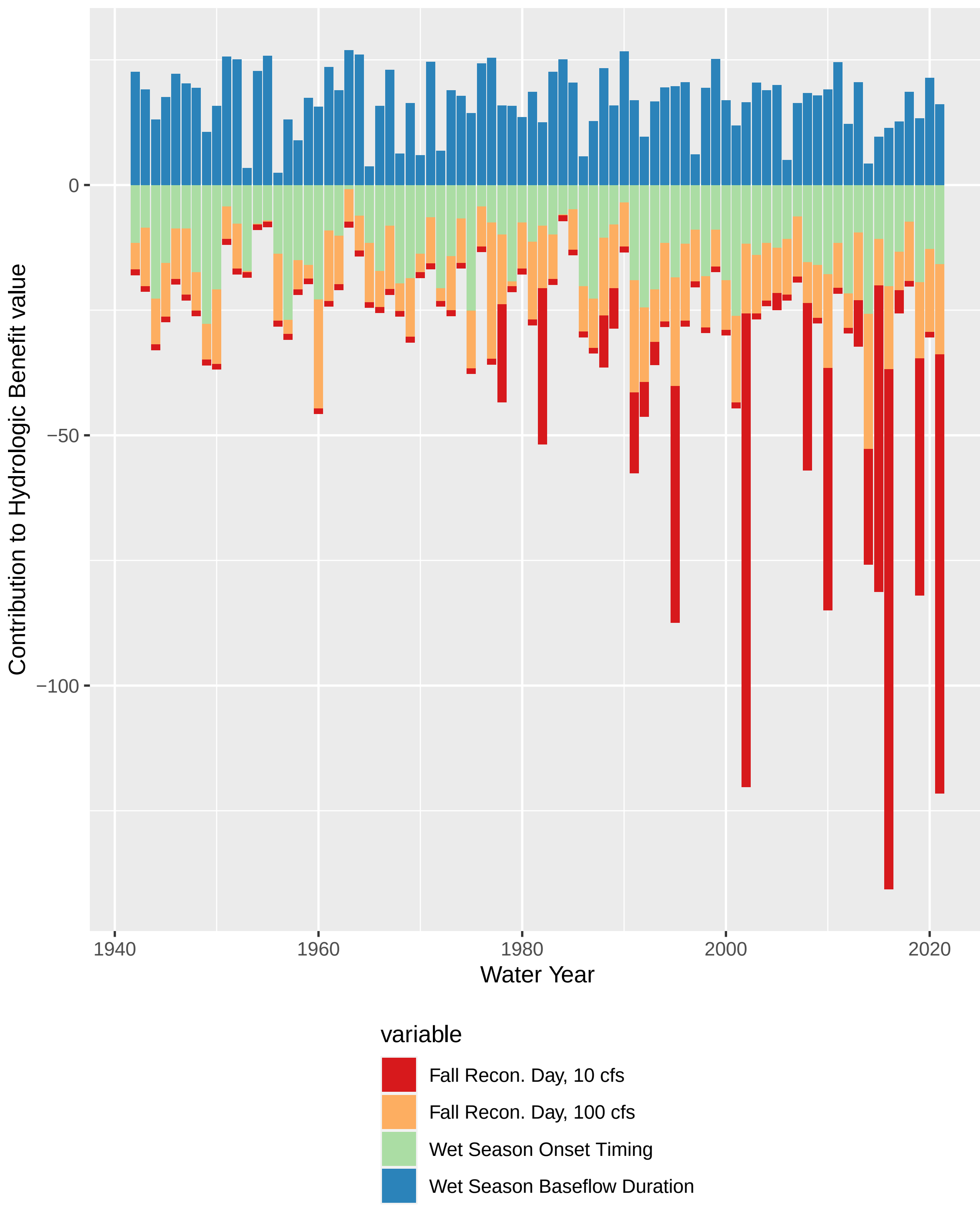


Figure 12: Contributions to annual Hydrologic Benefit values (coho spf-equivalent). A positive value (i.e., one associated with a water year's Wet Season Baseflow Duration) indicates that a longer wet season baseflow duration contributes a positive value to the predicted number of coho spf produced in that cohort. A negative value (e.g., one associated with a water year's Fall Reconnection Day at 10 cfs) indicates that a later reconnection date contributes a negative value to the predicted number of coho spf produced in that cohort.

(101.8), the coefficient is calculated as -0.09 coho spf/day. The other three coefficients are not as sensitive to the new value, ranging from -0.17 – -0.19, -0.20 – -0.18, and 0.12 – 0.13 for BY_recon_100, RY_Wet_Tim, and RY_Wet_BFL_Dur, respectively, when the missing value is replaced by a range from 0 to 101.8.

1.6 Discussion

1.6.1 Previous work on hydrologic indices and ecological responses

A river's flow regime is often referred to as a "master variable" controlling geomorphic, chemical, and other conditions in its aquatic ecosystems, and organisms that have evolved to persist in specific flow regimes are commonly negatively affected by flow alteration (Bunn and Arthington 2002; N. Leroy Poff et al. 2010). Consequently, a diversity of methods have been used to predict regional ecological responses to changes in key flow metrics. Many regional case studies predict ecological responses in terms of species richness or macroinvertebrate composition at dozens or hundreds of bioassessment sites (e.g., Mazor et al. 2018; McManamay et al. 2013; Hain et al. 2018; White et al. 2018; Larsen et al. 2021; Peek et al. 2022), and the temporal framework is often a snapshot of the biological changes between natural and altered flow conditions (Wheeler, Wenger, and Freeman 2018; Peek et al. 2022). Methods of generating the predictive models include boosted regression trees (Mazor et al. 2018; Hain et al. 2018), stochastic matrix models (Sakaris and Irwin 2010), and probabilistic Bayesian Network models (Bestgen et al. 2020), among others.

In most of these studies, because flow data is often continuous and more abundant than other data types, all the predictors used to model the ecological response are flow-derived metrics. Such models rely on the assumption that habitat or flow availability is the limiting factor in ecological recruitment, and thus that change in flow can be directly translated to a fish population response. However, this ignores ecological theory. Under many circumstances, complex internal population feedbacks (such as high juvenile fish density leading to some juvenile fish mortality) will be the limiting factor on fish population size. Consequently many authors have argued that models of fish population responses to hydrologic changes should explicitly include ecological population modeling in addition to physical factors such as flow or geomorphology (Rosenfeld 2003; Anderson et al. 2006; Lancaster and Downes 2014; Acreman et al. 2014; Shenton et al. 2012). Additionally, in at least one case, fish population differences were not successfully predicted with a model based only on a predictor of flows; other variables such as water temperature were necessary to capture population shifts (McManamay et al. 2013).

In spite of these known limitations, the HB function proposed here uses only hydrologic predictors. In part this is a pragmatic approach, as this work is intended for assessing flow conditions in speculative hydrologic models, which do not simulate non-hydrologic, ecologically-relevant factors such as water quality or internal population dynamics. Furthermore, the hydrologic-only predictor approach may be more valid in this watershed than in a general case, as previous work suggests that flow availability is the major limiting factor on the local salmon fishery (SRWC and Siskiyou RCD 2005; NMFS 2014). Lastly, the proposed HB function avoids some of the disadvantages of the snapshot method of comparing the two states of natural and altered flows (Wheeler, Wenger, and Freeman 2018), because the hydro-ecological dataset is relatively long. This temporal structure, covering a wide range of water year types, makes it possible to test the hypothesis that a measurable relationship exists between hydrologic signal and ecologic response, even within an otherwise more complex relationship involving many non-hydrologic factors.

1.6.2 Critical flow thresholds

The river reconnection dates of multiple flow thresholds are correlated, to varying degrees, with biological monitoring data (see Results). These correlations support the current scientific understanding that the timing of restoration of habitat connectivity after dry periods in the Scott River is related to the reproductive success of spawning salmon (e.g., Siskiyou County 2021; *pers. comm.*, Sommarstrom 2020; SRWC 2018).

The selection of 10 and 100 cfs thresholds for fall flow reconnection dates is informed by both the empirical relationship between thresholds and coho spf observations (Figure 9) and professional judgment regarding which flows typically facilitate coho spawning passage into the valley and access to a large amount of tributary habitat. However, multiple caveats apply to these thresholds. First, though the timing of the 10 cfs reconnection had the strongest correlation with observed coho spf values, a flow of 18 to 25 cfs has been reported in stakeholder meetings as the minimum flowrate during which fish can pass upriver into Scott Valley (SVGAC 2020). Second, the extent to which the flow at the Fort Jones gauge represents conditions in the rest of the watershed depends on the speed of hydrologic processes taking place. When the transition from the dry season to the wet season is especially abrupt, flow in the tributaries may increase hours before the Fort Jones gauge flow responds (e.g. as was observed in response to the storm in late October of 2021).

Additional fish population monitoring in future water years will be instrumental in better constraining the nuances of these hydro-ecological relationships and the conditions in which hydrology can be used to predict outcomes for anadromous fish.

1.6.3 Hydrologic Benefit (HB) function predictive performance and sensitivity

For the 11 years in which observed coho spf values are available, the HB function was reasonably accurate in its predictions (Figure 11). In particular, it succeeded in predicting whether a coho spf year would be above or below 40 (an arbitrary threshold based on visual inspection of the grouping of the 11 observed values). A more conservative use of this model would be to assign a high-low threshold, and categorize each water year as a "high-coho spf" or "low-coho spf" year based on its relation to this threshold. However, for purposes of this discussion we retain the full distribution of values.

These linear models have been developed for a Coho Freshwater Life Period (see Figure 3), but the relevant time period for decisionmakers is typically a water year or shorter. It was possible to select a set of best models that fit within one water year, in that they range from the fall of the Brood Year through the wet season of the immediately following Rearing Year. With this formulation, a prediction could be made each fall, using the flow record of the preceding water year and the estimated number of female spawners during the previous fall-winter, regarding the number of smolts to be observed in the coming spring. This smolt abundance prediction could be made to test the model quality when confronted with new data.

The predictive power of the Hydrologic Benefit formula beyond the hydrologic conditions of water years 2007-2020 remains untestable; for this reason the coho spf prediction values of water years pre-2007 should be treated with skepticism. Notably, the hydrologic phenomena that constitute the limiting factors on salmon reproduction might have been very different in the watershed in past decades (e.g., if fall flows were not a major constraint, then spring rearing habitat, or possibly scouring storm flows in winter, might show stronger correlations with coho reproduction).

Additionally, the sensitivity exercise indicated that even one additional data point can alter the ensemble coefficient, or weight, of the most important predictor (Brood Year reconnection timing, 10 cfs) by at least 24%; thus it is reasonable to assume that if more data is collected in the future, the HB function coefficients and possibly even the set of best hydrologic predictors may shift. Nevertheless, the limited data available can be used to draw some preliminary conclusions regarding bio-hydrologic relationships in the Scott River watershed.

1.6.4 Metric weights and importance

The relative contributions of each metric, shown in Figure 12, indicate that the weighted metric introducing the greatest variability in coho spf predictions is the reconnection date at the 10 cfs threshold; in other words, an important common feature of the water years that yield very low coho spf predictions is a relatively long fall period of flow <10 cfs.

Figure 12 also highlights that three of the four selected hydrologic metrics are negatively correlated with coho spf values. This means the HB function relies on a positive intercept value to generate positive coho spf predictions, and because the intercept value can be outweighed by combinations of flow metric values that are within the range of possibility, this formulation allows the prediction of negative values. A negative value, or a prediction of coho smolt consumption rather than production, is obviously not possible based on our understanding of the coho salmon life cycle (Figure 3).

Unfortunately, observed coho spf values are not available for any of the water years in which a negative value is predicted (2002, 2016 and 2021; Figure 11), so a direct comparison of prediction accuracy is not possible in these water years. However, given that the coho run persisted in the Scott River watershed beyond the 3-year cohort-return interval (i.e., water years 2005 and 2019), some smolt production greater than 0 in these years is highly likely.

The metrics most related to watershed-scale coho spf occur during the window of their parents' spawning and, to a lesser extent, in the winter through summer of their early rearing. At least three potential mechanisms have been hypothesized regarding the importance of fall flow timing and magnitude to coho salmon. During dry water years, when fall reconnection dates are delayed, coho have been known to spawn in suboptimal habitat (e.g., Siskiyou RCD 2014). Eggs laid in suboptimal conditions suffer from higher mortality rates for multiple reasons, including egg burial by transported sediment, channel bed scouring, or unfavorable water quality (Bjornn and Reiser 1991). Additionally, anadromous fish do not eat during spawning, and a delayed reconnection date, with a corresponding longer waiting period before spawning habitat becomes accessible, leads to higher rates of exhaustion and potentially higher mortality during spawning in long high-elevation spawning migrations (e.g., sockeye salmon in Crossin et al. 2004). Finally, early reconnection flows and related access to more and higher-quality habitat may allow spawning salmon to select more favorable nesting sites, which could exert a controlling influence on the mortality rates of the young produced that year.

It is also notable that the metrics with the highest predictive power are associated with negative values, or coho spf penalties. One possible interpretation is that hydrologic metrics can be useful for identifying unfavorable conditions for coho salmon, but are not sufficient to describe favorable conditions. The ecological theory that may explain this further is beyond the scope of this paper, but could be a focus of future studies.

1.6.5 Implications for water and fisheries management

This study represents a contribution to the large body of work seeking to understand and conserve aquatic ecosystems in the Klamath basin and Mediterranean climates more generally. Viability of the SONCC ESU of coho salmon has been examined at a regional scale in the past, though conclusions were preliminary, due to data limitations (Williams et al. 2006, 2008). A proposed framework to assess viability included the following factors (Williams et al. 2008):

- Effective population size
- Population size per generation
- Population decline (rate of decline)
- Catastrophic decline (order of magnitude decline within 1 generation)
- Spawner density
- Potential spatial habitat capacity, in units of Intrinsic Potential (IP)
- Hatchery influence
- Extinction risk from population viability analysis model

This work can potentially help managers understand some of the mechanisms driving the population size per generation dimension of this viability schematic - though its predictive power is limited to being relative to the size of the escapement.

We note also that any adaptive management other than flow management (e.g., habitat restoration) will introduce (and surely has already introduced) confounding factors into this modeling exercise. For example, extreme dry conditions and high occurrence of fish stranding in water year 2014 led agencies and local organizations to conduct an unprecedented juvenile salmon rescue operation (CDFW 2015a). It is possible the coho spf for water year (and Rearing Year) 2014 would have been even lower without that intervention (although this is hard to judge; it is also possible that the translocation stressed the fish and may have led to increased mortality rates). Future work may be able to estimate the independent coho population impact of these non-flow adaptive management tactics.

We expect pieces of this approach could be employed in other regional studies, though in systems with shorter or minimal ecological monitoring records, opportunities to find correlations between flow and biological metrics may be sample size-limited to an even greater degree than in this study. However, this study may show the value of even a dozen years of monitoring data in a range of water year types, and could provide motivation to continue investing in data collection and the monitoring of sensitive species.

1.7 Conclusions

This case study uses the functional flow framework and long-term biological monitoring to relate hydrologic conditions to watershed-scale anadromous fish reproduction rates. The empirical flow-biology relationships evaluated here also suggest hypotheses regarding the watershed-specific mechanisms of ecological response to flow variability.

To learn if it was possible to empirically quantify a hydrologic regime that meets the ecological needs of coho salmon in the Scott River watershed, we examined correlations between several dozen hydrologic metrics and local salmon observations. We found several metrics, both from prior studies (Patterson et al. 2020; Yarnell et al. 2020) and designed for this study (Figure 5), that appeared correlated with the number of coho smolts produced per female spawner (coho spf). The two flow metrics most correlated with the coho spf of a given smolt cohort were the first date after the dry season of flows rising above 10 and 100 cfs, respectively, during the spawning window for the cohort's parents. This suggests that in the Scott River watershed, flow conditions and habitat access during spawning may be the greatest single factor in a brood's success, affecting the cohort from the egg stage through outmigration to the ocean.

We used linear models to predict coho spf values for each water year based on potential combinations of one and two hydrologic metric predictors. The intercept and slopes of the three best of these linear models were aggregated to formulate a Hydrologic Benefit function (Figure 11). With this formulation, a prediction could be made each fall, using the flow hydrology of the preceding water year and the estimated number of female spawners during the previous fall-winter, regarding the number of smolts to be observed in the coming spring. It can also be applied to the river flow output of hydrologic models simulating various management scenarios, to estimate the impact of infrastructure or regulation on local salmon reproduction.

With continuing trends of a narrowing wet season in the Scott River watershed (e.g., Figure 7), entities aiming to sustain local fisheries may find themselves working with ever-thinner margins for error. Globally, in communities living and working with local natural resources, climate change may transform biodiversity-preservation activities into long-term engineering of novel ecosystems. If this occurs, long-term monitoring and frequently re-evaluated flow-ecology relationships will be necessary to support such efforts.

2 Chapter 2. Multi-objective assessment of a stakeholder-defined portfolio of groundwater and stream management actions in an agricultural basin

2.1 Abstract

In rural areas of western North America, agricultural and environmental water needs often come into conflict, and robust management of water resources may require predicting the hydrologic response of complex interconnected surface and groundwater systems to various management actions. Increasingly, to support policy choices, managers in California rely on analyses using hydrologic models, but in many cases these models can provide confusing or overwhelming amounts of information. In this study, we address these challenges for a case study jurisdiction in northern California, which recently finalized a long-term Groundwater Sustainability Plan (GSP). We developed a summary statistic or proxy for each of the three primary policy objectives in the GSP (environmental, agricultural, and project cost). We then used them to summarize the results of 40 management scenarios developed for the Groundwater Sustainability Plan (GSP) in Scott Valley in Northern California, which were simulated using an existing integrated surface- and groundwater model.

We found that a trade-off in benefits for fish and farms was evident in every category of infrastructure investment (a proxy for project cost), though greater infrastructure investment can achieve some reductions in this trade-off. Additionally, although the GSP management priorities emphasized infrastructure investments, both infrastructure-based and regulatory approaches fell within the Pareto-optimal set of management options under a strict application of these objective functions. Finally, regarding regulatory actions, management interventions targeted at low-flow periods produced a more efficient gain in environmental flow value per cost in agricultural productivity. The development of basin-specific objective functions, especially ones using output from existing hydrologic models, could help quantify management decision trade-offs and improve stakeholder communication in ongoing water planning efforts throughout the region.

2.2 Introduction

Sustainable development of water resources, in an era of climate change and increasing human water consumption (e.g., Williams et al. 2020; Rodell et al. 2018), requires an interdisciplinary understanding of connected socio-hydrologic systems (Reuss 1992; Di Baldassarre et al. 2019). One such interdisciplinary approach is water resources systems analysis (WRSA), which involves applying optimization methods to water resource planning (Maass et al. 1962; Cohon and Marks 1975; Brown et al. 2015). The utility of such studies typically depends on robust definitions of the "objective function(s)", which summarize and quantify the desired outcome(s) of the proposed project or management scenario (Gorelick 1983). In practice, classical WRSA approaches have been criticized as being too removed from stakeholder concerns (e.g., Rogers and Fiering 1986). In this study, we take advantage of the authors' involvement in an existing water resource planning process, and a previously-developed integrated surface- and groundwater model (the Scott Valley Integrated Hydrologic Model, or SVIHM; Tolley, Foglia, and Harter 2019), to test the utility of introducing elements of multi-objective optimization into the prioritization of groundwater management alternatives.

In our study area, the intermontane rural Scott Valley in northern California (Figure 13), the local government and public stakeholders recently spent three years developing a plan for the long-term use of groundwater (a Groundwater Sustainability Plan or GSP). In that process, they evaluated dozens of potential water management scenarios (Siskiyou County 2021). In public meetings, different objectives were often championed by individual stakeholders or interest groups. An integrated hydrologic model was available to support this policy-making process, and the numerical streamflow results of simulated management scenarios drove decision-making, but discussions on the balancing of multiple objectives were typically qualitative. In effect, the optimization framework used to arrive at the ultimate list of management priorities was implicit, and the conceptual weight given to different objectives varied between stakeholders.

Differences between stakeholders in what is considered an acceptable trade-off are common in policy decisions (Monarchi, Kisiel, and Duckstein 1973). Consequently, multi-objective optimization studies commonly avoid proposing a single optimal solution; instead they identify a Pareto-optimal or non-inferior set of options, which can clarify the unavoidable trade-offs in the performance of various system objectives (e.g., Cohon and Marks 1973). Methods for finding the non-inferior set often involve uniform or randomized initial sampling of the decision space (e.g., Monarchi, Kisiel, and Duckstein 1973; Yeh and Becker 1982; Kapelan, Savic, and Walters 2005). In the case of the Scott Valley GSP, the management actions considered by stakeholders covered a wide range of decision variables (e.g., land use changes, technology and/or infrastructure investment, and regulatory interventions on a range of growing season dates). Because a full randomized sampling of this decision space would be computationally prohibitive, this study instead focused on a set of simulated management scenarios that were effectively pre-screened by stakeholders for feasibility in the landscape of existing land uses and political dynamics.

To investigate whether an explicit optimization framework would yield different prioritization of management actions than the set agreed upon in public meetings, we developed numerical representations of three objectives: 1) maximizing specific environmental flows, 2) minimizing reduction in agricultural water supplies, and 3) minimizing new infrastructure costs. With these, we quantitatively summarized the management benefits and trade-offs within the existing suite of several dozen stakeholder-proposed management scenarios.

2.3 Case study and summary of GSP development

2.3.1 Hydrography and climate

The Scott River drains a 2,109 km^2 (814 square mile) intermontane watershed known as Scott Valley, surrounded by several mountain ranges, including the Scott Bar, Marble, Salmon and Scott Mountains to the north, west, southwest, and south, respectively. The valley floor overlies unconsolidated alluvial sediments of up to 79 m (260 ft) thickness (SWRCB 1975). The sediments form a mostly unconfined aquifer system bordered by low permeable, fractured underlying and adjacent bedrock composed of mostly Paleozoic metasedimentary formations (Mack 1958).

The Scott River begins near the community of Callahan, where the East and South Forks of the Scott River converge, and flows north through the agricultural and residential areas of Scott Valley (Figure 13). Then, 58.0 km (36.0 mi) downstream of Callahan, it passes a key stream gauge (USGS Station ID 11519500, or the Fort Jones Gauge or FJ Gauge) and enters more rugged terrain, flowing 34.7 km (21.6 mi) through a steep canyon until it meets the Klamath River. Because practically all water use in Scott Valley occurs upgradient of the FJ Gauge, it is used to assess hydrologic conditions and inform water management decisions in the populated areas of the valley (e.g., Siskiyou County 2021).

Scott Valley has a Mediterranean precipitation regime with distinctive seasons of cold, wet winters and warm, dry summers (Figure 14, panels A and B). Melting snowpack in the surrounding mountains generates streamflow from April through July, though onset and duration of snowmelt varies based on the snowpack volume and timing of warm air temperatures. This seasonality in water input creates seasonal flow in the Scott River and tributary streams, which experience a pronounced wet season and dry season with high and low flows, respectively (Figure 14, panel C).

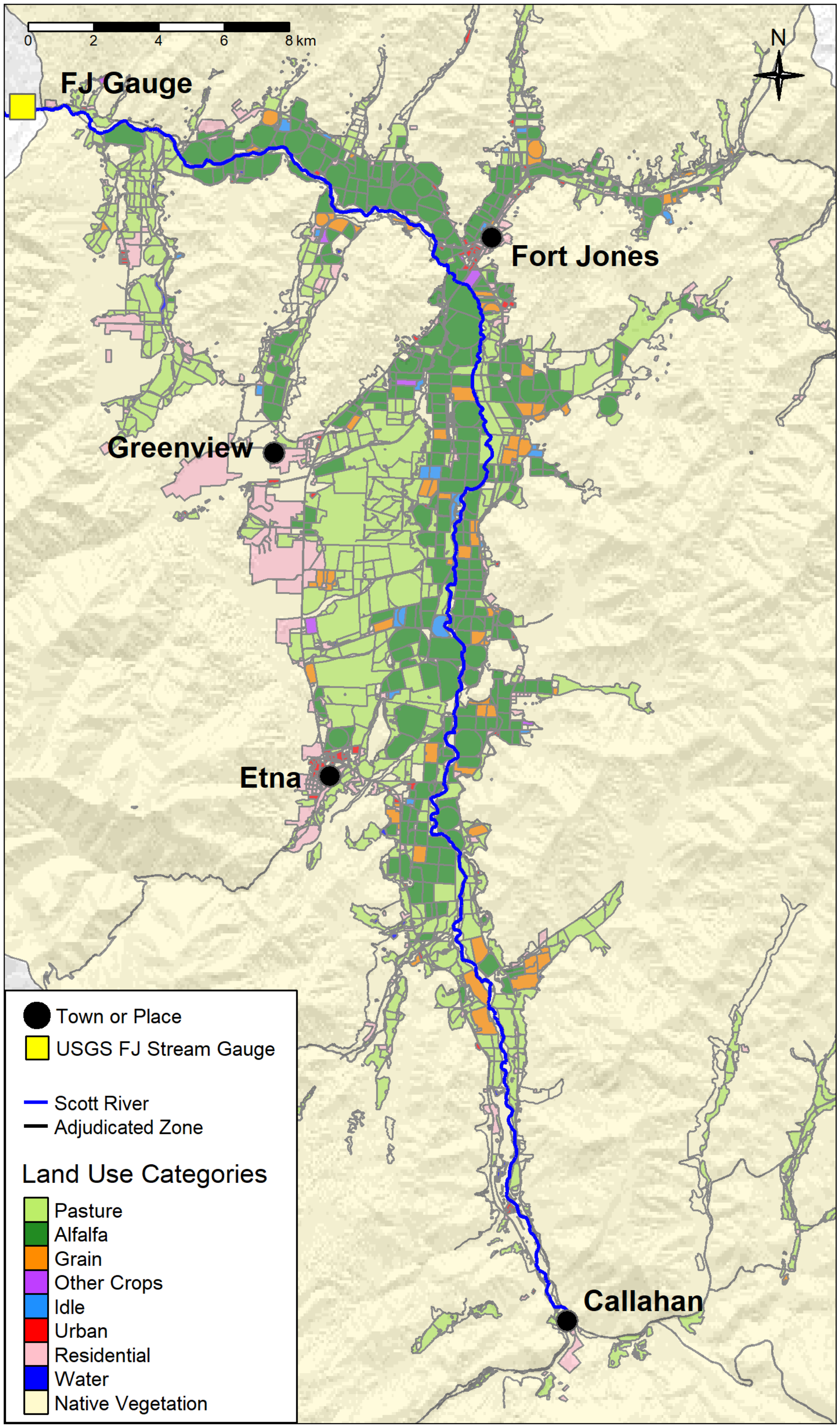


Figure 13: The Scott River flows south to north through Scott Valley before flowing through a canyon and joining the Klamath River. Land uses in the cultivated areas of the Scott River watershed are shown (adapted from the 2016 DWR Land Use Survey), as well as the location of several communities and the Fort Jones streamflow gauge (USGS Station ID 11519500).

Streams and groundwater are highly interconnected in the Scott River watershed. Tributary streams and the Scott River are a source of recharge to the aquifer, and groundwater discharge sustains streamflow in some areas, especially during the dry season of August-October or November. In the past two decades, in most dry-to-average type water years, the water table elevation has fallen below the stream bed and reaches of the Scott River have gone dry (Tolley, Foglia, and Harter 2019).

2.3.2 Human population, land use, and local economy

The population of Scott Valley is approximately 5,200, based on area-weighted block-level 2020 census data, including the populations of the two incorporated towns of Etna and Fort Jones (population 678 and 695, respectively; U.S. Census Bureau 2021). About two thirds of the land within the Scott River watershed is under private ownership with the remaining area managed by the Quartz Valley Indian Reservation, the United States (U.S.) Department of the Interior Bureau of Land Management (BLM) and U.S. Forest Service (USFS) (Harter and Hines 2008). Much of the upper mountainous area of the watershed is part of the Klamath National Forest. On the valley floor, according to land use surveys conducted by DWR (DWR 2017), half of the area overlying the alluvial aquifer is covered by agriculture, with most of that split approximately evenly between pasture and an alfalfa/grain rotation (Figure 13; Table 5).

Fort Jones and Etna are categorized as severely economically disadvantaged (defined as communities with an annual median household income [MHI] of less than 60% of the average annual MHI in California). Based on the 2013–2017 American Community Survey Five Year Estimates, the statewide annual MHI is $67,169, and Fort Jones and Etna both qualify as SDACs with annual MHIs of $29,662 and $35,333, respectively (U.S. Census Bureau 2018). The unincorporated community of Greenview is listed in government databases as a disadvantaged community (defined as an MHI of less than 80% of average state MHI), but no MHI data are available for this community (DWR 2019).

Land Use Category	Acres	Percent of Watershed Area
Native Vegetation	378,005	89.4
Pasture	20,483	4.8
Alfalfa	13,931	3.3
Residential	4,908	1.2
Grain	2,152	0.5
Urban	1,584	0.4
Water	1,220	0.3
Idle	454	0.1
Other Crops	175	0.0

Table 5: Acreage and percent of total Basin area covered by generalized land uses as reported in DWR's 2016 land use survey.

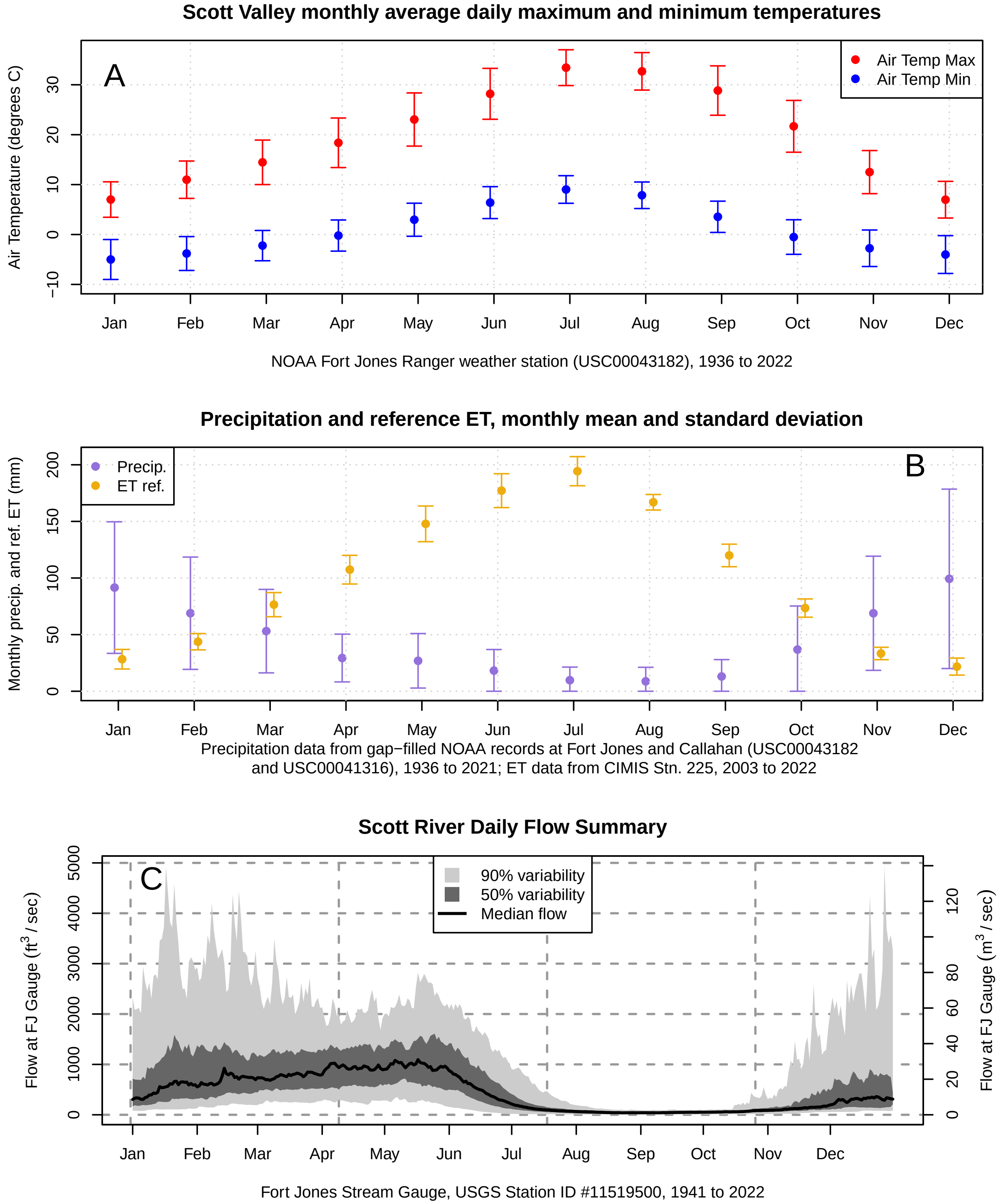


Figure 14: Summary of temperature (Panel A), rainfall and reference evapotranspiration (Panel B), and daily streamflow values (Panel C) in Scott Valley. For precipitation, regression relationships between the Callahan and Fort Jones weather station records and the records of NOAA stations in Greenview, Etna, and Yreka (USC00042899, USC00043614, USC00049866, and US1CASK0005) were used to predict missing values (i.e., fill gaps) in the Callahan and Fort Jones records; the daily mean of the two stations was used as the final precipitation record for purposes of this figure and the SVIHM precipitation input.

2.3.3 Water uses and management objectives

Like many rural watersheds in arid to semi-arid regions, balancing environmental and agricultural water demands is a significant challenge faced by local water managers. Water uses, land management, and the measurement units used in local regulatory documents were discussed in Chapter 1 of this dissertation:

> ”Water in Scott Valley is used for agricultural, domestic, and municipal supply. It also facilitates recreation and provides Native American cultural services, among other designated beneficial uses (NCRWQCB 2006). Because the watershed is undammed, managers and water users influence Scott River flow primarily via diversion of surface waters or pumping of groundwater. Consequently the most powerful tool available to manage Scott River water flow is regulation of land use and thus water demand (Siskiyou County 2021).
>
> Historically, local regulation of land use has focused on maintaining the rural and agricultural character of Scott Valley (Scott Valley Area Plan Committee 1980). Regulating land use to improve ecological outcomes would entail significant economic, political and social risks, because much of the economic activity in this area is related to agriculture. The primary crops grown in Scott Valley are alfalfa and pasture for cattle feed (Siskiyou County 2021). In addition to local economic impact, Scott River conditions influence fish population dynamics both within the watershed and in the broader Klamath system. The health of the Klamath salmon run has implications for commercial fishing, recreational activities, and cultural practices of Native American tribes in the region, including the Quartz Valley Indian Community and the Karuk and Yurok Tribes (Graham 2012).
>
> All of the regulatory and management programs in this region, including recommended instream flows (CDFW 2017) and legal rights governing surface water diversion (Superior Court of Siskiyou County 1980), are tabulated in units of cubic feet per second (cfs). For consistency, this document will also use primarily cfs units, with metric units in parentheses.”

Environmental stream flows

Sufficient environmental flows at certain times of year are necessary to the survival of vulnerable species in the Scott River watershed. Coho salmon (*Oncorhynchus kisutch*) in Scott Valley belong to the Southern Oregon / Northern California Coast (SONCC) Evolutionarily Significant Unit (ESU), and were listed as threatened under the federal and California Endangered Species Acts (ESAs) in 1997 and 2005, respectively. Statewide coho populations have declined by an estimated >90% since the 1940s (Brown, Moyle, and Yoshiyama 1994).

To complete their life cycle, coho salmon require several key functional flows in the Scott Valley freshwater stream system, including the following:

- Fall flows, increasing after the dry season in response to early wet season storms, that occur early enough to provide adult fall-run spawners access to preferred spawning reaches
- Flows providing habitat for rearing juvenile salmon for their ~12-15 months of freshwater residence
- Sufficient flow in the spring for yearling smolts to emigrate to the ocean

Other species may require other functional flows (e.g., cottonwood trees require flood-stage flows to disperse their seeds; Mahoney and Rood 1998), but in this work we focus on coho salmon, the most vulnerable species in the watershed. Future work could evaluate the suite of flows needed by a larger set of species in Scott Valley.

Agricultural water demand

Agricultural water demand in Scott Valley has been simulated for a historical model period of water years 1991-2018 (Oct. 1 of 1990 to Sept. 30 of 2018), using the calibrated Scott Valley Integrated Hydrologic Model (SVIHM; Harter and Hines 2008; Foglia et al. 2013; Tolley, Foglia, and Harter 2019). Water demand for crops and native vegetation (ET in Figure 15) and applied irrigation volumes (diverted surface water and pumped groundwater, noted as SW and GW Irrigation in Figure 15) are highest in the late summer. In dry water years, initial soil moisture levels may be lower, and irrigation demand may be somewhat higher, though annual crop ET and irrigation demand is relatively stable year to year (Figure 16).

In this intermontane valley, the growing season is constrained by hard frosts, and begins in March-April and extends through September-October. Both of the primary crops (alfalfa and pasture) are perennial, and will continue producing through the growing season as long as soil moisture is available. Alfalfa cultivation since the 1970s has commonly involved three to four harvests (referred to as cuttings) per growing season; it is typically irrigated several times and then left to dry before cutting (Tolley, Foglia, and Harter 2019).

In the mid-twentieth century, farms and ranches irrigated grain, alfalfa and pasture crops mainly with diverted surface water, which was abundant until mid or late summer, and many utilized flood irrigation. On this schedule two alfalfa cuttings were harvested, with the last irrigation typically occurring in July. Since the 1970s, widespread construction of irrigation wells has effectively extended the irrigation season and allowed alfalfa farmers to harvest three or four cuttings in a growing season. (Additionally, higher-irrigation efficiency technology like wheel-line and center-pivot sprinklers became common, though this does not alter the consumptive demand of the cultivated crops.) Based on historical crop coverage and water demand estimates by Harter and Hines (2008), “the amount of water likely used by crops has increased from 1958 to 2000 by between 15 percent (10,000 more acre feet) and 30 percent (20,000 acre feet) depending on the date when surface irrigation [is assumed to have ceased historically], i.e. July 15, Aug 1 or Aug 15.”

The tension between agricultural and ecological water demands is highest at the end of the dry season, when groundwater elevations and surface flows are at their lowest, crop demand remains high, and anadromous fish require access to spawning habitat. The management of these fall flows was a central concern of GSP development in 2018-2021.

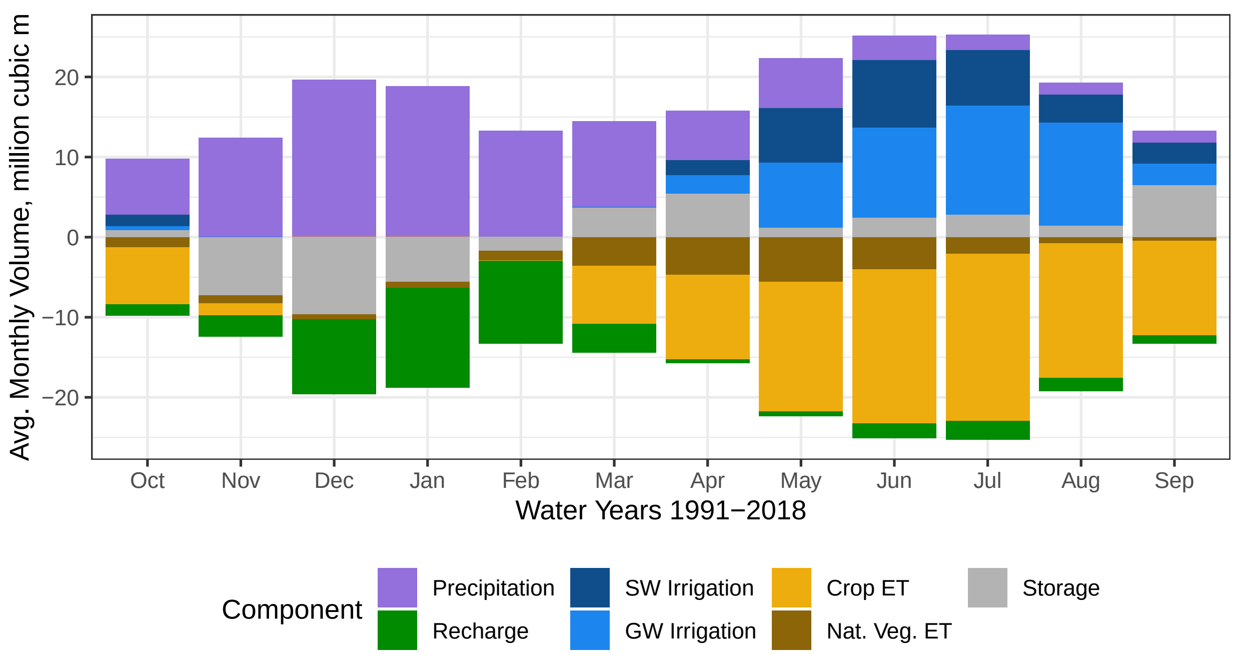


Figure 15: Average monthly water budget for the soil zone, simulated with SVIHM, for the model simulation period (water years 1991-2018). Positive and negative values indicate average net monthly fluxes into and out of the soil zone, respectively.

2.3.4 GSP development

The Scott Valley Groundwater Sustainability Plan (GSP) was developed by the Siskiyou County Flood Control and Water Conservation District, which is the designated Groundwater Sustainability Agency (GSA) charged by the state of California to sustainably manage local groundwater resources pursuant to the Sustainable Groundwater Management Act (SGMA) of 2014. GSP development took place between 2018 and

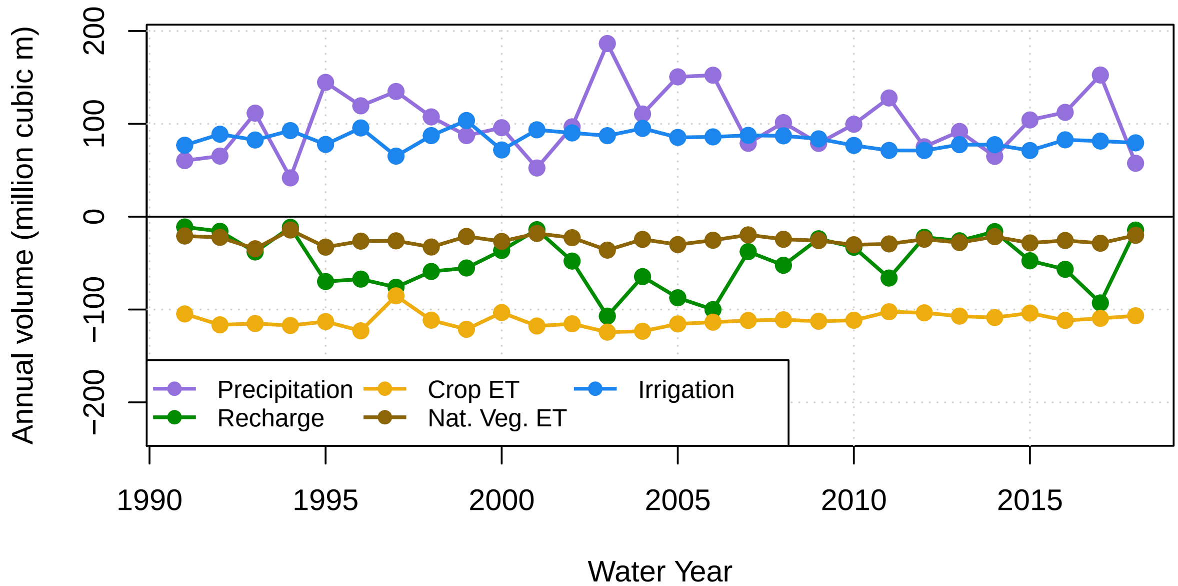


Figure 16: Annual values for inflowing (positive) and outflowing (negative) water budget components in the SVIHM soil zone (historical basecase simulation). Irrigation refers to both groundwater and surface water sources; Recharge refers to water percolating through the soil column and recharging the aquifer below. Both crop ET and ET from native vegetation remain relatively stable year to year, while precipitation inputs, and thus recharge to the aquifer, have higher interannual variability.

2021, and was guided by discussions in the monthly public meetings of an Advisory Committee composed of nine local stakeholders. Technical analyses supporting the public meeting deliberations and GSP policies were provided by several technical experts, including the authors of this study (Siskiyou County 2021).

SGMA requires each local GSA to define sustainability in the negative, by quantifying and then avoiding "undesirable results" that would be "significant and unreasonable". The central undesirable result in Scott Valley is streamflow depletion due to groundwater pumping. Consequently, a central challenge of GSP development was defining a reasonable amount of streamflow depletion reversal, accounting for environmental water demand and what degree of agricultural water security was necessary to sustain the local economy.

The authors of this study simulated dozens of land and water use scenarios to facilitate the comparison of management alternatives that could reduce streamflow depletion to various degrees. Simulations were conducted with a spatially explicit, integrated surface water-groundwater model (Tolley, Foglia, and Harter 2019), as described below.

2.3.5 Hydrologic model summary

The Scott Valley Integrated Hydrologic Model (SVIHM) is a surface and groundwater model driven by tributary stream inflows, precipitation inputs, and reference evapotranspiration (ET_0). The boundary of the model domain corresponds approximately to the extent of the alluvial aquifer. For detailed information about the model structure, sensitivity, calibration, uncertainty, and validation of results, see recent work by Tolley et al. (2019). Like all models, it does not perfectly reproduce observed historical measurements, but it successfully captures key watershed-scale hydrologic phenomena that can be used to evaluate potential outcomes of specific management actions.

The SVIHM is composed of three cascading sub-models. First, complete daily records of tributary stream inflow are generated using a statistical streamflow regression model, in which the continuous Fort Jones record was used to predict missing values in the daily flow records of 12 major tributaries (Foglia et al. 2013). Second, a custom-built soil water budget model simulated irrigation demand, irrigation applied (surface and groundwater), ET and percolation to aquifer calculated on a field-by-field, daily time step basis. This model simulates individual irrigation applications and assumes the farmer has perfect foresight of daily irrigation demand. Finally, the boundary conditions of stream inflow, aquifer recharge, and groundwater extraction are used to drive an integrated groundwater-surface water model using MODFLOW; stream-aquifer flux and surface flow routing was simulated using the MODFLOW SFR package (Tolley, Foglia, and Harter 2019).

For GSP development, SVIHM was used extensively to perform what-if scenarios using the historic climate and land use forcing period, 1991-2018. Scenario simulations repeat the calibrated historical basecase simulation of SVIHM using specified sets of changes in SVIHM boundary conditions (BCs). The set of changes in the BCs of a particular scenario represent specific changes in land use, irrigation management, climate, water management rules, etc. Scenario outcomes are compared against those of the basecase simulation. Key results of each SVIHM scenario, used in the objective functions described below, are:

1. A prediction of Scott River flow the Fort Jones Gauge, which is co-located with the surface water outlet of the model domain; and
2. Simulated total ET of crops and native vegetation within the model domain.

2.4 Methods

We developed two objective functions and one categorical objective proxy to evaluate the management scenarios developed for the GSP. The three objectives were: maximizing specific environmental flows, maintain current levels of agricultural productivity (represented as minimizing reduction in agricultural water use), and minimizing new infrastructure costs (represented as a categorical infrastructure/feasibility proxy) (Table 6). We then applied these to the results of each simulated management scenario, found the Pareto-optimal set of scenarios, and compared them to the prioritization of management actions adopted in the GSP (Siskiyou County 2021).

We should note that protecting domestic water use was also discussed as a management objective, but this was not evaluated as an objective function in management scenarios, for three main reasons: it was assumed that solving the environmental flows problem would intrinsically keep groundwater levels sufficiently high to protect domestic groundwater use from well outages; the number of reported well outages in recent dry years was minimal; and the data necessary to assess domestic well outages (specifically, total well depth and pump depth information) was available only for a small number of wells.

Management Objective	Objective Function
Maximize specific environmental flows	Hydrologic Benefit function, based on flow metrics empirically correlated with coho salmon reproduction rates (higher values preferred)
Minimize reduction of agricultural water use	Crop ET volume over model domain (higher values preferred)
Minimize new infrastructure investment	Feasibility category of 1-4 (lower values preferred)

Table 6: Management objectives and description of objective functions applied to summarize scenario performance.

2.4.1 Objective functions

Hydrologic Benefit function

In Chapter 1 of this dissertation, we showed that the degree to which the water year provided ecological services needed by coho salmon can be estimated using a Hydrologic Benefit (HB) function, which summarizes environmental flows in a single index value for a given water year. A set of streamflow metrics related to the timing, amplitude, and duration of flow phenomena were weighted according to their power to predict salmon coho smolt production per female spawner. These weighted metrics are combined linearly to predict a value for coho salmon reproduction. See Chapter 1 for more details on these calculations. Specifically, the HB function predicts a higher number of coho salmon produced per female spawner (coho smolts per female, or coho spf-equivalent) when fall flows rise above 10 and 100 cfs earlier in the fall, when the wet season onset is earlier, and when the wet season duration is longer. The equation to calculate the HB value for a given water year is as follows:

$$HB_{wy} = b + m_1 * metric_{1,\ wy} + ... + m_4 * metric_{4,\ wy}$$

Where:

HB_{wy} is the Hydrologic Benefit value for a given water year (predicted coho spf or coho spf equivalent)

$b = 93.4$ coho spf equiv.

$m_1 = -1.15$ coho spf equiv. per day of reconnection after Aug. 31, 10 cfs

$m_2 = -0.17$ coho spf equiv. per day of reconnection after Aug. 31, 100 cfs

$m_3 = -0.20$ coho spf equiv. per day of wet season onset after Sep. 30

$m_4 = 0.12$ coho spf equiv. per day of wet season baseflow duration

The HB function was formulated based on functional flow metrics of the observed daily average flow record of the FJ gauge (FJ_{obs}). One key result of the historical basecase scenario is a simulated estimate of the historical FJ gauge record ($FJ_{sim,\ basecase}$); however, although SVIHM was extensively calibrated (Tolley, Foglia, and Harter 2019), because all models involve structural simplifications of a full-scale watershed, $FJ_{sim,\ basecase}$ sometimes over- or under-estimates FJ_{obs}. As a result of these differences, HB values calculated from flow metrics of $FJ_{sim,\ basecase}$ tend to be higher than HB values derived from FJ_{obs} by a mean of 4.5 coho spf-equiv.

To control for this, all basecase HB values used in this study are derived from $FJ_{sim,\ basecase}$, making them directly comparable to HB values derived from the simulated FJ flow records in the hypothetical management scenarios.

ET volume function (agricultural benefit proxy)

The annual crop ET volume, which is explicitly simulated in the hydrologic model, is used here as a proxy for agricultural productivity. Other options for framing the agricultural water use objective function include crop yields and total revenue, which may be of greater concern to stakeholders; however, annual crop ET was selected because the impacts of reduced water availability on yield or revenue will likely vary by grower and over time.

Specifically, conversion of ET to yield or revenue would introduce multiple uncertainties, such as those related to marginal crop production costs and available technology (Howitt 1995). In studies that do implement a water-to-yield or -revenue conversion, multi-year average values for per-acre yield and/or revenue are commonly used (e.g., Cole and Medellín-Azuara 2021 for the Scott Valley case), since those are typically the only values available. This approach is most valid when the marginal change in productivity is small relative to the average (Howitt 1995). Additionally, average values cannot account for time-varying costs of a management action (e.g., the increase in cost of lettuce cultivation due to banning a certain pesticide is higher in some seasons than in others, as described in Sunding 1996).

Additionally, for alfalfa and pasture, which continue growing as long as water is available, a strong relationship between crop ET and yield is assumed (Carter and Sheaffer 1983). The assumption that crop ET is consistently related to yield or revenue breaks down for a management scenario that includes changing crops; this is explored further in the Discussion section. But on the merits of these options, annual crop ET was selected to represent agricultural benefit.

Proxy for scenario infrastructure investment

In lieu of detailed cost estimates or feasibility studies, we chose to group management alternatives in qualitative categories approximating the degree of new infrastructure investment needed in each alternative. The categories describing project feasibility and timeframe are as follows:

0. No feasibility barriers (basecase; maintain current practices)
1. Implementable with current infrastructure
2. Requires new infrastructure that would take 1-2 years to build

3. Requires new infrastructure that would take 3-5 years to build
4. Requires new infrastructure that would take 5+ years to build

This reflects the first-order understanding that, for example, building a reservoir (assigned to category 4) will take more effort and resources in terms of permitting and construction than widespread installation of highly efficient irrigation systems (assigned to category 2). See Table 8 for full list of assigned categories.

2.4.2 Analyses of objective function values

Trade-off efficiency and "low-coho" years

As discussed previously, balancing agricultural and environmental water demands in this watershed typically takes the form of seeking management actions that can improve flow conditions while minimizing the resulting reduction in agricultural water availability. These objectives are non-commensurable (i.e., an estimated level of fish reproduction cannot be converted into units of agricultural productivity), making an explicit quantification and consideration of benefit trade-offs a critical feature of this decision-support analysis (Cohon and Marks 1975). Environmental benefits are less commonly quantified than agricultural costs (e.g., Sunding 1996, which assessed numerical costs of a management action and assumed qualitative environmental/human health benefits), but the HB function makes this trade-off quantification possible in the Scott Valley case.

For this analysis, which is not intended to identify one "best" or optimal solution, these trade-offs can be considered using scenario objective value differences relative to their basecase (historical simulated) values. We will call this quantity the "trade-off efficiency" of a management scenario. For a given scenario, the trade-off efficiency, or $\mathrm{Eff}_{\mathrm{scen}}$, is unitless (i.e., it has units of coho spf-equiv. per coho spf-equiv. / million m^3 per million m^3), as shown in the formula below.

An efficiency for a subset of years can be calculated by averaging the efficiency values over that set of water years only. The set of years with low basecase HB values (operationally defined as values lower than 45 coho spf-equivalent, composed of 1993, 1995, 2002, and 2014-16) is relevant to water managers (see Discussion), and is henceforth referred to as the set of "low-coho" years. A low-coho year efficiency was calculated in addition to the efficiencies averaged over all water years.

$$HB_{avg} = \frac{1}{n_{wy}} \sum_{i=wy_1}^{wy_n} HB_{wy_i}$$

$$ET_{avg} = \frac{1}{n_{wy}} \sum_{i=wy_1}^{wy_n} Crop\ ET_{annual,\ wy_i}$$

$$Eff_{scen} = \frac{(HB_{avg,\ scen} - HB_{avg,\ basecase})/HB_{avg,\ basecase}}{-1 * (ET_{avg,\ scen} - ET_{avg,\ basecase})/ET_{avg,\ basecase}}$$

Pareto-optimal set of management actions

After calculating the objective function values for each scenario, we applied a simple algorithm to identify the Pareto-optimal set of scenarios (Pareto 1896). A scenario was identified as Pareto-optimal if there were no other scenarios that performed better in two or more objectives. In other words, the Pareto-optimal set is the collection of scenarios in which it is not possible to improve on one objective without reducing performance in another objective. By definition, this set cannot identify a single best scenario or evaluate trade-offs between objectives; we use it here to identify obviously suboptimal scenarios.

For example, the objective function values for the scenario simulating managed aquifer recharge and in-lieu recharge (MAR and ILR, or scenario identifier `mar_ilr`) are 76.1 predicted coho smolts per female equivalent (HB value), 111.0 million m^3 of crop ET, and infrastructure category 3. Most scenarios (33) have a higher HB value than `mar_ilr`, but only eight have a higher ET value. Only the reservoir scenarios show up in both sets, with higher ET and higher HB value than `mar_ilr`. However, the reservoir scenarios are more difficult to implement, so any of those scenarios would have less desirable performance on the infrastructure objective. Consequently, since no scenarios perform better than `mar_ilr` in more than one objective, it must be included in the Pareto-optimal set.

2.4.3 Scenario descriptions

For the Scott Valley GSP, this study simulated 64 management action scenarios, compared to between one and five scenarios modeled in most other California GSPs (e.g., FCGMA 2019; YSGA 2022). This high number of scenarios was possible because the SVIHM had been under development for 8 years prior to the start of GSP work (e.g., Foglia et al. 2013; Tolley, Foglia, and Harter 2019), and cost-effective technical support was provided by graduate students at the University of California, Davis. Of the 64 scenarios, only 40 are considered here. Several were ruled out as obviously unfeasible (e.g., construction of a 134 thousand acre-foot reservoir to ensure 100% flow reliability even during severe drought, in an area with topography that could not support such a large capacity), and some were excluded because they are largely redundant with some of the 40 considered here.

The scenarios are grouped here by category (Table 7). Within each category various details were altered (e.g., an alfalfa irrigation cessation date of July 10 versus August 15, or an assumed crop water consumption of 80% versus 90% of historical). See *Chapter 2 Supplement* for more detailed scenario descriptions.

Category	Scenario Category Description	Num. Scen.	Infra. Proxy	Mgmt. Type
Basecase	Basecase	1	0	Basecase
EnhRch	Enhanced Recharge	3	3	Infrastructure
EnhRchEx	Expanded Enhanced Recharge	3	3	Infrastructure
IrrEff	Improved Irrigation Efficiency	2	2	Infrastructure
Res	Small Reservoir	5	4	Infrastructure
CropCh	Crop Change (lower ET)	2	2	Infrastructure
AlfIrr	Cease Alfalfa Irrigation Early	5	1	Regulatory
Curtail	Cease (Curtail) All Irrigation Early	6	1	Regulatory
FlowLims	Low Flow Diversion Limits	1	1	Regulatory
NatVeg	Some Nat. Veg. Land Use	6	2	Nat. Veg.
NatVegET	Some Nat. Veg. (higher ET)	6	2	Nat. Veg.

Table 7: Management scenario categories (abbreviated), a general description, the number of scenarios in each category, the feasibility proxy and the type of management action.

2.5 Results

As described above, objective functions were used to quantitatively summarize the achievement of environmental and agricultural goals for the basecase and 39 management scenarios. A Hydrologic Benefit (HB) value (in units of predicted coho smolt production per spawning female, or coho spf-equivalent) and a total crop ET volume was calculated for each water year in the 28-year simulation period, for each scenario. Each scenario has also been given an infrastructure feasibility proxy (Table 8).

2.5.1 Environmental and agricultural objective function values

The aggregate hydrologic impact of each management scenario can be compared against the historical basecase using the annual objective function values over the full 28-year record (e.g., Figure 17) or using the 28-year mean values for each scenario (Figure 18; Table 8). In the basecase scenario, the 28-year mean annual ET volume is 111 million m^3 of water, and the 28-year mean of annual HB values is 68.9 coho spf-equivalent (Table 8). Annual ET volume is relatively stable over the model period of water years 1991-2018, while annual HB values are much more variable (Figure 17). Among the 39 management scenarios, mean ET values ranged from 0 to 112 million m^3 of water, while HB values ranged from 70 to 93.2 coho spf-equivalent.

Four scenario categories fall in a cluster with relatively high ET values, indicating that these scenarios conserve nearly all the basecase economic benefits for local growers: Enhanced Recharge, Expanded Enhanced Recharge, Irrigation Efficiency, and Small Reservoir (Figure 18). The scenarios in this group all require some degree of infrastructure investment, and they have a minimal impact on crop ET: the mean ET values of

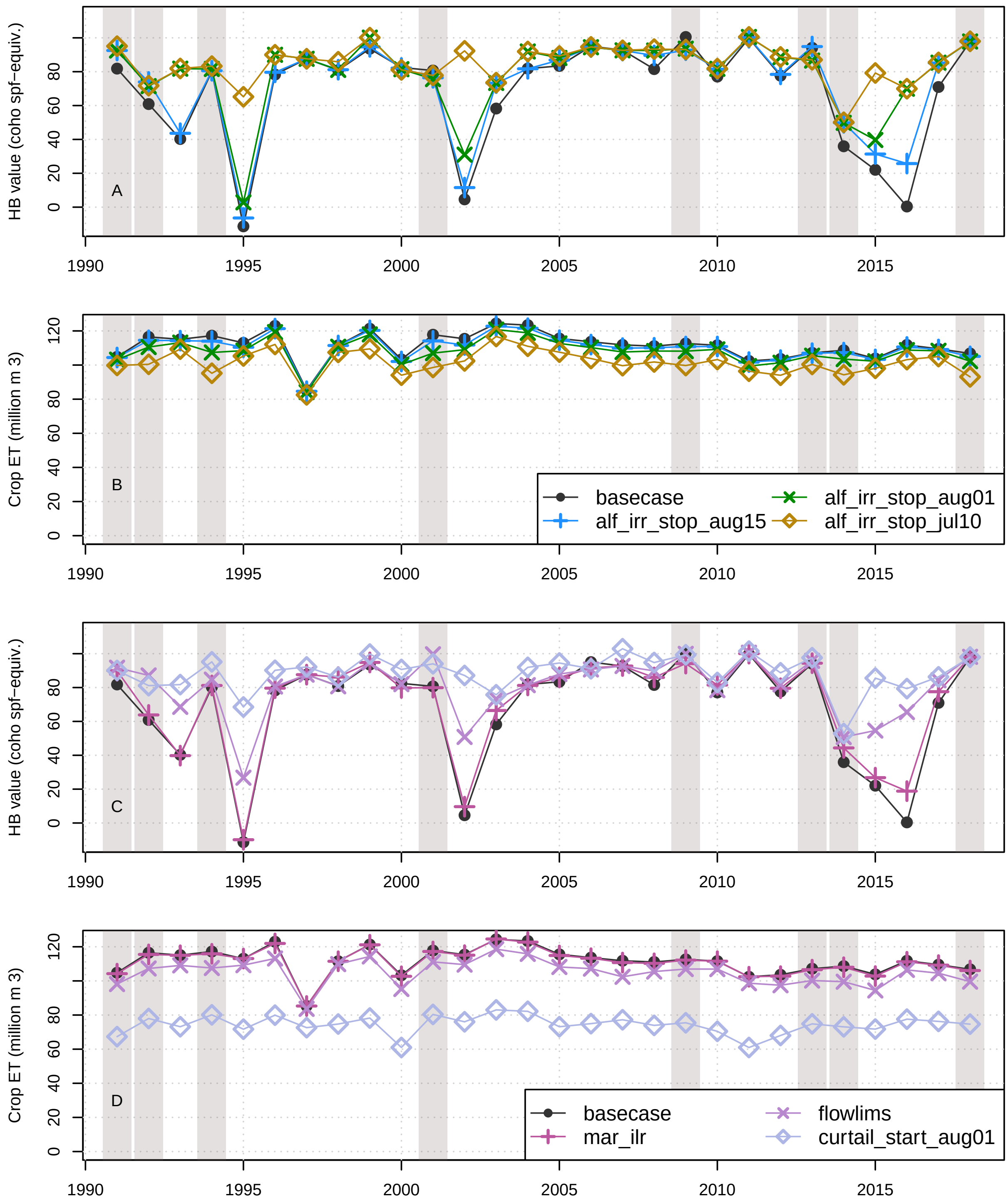


Figure 17: Comparison of annual performance in two objective functions (HB and ET, representing environmental and agricultural objectives, respectively), in the basecase (black circles) and management scenarios (diamond, cross or x symbols) for water years 1991-2018. Panels A and B show comparisons between basecase and one example scenario in each of three categories: Enhanced Recharge, Low Flow Diversion Limits, and Curtailment. Panels C and D show comparisons between basecase and different cutoff dates within the Alfalfa Irrigation category: July 10th, August 1st and August 15th. Dry-type water years (vertical bars) are 1991, '92, '94, 2001, '09, '13, '14, and '18.

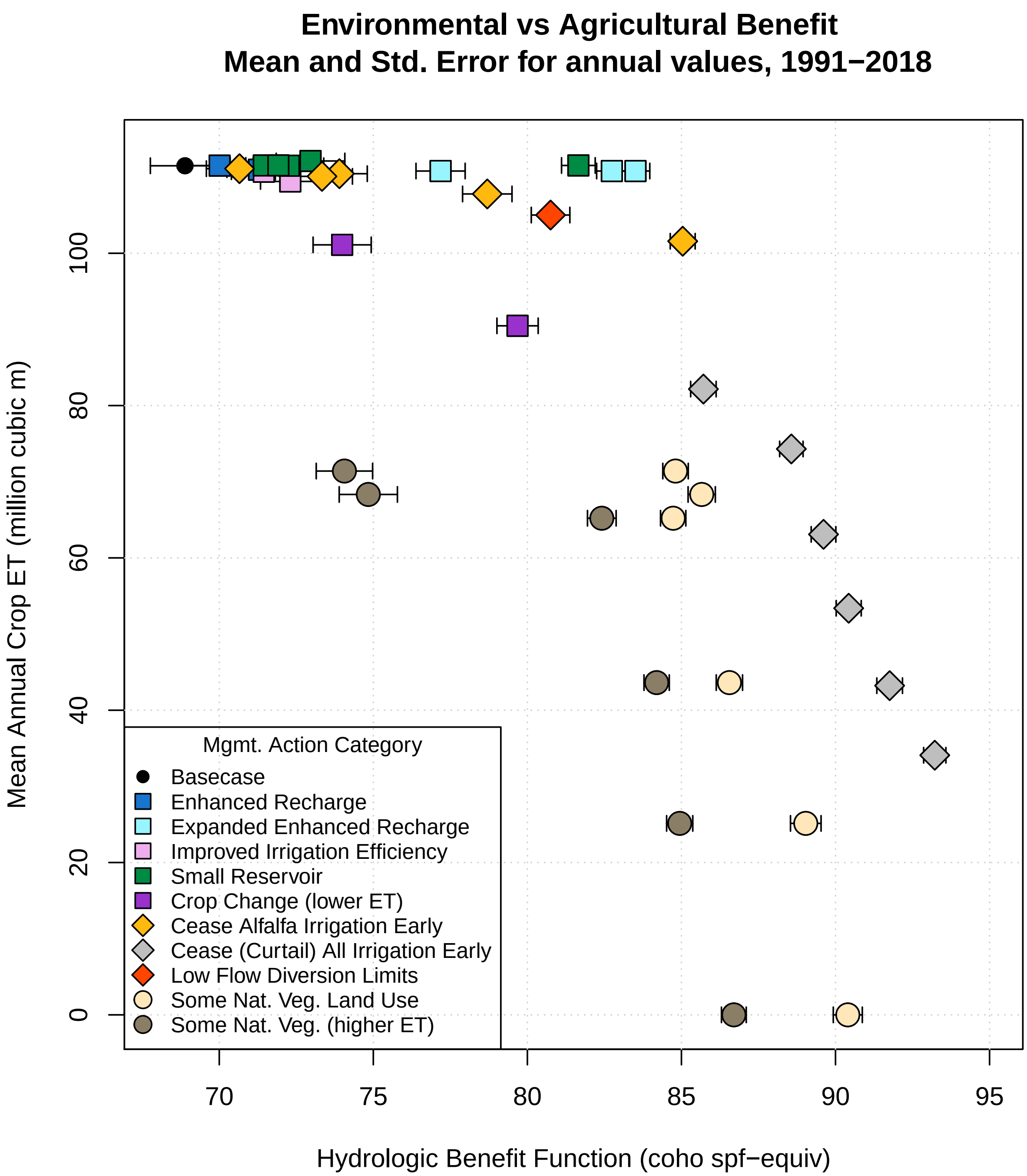


Figure 18: Environmental and agricultural objective function performance (in terms of Hydrologic Benefit, or HB, value; and crop ET volume) for basecase (black circle in upper left) and 39 management scenarios. Symbol x and y coordinates are the average of 28 annual HB and ET values for each scenario over the full model period (water years 1991-2018). Whiskers show standard error of the 28 years of annual HB values; standard errors in the direction of the y-axis are smaller than the height covered by each symbol.

scenarios in this cluster are 109 to 112 million m^3, or 2 percent less to 0.6 percent more than basecase. Their mean improvement in HB values over the basecase ranges from 1 to 15 coho spf-equivalent.

The mean ET volumes of the two Crop Change scenarios fall below those in the aforementioned cluster, with 90 and 101 million m^3, while HB values are 79.7 and 74 respectively (Figure 18). In these scenarios, existing crop coefficients are multiplied by a factor of 0.8 or 0.9; conceptually, this would involve replacing all existing irrigated acreage with unspecified crops which had a designated 80% and 90% of historical ET demand. As discussed later, in this scenario the relationship between water use and revenue may be distinctly different from that of alfalfa and pasture, so the actual "farmer benefit" may be higher or lower than this proxy suggests.

Two regulatory management categories, Alfalfa Irrigation and Curtailment, involve irrigation schedule changes, and result in a range of reductions in applied irrigation volume, depending on the date of intervention. The scenarios in these categories trace two trade-off arcs in average HB-ET space (Figure 18). The first category, early cessation of alfalfa irrigation (during all or only dry water years), is intended to simulate growers harvesting two cuttings only (i.e., one or two fewer cuttings than current) in a given year. This was simulated by ceasing alfalfa irrigation earlier in the growing season (with cutoff dates on July 10, August 1 and August 15) than the basecase default date of Sept. 1. (The Sept. 1 cutoff date assumes that growers obtain three cuttings, but does not incorporate the known small number of growers which occasionally irrigate longer to obtain a fourth cutting.) Alfalfa acreage is concentrated near the Scott River channel, much of it in the Adjudicated Zone (Figure 13), with predominately groundwater irrigation sources. The second regulatory category, Curtailment of all irrigation starting on a range of dates (June 1st through August 15th), represent book-end scenario simulations to approximate regulatory actions proposed by state resource management agencies in response to extreme drought conditions (CDFW 2021). The mean ET values of scenarios in these two categories are 34 to 111 million m^3, or 69 to 0.3 percent less than basecase; HB gains over basecase are 2 to 24 coho spf-equivalent.

The third regulatory category, Low Flow Diversion Limits, regulates surface water diversion for irrigation, and contains only one scenario (Figure 18). Among all scenarios, it is the only scenario that focuses solely on management of surface water diversions for irrigation. It assumes the FJ Gauge flowrate is representative of watershed conditions, and limits diversions of surface water from all tributaries on days when the FJ Gauge flowrate falls below a recently proposed instream flow regime that is considered to be protective of anadromous fish in the Scott River (CDFW 2017). Under this Low Flow Diversion Limits scenario, the mean crop ET volume is 6 million m^3 (~6%) less than basecase, while the mean HB value is 12 coho spf-equivalent greater than basecase.

The remaining two categories, abbreviated as “NatVeg” and “NatVegET”, relate to land cover type and are not proposed as management actions. Rather, these provide reference scenarios for conditions in some or all parts of the valley that could be considered to stand in for undefined “pre-historic”, “unimpaired”, or “conservation” conditions. They involve simulating native vegetation in place of irrigated acreage, and were designed to estimate the streamflow depletion attributable to agricultural water use in different areas of Scott Valley. These scenarios produce substantial HB gains at a high ET cost relative to basecase (Figure 18).

The key geographic feature in the NatVeg and NatVegET scenarios is the “Interconnected Zone” in the 1980 Scott Valley surface water adjudication (Superior Court of Siskiyou County 1980), referred to here as the “adjudicated zone” of groundwater pumping (Figure 13), and the six scenarios in each category represent the cessation of all irrigation or the cessation of only groundwater pumping in three spatial configurations: within the adjudicated zone, outside of the adjudicated zone, or in both areas. All areas where irrigation or pumping is turned off are assumed to return to (unirrigated) native vegetation.

On average, area-normalized ET from native vegetation is 45 cm/year (56% of average annual crop ET). Simulating native vegetation in place of irrigated acreage results in a greater proportion of water leaving the SVIHM model domain via surface flows rather than as transpiration. Consequently the NatVeg and NatVeg ET scenarios generate higher simulated FJ streamflow in most months of the model period. The first category (NatVeg) assumes a native vegetation crop coefficient of 0.6, while the second category (NatVegET) assumes a native vegetation crop coefficient of 1.0 and a maximum rooting depth of 4.5 m. The first category could be interpreted as chaparral or sage scrub-type vegetation cover, while the second category could represent a mixed bunchgrass and clover prairie with extensive riparian vegetation corridors and wetlands. (See *Supplemental Material* for more details on this scenario design.)

Scenario ID	Category	Feas.	Mean HB	Mean ET	Pareto	Efficiency	Eff. (L-C)
basecase	basecase	0	68.9	111.5	Yes	–	–
mar	EnhRch	3	70.0	111.5	Yes	–	–
ilr	EnhRch	3	71.3	111.0	Yes	7.6	12.6
mar_ilr	EnhRch	3	71.5	111.0	Yes	8.5	14.8
mar_ilr_max_0.003	EnhRchEx	3	77.2	110.8	Yes	19.5	41.5
mar_ilr_max_0.019	EnhRchEx	3	82.7	110.8	Yes	32.5	78.9
mar_ilr_max_0.035	EnhRchEx	3	83.5	110.8	Yes	34.3	83.1
irr_eff_improve_0.1	IrrEff	2	71.4	110.7	Yes	5.3	5.3
irr_eff_improve_0.2	IrrEff	2	72.3	109.4	–	2.7	4.3
reservoir_shackleford	Res	4	81.7	111.5	Yes	–	–
reservoir_etna	Res	4	71.4	111.5	Yes	–	–
reservoir_french	Res	4	72.3	111.5	Yes	–	–
reservoir_sfork	Res	4	73.0	112.1	Yes	–	–
reservoir_etna_29kAF	Res	4	71.9	111.5	Yes	–	–
irrig_0.8	CropCh	2	79.7	90.5	–	0.8	1.8
irrig_0.9	CropCh	2	74.0	101.1	–	0.8	1.4
alf_irr_stop_jul10	AlfIrr	1	85.0	101.6	Yes	2.6	6.3
alf_irr_stop_aug01	AlfIrr	1	78.7	107.8	Yes	4.3	8.1
alf_irr_stop_aug01_dry_yrs_only	AlfIrr	1	73.9	110.5	Yes	7.8	11.8
alf_irr_stop_aug15	AlfIrr	1	73.3	110.1	Yes	5.2	6.3
alf_irr_stop_aug15_dry_yrs_only	AlfIrr	1	70.7	111.1	Yes	7.6	6.4
curtail_start_jun01	Curtail	1	93.2	34.1	Yes	0.5	0.9
curtail_start_jun15	Curtail	1	91.8	43.2	Yes	0.5	0.9
curtail_start_jul01	Curtail	1	90.4	53.4	Yes	0.6	1.1
curtail_start_jul15	Curtail	1	89.6	63.1	Yes	0.7	1.3
curtail_start_aug01	Curtail	1	88.6	74.3	Yes	0.9	1.6
curtail_start_aug15	Curtail	1	85.7	82.2	Yes	0.9	1.9
flowlims	FlowLims	1	80.8	105.0	Yes	3	5.7
natveg_all	NatVeg	2	90.4	-0.0	–	0.3	0.5
natveg_gwmixed_all	NatVeg	2	89.0	25.1	–	0.4	0.7
natveg_inside_adj	NatVeg	2	85.7	68.3	–	0.6	1.3
natveg_gwmixed_inside_adj	NatVeg	2	84.8	71.4	–	0.6	1.4
natveg_outside_adj	NatVeg	2	86.6	43.6	–	0.4	0.8
natveg_gwmixed_outside_adj	NatVeg	2	84.7	65.2	–	0.6	1.2
natveg_all_et_check_1.0nvkc_4.5m_ext	NatVegET	2	86.7	-0.0	–	0.3	0.5
natveg_gwmixed_all_et_check_1.0nvkc_4.5m_ext	NatVegET	2	84.9	25.1	–	0.3	0.6
natveg_inside_adj_et_check_1.0nvkc_4.5m_ext	NatVegET	2	74.8	68.3	–	0.2	0.4
natveg_gwmixed_inside_adj_et_check_1.0nvkc_4.5m_ext	NatVegET	2	74.1	71.4	–	0.2	0.4
natveg_outside_adj_et_check_1.0nvkc_4.5m_ext	NatVegET	2	84.2	43.6	–	0.4	0.8
natveg_gwmixed_outside_adj_et_check_1.0nvkc_4.5m_ext	NatVegET	2	82.4	65.2	–	0.5	1.1

Table 8: Scenario attributes for 40 scenarios. Units for Hydrologic Benefit (HB) value are coho smolt per female-equivalent; for ET are million cubic meters; both are averages of 28 annual values. Efficiency not calculated for scenarios with no average ET loss. (L-C) indicates the efficiency is averaged over the six low-coho years that occurred within that period, rather than the full model period 1991-2018.

2.5.2 Agricultural-environmental trade-off efficiency

The trade-off efficiency between the environmental and agricultural objective functions is defined as the average HB value gained, relative to $HB_{basecase}$, per ET value lost relative to $ET_{basecase}$ (see formula in Methods). However, six scenarios (the five reservoir scenarios and managed aquifer recharge, or MAR) actually resulted in an average ET volume slightly greater than the basecase, and so avoided any ET cost. These scenarios were excluded from the efficiency calculations because including them would produce nonsensical negative efficiencies.

For all other scenarios, trade-off efficiencies ranged from 0.21 to 34.3 when averaged over all years, and were higher (ranging from 0.38 to 83.1) in low-coho years (Table 8). The range covers two orders of magnitude because the denominator of the ratio, lost ET, ranges from 0.3% to 100%, while the HB gains fall more narrowly between 2.6% to 35.3%. Efficiencies greater than 1 indicate that a scenario produces more than a 1% increase in HB value per 1% loss in ET value. However, because the HB and ET units are non-commensurable, the absolute value of the trade-off efficiency is not of great significance; the trade-off efficiency metric is most useful for scenario comparisons.

Four scenario categories form a "low-efficiency" cluster, with all-years efficiencies of less than 1: Crop Change, Curtailment, and the two Natural Vegetation categories (Figure 19). These scenarios can produce substantial HB gains (ranging from 5 to 24) coho spf-equiv., but result in severe agricultural productivity reductions (9.3% to 100%). The "high-efficiency" scenarios, which have an all-years trade-off efficiency greater than 1 (the Enhanced Recharge, Low Flow Diversion Limits, Irrigation Efficiency and Alfalfa Irrigation scenarios), tend to be associated with a small ET cost relative to basecase (0.4 to 9.9 million m^3, or 0.3 to 8.9 percent of basecase crop ET).

2.5.3 Infrastructure objective, Pareto-optimal set and GSP priorities

By plotting the environmental, agricultural, and infrastructure objectives in a three-dimensional scatterplot, it is possible to visualize the combined set of management scenarios as four different trade-off arcs in different infrastructure categories (Figure 20).

The Pareto-optimal set of management actions include more than half (25) of the simulated scenarios (Table 8; Figure 20). All the suboptimal scenarios are in infrastructure category 2 (infrastructure timeline of 1-2 years). The suboptimal set are either related to land use change (Crop Change, NatVeg, and NatVegET), which reduce crop ET demand or irrigated acreage, or they involve deployment of more efficient irrigation (Irrigation Efficiency), which has little impact on either HB or ET values.

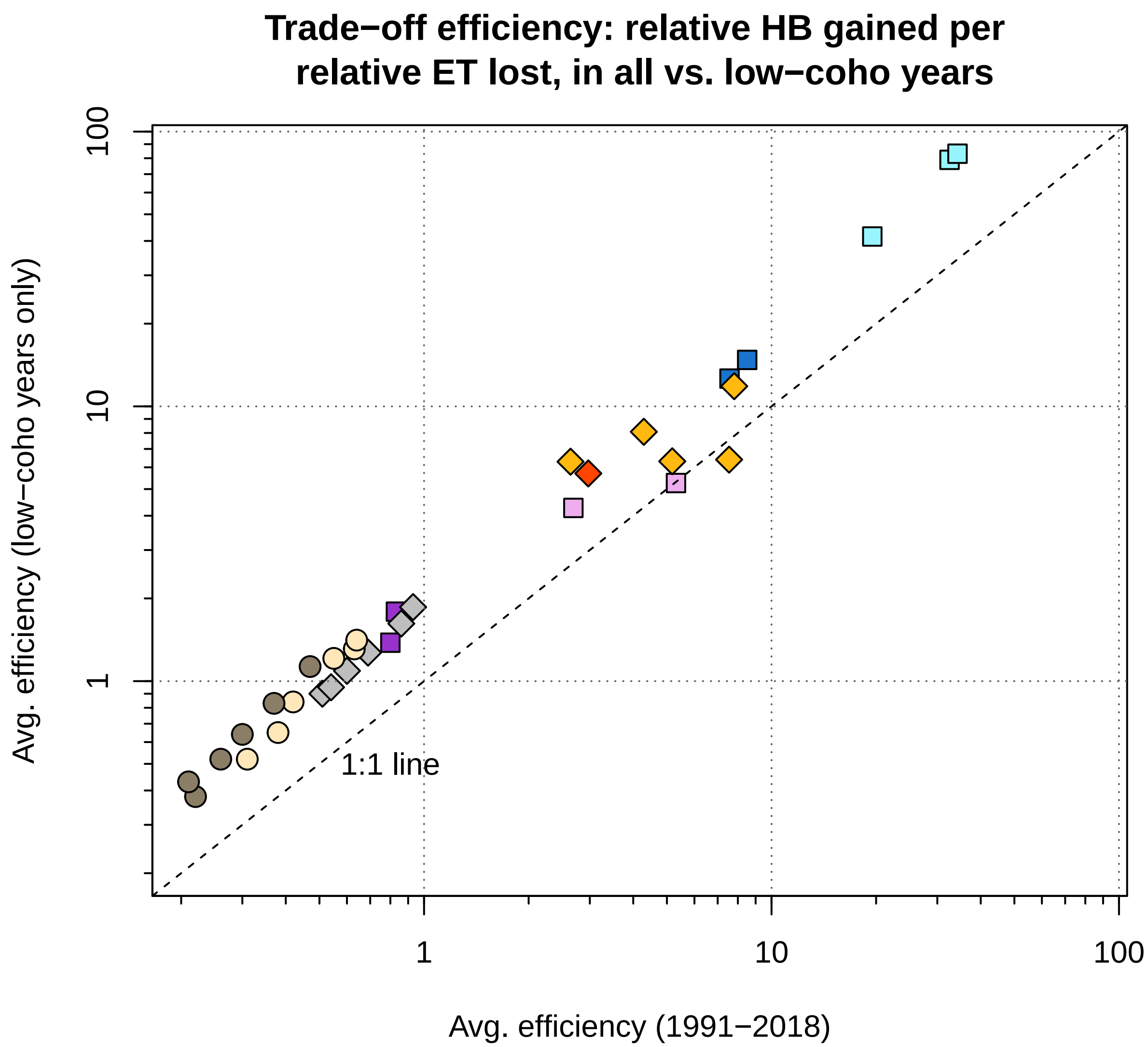


Figure 19: Scenario trade-off efficiencies, or average HB value gained per crop ET value lost (normalized to average basecase HB and ET values, respectively), in all 28 years (x-axis) and in six low-coho years (y-axis; i.e., the six years with basecase predicted HB values of less than 45 coho spf-equiv.). Basecase, Reservoir scenarios and one Enhanced Recharge scenario (MAR) are not included as they have on average no or negative ET loss.

Infrastructure category 1 (no infrastructure investment needed) contains all the Regulation-type scenarios. In the Alfalfa Irrigation and Curtailment scenario categories, the trade-off arcs show the effect of intervention date: an earlier date of intervention (irrigation cutoff) produces a greater HB value at a higher ET cost, compared to a later date of intervention. The scenarios in infrastructure categories 3 and 4 (infrastructure timeline of 3-5 and 5+ years) involve no or minimal ET cost, and a range of HB gains on the middle-to-lower end of the HB gain spectrum (Reservoirs, Enhanced Recharge, and Expanded Enhanced Recharge; Figure 18).

To determine if the strict application of objective functions would produce different management priorities than the public policy development process that took place 2018-2021, we made a high-level, conceptual comparison of the Pareto-optimal set of management actions and the management actions and projects listed for consideration in the GSP (Siskiyou County 2021). Management actions considered in the GSP have some analogs in the set of 40 simulated scenarios.

High-priority scenarios tend to be associated with higher average crop ET values and modest HB gains relative to basecase (Table 9); i.e., the GSP priorities demonstrate a preference for management actions with high trade-off efficiencies. Specifically, Enhanced Recharge and Irrigation Efficiency are represented in Tiers I and II, signifying they are considered implementable in the short- or medium-term. Another high-efficiency scenario, Low Flow Diversion Limits, is represented three times in Table 9: the two analogs for it in Tier I are limited either in time (Water Trust Leasing, which occurs opportunistically in extreme droughts) or in space (the current two-creek extent of the existing watermaster program). An expanded watermaster program, which would more closely resemble the Low Flow Diversion Limits scenario, appears in Tier III.

The final high-efficiency scenario category, Alfalfa Irrigation, is not included in the list of management actions; conversely, low-efficiency scenarios in categories NatVeg and Crop Change were included, in a spatially-limited form, in Tier II under the umbrella of "Voluntary Managed Land Repurposing". This indicates that political considerations not currently included in the three objective functions produce a preference for some amount of land repurposing rather than imposing limitations on alfalfa irrigation.

Notably, direct comparisons between the set of simulated scenarios and the management actions listed in the GSP are somewhat limited. The primary reason for this is that the simulated scenarios assume that all water users in the valley are acting in concert. Conversely, management actions included in the GSP generally assumed voluntary/incentivized participation by individual landowners in scenarios involving land use change, and in some cases are located only in specific sub-areas of the watershed.

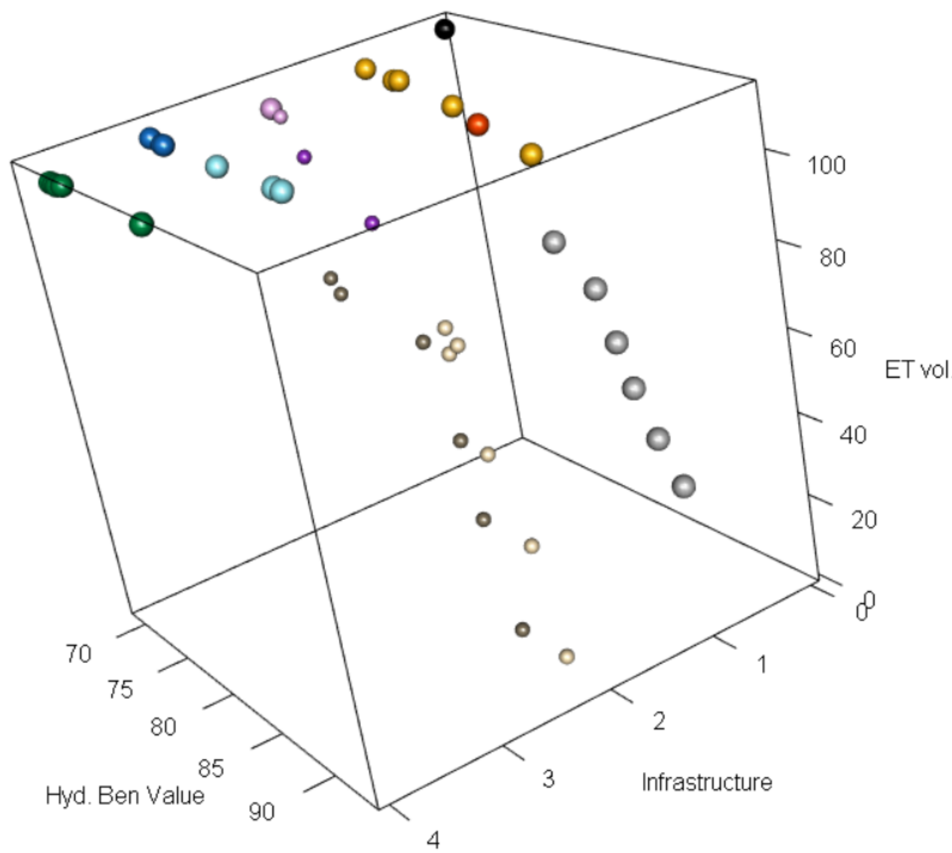


Figure 20: A three-dimensional scatter plot of the objective function values for basecase and 39 management scenarios, averaged over 28 water years (1991-2018). Larger spheres are shown for the Pareto-optimal set of scenarios. Scenario colors correspond to legend in Figures 6 and 7.

Tier	GSP Management Action	Closest Simulated Analogue	HB Range	ET Range
I	Watermaster Program (two creeks)	Low Flow Diversion Limits (FlowLims)	81	105
I	Scott River Water Trust Leasing Program	Low Flow Diversion Limits (FlowLims)	81	105
I	Irrigation Improvements	Improved Irrigation Efficiency (IrrEff)	71-72	109-111
II	Irrigation Efficiency Improvements	Improved Irrigation Efficiency (IrrEff)	71-72	109-111
II	MAR & ILR - NFWF Scott Recharge Project	Enhanced Recharge (EnhRch)	70-71	111-112
II	MAR & ILR	Enhanced Recharge (EnhRch)	70-71	111-112
II	Voluntary Managed Land Repurposing	Possibly Crop Change (CropCh) and possibly some amount of Natural Vegetation Land Use (NatVeg)	74-87	44-101
III	Alternative, lower ET crops	Crop Change (CropCh)	74-80	90-101
III	Floodplain Reconnection/ Expansion	Enhanced Recharge (EnhRch)	70-71	111-112
III	Reservoirs	Small Reservoir (Res)	71-82	111-112
III	Strategic Groundwater Pumping Curtailment	Possibly Cease Alfalfa Irrigation Early (AlfIrr); Possibly Curtail Irrigation Early (Curtail)	71-93	34-111
III	Watermaster Program (expanded)	Low Flow Diversion Limits (FlowLims)	81	105

Table 9: List of management actions in Chapter 4 of the GSP and analogues in the set of 40 simulated scenarios. The Tier indicate the priority given to each management action, though the Tier also incorporates information about difficulty of implementation (hence Reservoirs being placed in Tier 3).

2.6 Discussion

The portfolio of scenarios proposed by stakeholders and simulated for this study included a range of infrastructure investments, regulatory actions and major land use changes. The number and diversity of simulated scenarios was made possible by a surface- and groundwater model designed to approximate existing land use and agricultural water use behavior in the local context (SVIHM; Tolley, Foglia, and Harter 2019). Though the ultimate future effect of these management actions would depend on climate variability and implementation details that have not been explicitly simulated (e.g., the precise location of pumps needed to divert surface water for the expanded enhanced recharge scenarios), it is possible to use objective functions and historical climate records to draw some high-level findings regarding their relative merits.

2.6.1 Contextualizing low objective function values

The HB function incorporates several hydrologic metrics, but years with low HB values (i.e., low predicted coho-spf equivalent) usually share several characteristics. A water year with a low HB value (e.g., <45 coho spf-equiv.) commonly occurs after a dry season with multiple dried-out mainstem Scott River reaches, culminating in a prolonged fall period (e.g., 4 to 8 weeks after September 1st) of FJ Gauge flows lower than 10 cfs. In a low-HB water year, high winter baseflows (e.g., > 200 cfs) may not arrive until December or January, and the rainy season may be short (e.g., < 100 days). These hydrologic features have implications for fishery stability. In water year 2014, for example, salmon access flows were significantly delayed, and coho salmon laid their eggs in the mainstem of the Scott River rather than in their preferred tributary stream habitat, which put them at higher risk of getting scoured away in a winter storm (CDFW 2015a).

Because no recent precedent exists for a low-crop-ET year, interpreting the numerical values of the ET objective function requires more speculation, and the specific impact of ET loss on the agricultural community depends on the specific management action and its enforcement. One method to address uncertainty related to impact of management actions on agricultural objectives is to survey regional agricultural practitioners and experts about the likely costs of a proposed management action (Sunding 1996). In the public meetings during GSP development, some informal (i.e., non-quantitative) surveying of stakeholder expectations of the costs of management actions took place. In terms of operational impacts, Scott Valley agricultural stakeholders stated that short-term interventions (such as fallowing an alfalfa field for one year, or curtailing pasture irrigation for a growing season) could have long-term impacts (such as affecting alfalfa yield the following year, or forcing a rancher to sell a herd (SVGAC 2021). The current agricultural benefit proxy, annual crop ET, does not capture these multi-year costs to the local agricultural sector, or the regional impact that reduced agricultural productivity will have on economically disadvantaged local communities.

These predicted on-the-ground consequences can facilitate interpretation of scenario results.

2.6.2 Environmental objective performance in historically low-coho years

Management scenario performance in dry years, rather than over the whole model period, is another informative metric for resource managers. For example, in potentially unstable fish populations, conditions during critical dry years can be more significant than long-term average conditions (e.g., Ohlberger et al. 2018). Eight dry years occurred during the 1991-2018 model period: 1991, '92, '94, 2001, '09, '13, '14, and '18 (Figure 17). Dry years were classified using quartiles of the distribution of total annual FJ Gauge flow over the full record of water years 1942-2021. The lowest to highest quartiles of total annual flow are classified as Dry, Below Average, Above Average, and Wet water year types, respectively.

However, in this system, the years following dry periods may be more informative. As mentioned in Methods, the lowest basecase HB values, operationally defined here as years with basecase HB values of less than 45 predicted coho spf-equivalent, tend to occur in years following one or more dry years (i.e., 1993, 1995, 2002, and 2014-16 in Figure 17; "low-coho years"). In the Scott River watershed, one mechanism producing this pattern is delayed onset of winter storms, which cannot be managed through policy. Another mechanism is the depletion of stored groundwater in dry years, which can reduce dry-season baseflow and delay stream system reconnection during the onset of the following wet season (Tolley, Foglia, and Harter 2019). Regardless of the primary cause of the low fall flows in a particular year, the HB value for each water year is sensitive to long periods in the fall with flow below 10 and 100 cfs (see Chapter 1 of this dissertation for more details on coho salmon sensitivity to low fall flows).

Because many aspects of scenario performance are relatively consistent (i.e., for any given scenario, ET costs are relatively static year to year, and most scenarios demonstrate consistently small HB gains over basecase in high-coho spf years; Figure 17), the low-coho year HB performance of various model scenarios is a key scenario differentiator.

2.6.3 Environmental-agricultural trade-offs

Balancing agricultural and environmental water demands in this watershed commonly takes the form of seeking management actions that can improve flow conditions while minimizing the resulting reduction in agricultural water availability. Consequently, a subset of the proposed scenarios rely on infrastructure investments to produce modest HB improvements with minimal-to-no ET reductions (Enhanced Recharge, Expanded Enhanced Recharge, Irrigation Efficiency, and Reservoirs) (Figure 18). The remaining categories tend to include some level of ET reduction, due to reduced water availability for irrigation.

The environmental gain-agricultural cost trade-off is evident both within individual categories and between distinct scenario categories, especially in HB performance in low-coho years.

Among Alfalfa Irrigation scenarios, HB gains in low-coho years are modest under cutoff dates of August 15th and August 1st (averaging 11 and 31 more coho spf than basecase in low-coho years, respectively), and ET costs are small (averaging 1 and 4 million m^3, respectively, in all years); conversely, the more extreme July 10th cutoff date produces an average of 58 more predicted coho-spf in low-coho years and an average of 10 million m^3, or 9%, reduction in ET in all years (panels A and B of Figure 17).

Trade-off is also evident between scenario categories. The Enhanced Recharge scenario `mar_ilr` has a minimal ET cost (an average of 0.5 million m^3 less than basecase in all years) and improves HB performance only slightly (6 coho spf gain over basecase in low-coho years). At the other extreme, the Curtailment scenario in which all irrigation is cut off on August 1st (`curtail_start_aug01`) produces significant HB improvements in low-coho years (with mean HB improvements of 61 coho spf-equiv.), but reduces ET by an average of 37 million m^3 or 33% (panels C and D of Figure 17). Compared to `curtail_start_aug01`, the Low Flow Diversion Limits (`flowlims`) scenario tends to have an intermediate effect on HB values in low-coho water years (HB improvement of 38 coho spf-equiv.), while reducing ET by an average of 6%.

The 33 scenarios with ET lower than basecase sort clearly into one high- and one low-efficiency cluster (Figure 19). The high-efficiency scenarios are composed of three infrastructure-type management actions (Enhanced Recharge, Expanded Enhanced Recharge and Irrigation Efficiency) and two regulatory-type management actions (Alfalfa Irrigation and Low Flow Diversion Limits), while the low-efficiency group contains one infrastructure-type (Crop Change), one regulatory-type (Curtailment), and the two native vegetation-type scenarios. The previously-stated caveat regarding the Crop Change scenario's true agricultural benefit potentially being higher or lower than the values in Table 8 apply to these efficiency calculations as well. The trade-off efficiencies provide an informal cost-benefit assessment, though interpretation is somewhat limited, as the unitless quantity tends to group together scenarios with widely varying absolute values of HB and ET (e.g., Crop Change and some Curtailment scenarios).

There is a clear positive relationship between efficiency in all years and in low-coho years, but in nearly all scenarios the low-coho year efficiency average is higher than over the 28-year model period (Figure 19). In other words, in low-coho years, a given amount of crop ET reduction produces a greater environmental flow enhancement than on average over all years. This is corroborated by annual scenario HB values: in high-coho years, HB gains are small or minimal, while substantial improvements are seen for some scenarios in low-coho years (panels A and C in Figure 17). One possible explanation is that, in high-coho years, environmental flows tend to already be sufficient, and most management scenarios can generate only marginal improvements in hydrologic conditions. This suggests that targeting management actions to dry years (which tend to precede the low-coho water years) may produce the highest efficiency management actions. This possibility was supported by the two cases where this comparison was explicitly simulated: the efficiencies for the Alfalfa Irrigation scenarios for dry years only (`alf_irr_stop_aug01_dry_yrs_only` and `alf_irr_stop_aug15_dry_yrs_only`) are higher than for their corresponding scenarios with an intervention in all years (`alf_irr_stop_aug01` and `alf_irr_stop_aug15`; Table 8).

2.6.4 Pareto-optimal solution set and GSP priority management actions

Within the proposed suite of management actions, more than half (25 of 40, including the basecase) fall within the Pareto-optimal set based on the infrastructure category and the 28-year average values of objective functions. This same set remains Pareto-optimal when the objective functions are averaged only over the six low-coho water years, with one exception (the French Creek reservoir scenario is Pareto-optimal when averaged in all years, but not in low-coho years).

The non-Pareto-optimal scenarios (i.e. the scenarios outperformed in multiple objectives) are in the Irrigation Efficiency, Crop Change and Native Vegetation categories. (The 20% improved Irrigation Efficiency scenario is outperformed in both HB and ET objectives by both of the alfalfa irrigation scenarios with a cutoff date of August 15; Table 8). Native Vegetation scenarios, under two different assumptions about vegetation type/ET demand of the vegetation replacing cultivated agriculture, can produce significant HB improvements, but at a relatively high cost in regional agricultural productivity; these two scenario categories have the lowest trade-off efficiency (Figure 19; Table 8).

Pareto-suboptimal status is less certain in the case of the Crop Change scenario, since the ET volume proxy for agricultural revenue/benefit may not be valid for alternative crops. (Crops that have been mentioned during stakeholder meetings as possibly suited to the climate of Scott Valley or have been cultivated in a trial setting are high(er) value annuals in lieu of the current perennial crops, e.g., potatoes, sunflowers, and carrots for seed, though notably, to the authors' knowledge no local grower has cultivated any of these commercially.)

Many of the simulated scenarios were included in the ultimate list of management priorities in the adopted GSP (Siskiyou County 2021), though in a variety of forms (e.g., the Low Flow Diversion Limits scenario, which is the closest simulated analogue for a watermaster program and a surface water leasing program; Table 9). Although the GSP management priorities emphasized infrastructure, in a strict application of these objective functions, both infrastructure-based and regulatory approaches fell within the Pareto-optimal set of management options.

2.6.5 Policy implications

Although the HB values are based on well-studied hydro-biological relationships (late spawning flows leads to lower fishery reproduction rates), the actual predicted values of coho smolt production per female spawner (coho spf) remain uncertain, because when the HB function was developed only 11 full years of coho spf data were available. If monitoring continues in future years and this sample size increases, the predictive power and weights of various hydrologic metrics may be reexamined. The ET values are estimated based on climate data, crop coefficients, and assumptions regarding grower decisions, and thus are subject to uncertainty in those data sources.

Due to this uncertainty, the results of this study should not be considered direct policy recommendations. However, some of the insights below could be used to support future management decisions, simply by summarizing the wealth of information provided in each model simulation using the proposed objective functions.

- Targeted interventions that only regulate water use in dry periods produce higher trade-off efficiencies than continuous interventions, as illustrated by the Alfalfa Irrigation scenarios (i.e., dry years only versus all years; Table 8).
- The Low Flow Diversion Limits scenario takes this concept to its logical extreme, by limiting intervention only to low-flow days in the hydrologic record, rather than low-flow years or seasons in the Alfalfa Irrigation category. As a result it produces considerable low-coho year HB gains with a trade-off efficiency of greater than 1.
- Key data gaps limit interpretability of some scenario results. An agronomic study of alternate crops that could be cultivated in Scott Valley, for example, could better constrain the agricultural benefits of a Crop Change scenario. Conversely, the acreage of land converted in various Native Vegetation scenarios is likely higher than any realistic land use change scenario, meaning that for a hypothetical management action involving a reduction of irrigated acreage in the valley, the HB gains and ET costs may be smaller than shown in Figure 18.
- In recent years, drought conditions have prompted state regulatory agencies to consider and then impose significant irrigation curtailments (CDFW 2021). The objective function summary of existing model results could help stakeholders and regulators weigh the trade-offs of various actions and potential irrigation cutoff dates in the context of the consequences of other proposed management scenarios. The modeling results suggest that if a decision is made to regulate water use, some later intervention dates may produce minimal gains in environmental flows in some water years (e.g., an alfalfa irrigation cutoff date of August 15 in water years 1995 or 2002 in panel A of Figure 17).

2.7 Conclusion

In this study, functions quantifying the achievement of the two management objectives (environmental and agricultural) were applied to 40 simulated management scenarios (including a historical basecase). In addition, scenarios were assigned a categorical proxy for new infrastructure costs. We used these numerical values to quantitatively explore trade-offs in environmental and agricultural benefit among the suite of proposed actions.

Due to decades of investment and significant ongoing labor, aggregate agricultural productivity in Scott Valley (as estimated through crop ET) is buffered against the weather and is relatively stable year-to-year. Conversely, flow in the undammed Scott River is subject to the full range of climate variability and human water uses. As a result, the historical performance in the environmental flows objective is much more variable than in the agricultural objective, and environmental flows measured with this objective function seem particularly vulnerable to multi-year dry periods.

Many management actions were proposed over the past four years to enhance environmental flows while minimizing negative effects on agricultural water security. In general, targeting irrigation reductions during low-flow periods (e.g. Early Cessation of Alfalfa Irrigation and Low Flow Diversion Limits) tends to be more efficient in terms of higher environmental flows per lost agricultural productivity than irrigation reduction over the whole growing season, such as the Native Vegetation scenarios (Figure 19).

Objective functions summarizing the predicted consequences of management actions is not a new technique; however, to be useful in a decision support context, they require careful design, sensitivity to local conditions, and ongoing feedback from affected stakeholders. Introducing these elements of optimization into existing water resource management processes can improve communication of management consequences and priorities, and thus potentially improve decision-making and our understanding of the interconnected socio-hydrologic system.

3 Chapter 3. Seasonal prediction of end-of-dry season watershed behavior in a highly interconnected alluvial watershed, northern California

3.1 Abstract

In undammed watersheds in Mediterranean climates, the timing and abruptness of the transition from the dry season to the wet season have major implications for aquatic ecosystems. Of particular concern in many coastal areas is whether this transition can provide sufficient flows at the right time to allow passage for spawning anadromous fish, which is determined by dry season baseflow rates and the timing of the onset of the rainy season. In (semi-) ephemeral watershed systems, these functional flows also dictate the timing of full reconnection of the stream system. In this study, we propose methods to predict, approximately five months in advance, two key hydrologic metrics in the undammed rural Scott River watershed (HUC8 18010208) in northern California. Both metrics are intended to quantify the transition from the dry to the wet season, to characterize the severity of a dry year and support seasonal adaptive management. The first metric is the minimum 30-day dry season baseflow volume, $V_{min,\ 30\ days}$, which occurs at the end of the dry season (September-October) in this Mediterranean climate. The second metric is the cumulative precipitation, starting Sept. 1st, necessary to bring the watershed to a "full" or "spilling" condition (i.e. initiate the onset of wet season storm- or baseflows) after the end of the dry season, referred to here as P_{spill}. As potential predictors of these two values, we assess maximum snowpack, cumulative precipitation, the timing of the snowpack and precipitation, spring groundwater levels, spring river flows, reference ET, and a subset of these metrics from the previous water year. We find that, though many of these predictors are correlated with the two metrics of interest, of the predictors considered here, the best prediction for both metrics is a linear combination of the maximum snowpack water content and total October-April precipitation. These two linear models could reproduce historic values of $V_{min,\ 30\ days}$ and P_{spill} with an average model error (RMSE) of 1.4 Mm^3 / 30 days (19.4 cfs) and 20.7 mm (0.8 inches), respectively. Although these predictive indices could be used by governance entities to support local water management, careful consideration of baseline conditions used as a basis for prediction is necessary.

3.2 Introduction

In regions that experience periodic drought, such as the western United States, indices summarizing hydroclimate or surface water supply conditions are often critical decision-support tools for water managers (e.g., Garen 1993). An index can be forward-looking, such as ones that forecast near-term seasonal water supplies (e.g., Null and Viers 2013; Verley 2020), or backward-looking, such as ones that evaluate drought severity (e.g., Palmer 1965; Guttman 1998; McKee, Doesken, and Kleist 1993; Wilhite and Glantz 1985; Wilhite, Hayes, and Svoboda 2000). In California, forward-looking seasonal indices are used extensively by water managers. The principal examples are the Sacramento Valley Index (SVI) and San Joaquin Index (SJI), which are seasonal forecasts used to determine water allocations through the State Water Project (Null and Viers 2013; DWR 2022). The state has more recently published a retroactive categorical water year type (WYT) dataset for sub-county level regions throughout California, based on a weighted combination of the cumulative precipitation of the two preceding water years (effectively, a partial one-year-holdover provision), and assigning categorical types using percentiles within a 30-year ranking window (DWR 2021).

Complementing such summary indices, functional ecosystem flows are a framework for providing a more detailed picture of the hydrologic effects of water year type, climate change, human water use, and other factors (e.g., Poff et al. 1997; Bunn and Arthington 2002; N. Leroy Poff et al. 2010; Wheeler, Wenger, and Freeman 2018). The flows are "functional" because they serve an ecological purpose, such as wet season flood flows, needed to disperse cottonwood seeds (Mahoney and Rood 1998) and fall pulse flows, needed to provide passage for spawning fall-run anadromous fish (see Chapter 1 of this dissertation). A California-specific functional flows framework has been developed to assess the degree of hydrologic alteration between modern and baseline conditions (Yarnell et al. 2020; Patterson et al. 2020).

In this study, to test the utility of locally-tailored predictive methods for hydrologic indices that incorporate functional flows, we focus on a single HUC8 basin, the Scott River watershed in northern California (HUC8 18010208). We review the hydrologic indices and methods currently used in decision-making, and propose two additional decision-support metrics, both designed as quantitative forecasts. The first is $V_{min,\ 30\ days}$, the minimum 30-day dry season baseflow volume in a given water year, which typically occurs in September or October. The second is a prediction of the cumulative rainfall needed to wet up the watershed after the dry season such that subsequent rainfall results in clear runoff events. This cumulative precipitation depth is referred to as P_{spill}. Both of these metrics have significance for environmental flows and could support near-term (seasonal) adaptive management, similar to the SVI and SJI in California's Central Valley. For example, the magnitude of the minimum baseflow rate sets the spatial extent of the aquatic ecosystem during the dry season and influences rearing conditions for oversummering juvenile salmonids (Gorman 2016), while P_{spill} is related to the timing of flows necessary for fall-run salmon passage: a greater amount of rain needed to generate stormflow is correlated with a prolonged dry season, which has delayed salmon access to spawning habitat in recent years (CDFW 2015a). After defining and developing seasonal predictions for $V_{min,\ 30\ days}$ and P_{spill}, we then evaluate trends over time and consider the effects that climate change and changing water use patterns may have on the metrics considered in this study, and the decisions they support.

3.3 Methods

The Scott River watershed has a snow-influenced Mediterranean climate, giving the river's annual hydrograph a characteristic high-flow season during the rainy winters, a gradual flow recession in the spring-summer as the snowpack melts, and a low-flow dry season after the snowpack is depleted (e.g., Figure 21). Water supplies for agricultural and domestic use are relatively reliable in the Scott River system (although some reports of dry wells occur in dry years; Siskiyou County 2021), and a key management challenge is persistent low environmental flows during the dry season baseflow period. In dry years, the lowest annual flowrates can overlap with the spawning periods for fall-run anadromous fish, potentially restricting fish passage and imperiling the long-term viability of the Scott River fishery (Siskiyou County 2021) (see also Chapters 1 and 2 of this dissertation). Post-1970s minimum dry season baseflows have been lower than pre-1977, and very low minimums ($<$ 10 cfs or 0.7 Mm^3 / 30 days) have been more frequent in the past two decades (Figure 26), making the management of these flows more urgent.

This study focuses on the transition between the dry season and the wet season, which at times can straddle the conventional water year boundary of October 1st, and cumulative precipitation is used both as a predictor and as a response variable (P_{spill}). When it is a predictor, a traditional October 1st start date is used and it is summed as the cumulative precipitation of October-April, to facilitate an end-of-April prediction of fall conditions. When it is the response variable, to capture uncommon September precipitation, cumulative precipitation is counted starting on September 1st of the preceding water year. This September 1st start date is also used in some graphs of climate and flow data (e.g. Figure 24), to establish and visualize baseline dry season conditions.

Additionally, all flows in this study are observed or simulated at the USGS Fort Jones streamflow gauge (ID 11519500), a key monitoring location downstream of nearly all water use and cultivated land in the HUC8 watershed (Figure 23), with an observation record covering water years 1942-2021.

To establish the context and meaning of the two proposed predictive indices $V_{min,\ 30\ days}$ and P_{spill}, a brief description of the behavior of the watershed is necessary.

3.3.1 Scott River watershed precipitation-runoff behavior and Q_{spill}

In an undammed catchment, the runoff response to one (or a series of) precipitation event(s) is dependent on multiple factors, including antecedent soil moisture conditions, the intensity and magnitude of the precipitation, and the volume of water in aquifer storage (Tarboton 2003). At a hillslope scale, in areas where soil directly overlays (relatively) impermeable bedrock and aquifer storage is not appreciably present, a threshold response to individual storm events has been observed: after a certain quantity of rainfall, subsurface flow increases dramatically (Tromp-Van Meerveld and McDonnell 2006). The proposed mechanism is the filling and connecting of various distributed storage volumes, such as soil pores and microtopographic relief in the bedrock surface (Tromp-Van Meerveld and McDonnell 2006). Recently this concept has been extended to the watershed or basin scale: relative to the beginning of a storm event, a much higher flow response is possible only when a critical number of storage volumes throughout a basin fill to a threshold level and become connected (McDonnell et al. 2021).

In this study we expand this concept to the temporal scale of a season, rather than a single storm event. Depending on current precipitation conditions and the volumetric proportion of the hydrologically connected reservoirs that are full of water, the condition of the Scott River watershed, as observed at a regional scale using the Fort Jones stream gauge, can be classified in four main categories (Table 10).

Water in the Scott River watershed is stored in three primary reservoirs: snowpack, soil moisture/subflow, and the alluvial groundwater aquifer. Accumulating snowpack is present only in the mountainous areas of the upper watershed, while the alluvial aquifer is present only within the bounds of the groundwater basin underlying the flat valley floor (Figure 23). (Though some groundwater may be stored in fractures in the surrounding mountains, it is rarely measured, and it is assumed to respond to hydrologic dynamics within the other three reservoirs.) In conditions with sufficiently high soil water content or groundwater elevations, soil moisture/subflow and groundwater become hydrologically connected to the surface water system, while the snowpack reservoir is not hydrologically connected until it melts and becomes water stored in one of the other two reservoirs. For convenience the soil moisture/subflow and aquifer will be referred to as “connected” storage.

Rainfall-runoff response and functional flows

At the end of the dry season, the watershed is in a “draining from low storage” condition, which is reflected

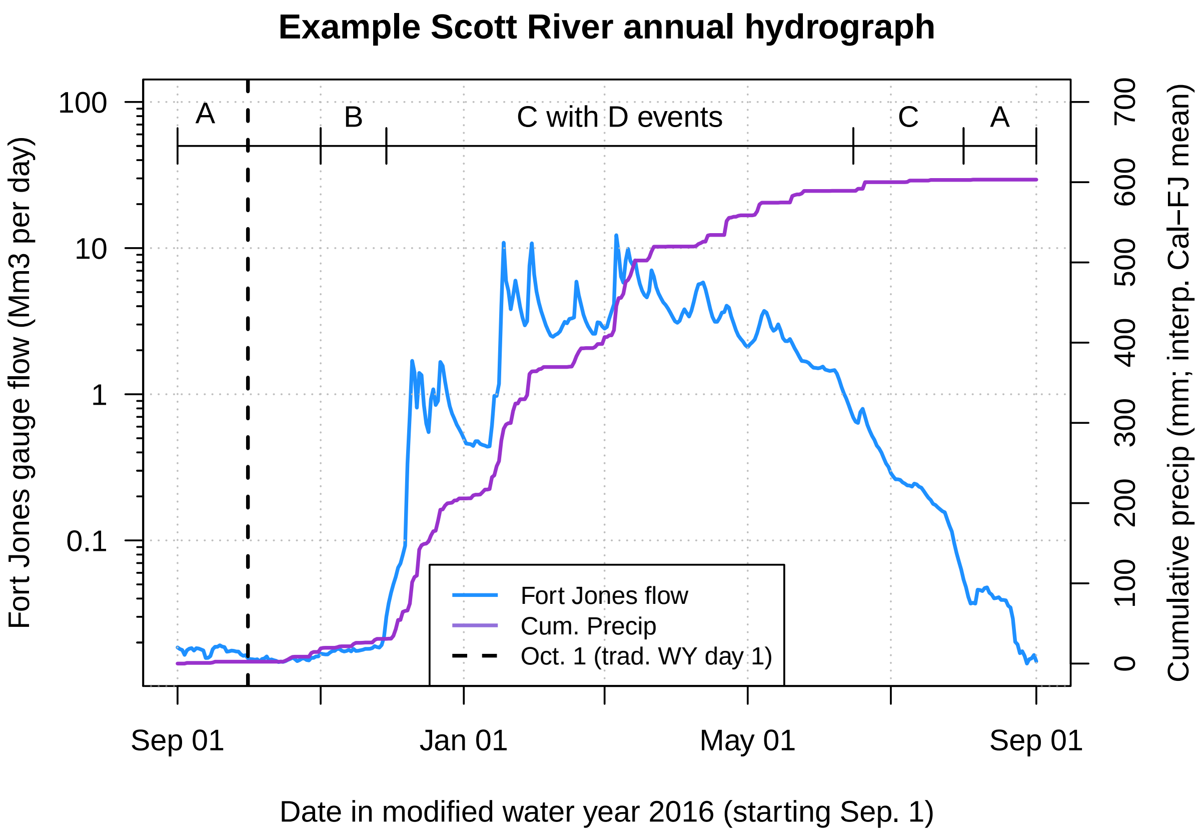


Figure 21: Illustration of four categories of Scott River watershed behavior. The hydrograph in the highlighted periods demonstrates the following watershed behavior: A, dry season baseflow – watershed draining from a low-to-medium storage level; B, moderate flow increase – muted hydraulic response to new precipitation; C, winter baseflow and early spring recession – watershed draining from a high storage level; and D, winter stormflow – rapid hydraulic response to new precipitation (storm spikes).

Water storage level	New precip. occurring?	Flow behavior description	Relevant functional flows
Low	No	(A) Watershed draining from a medium-to-low storage level	Late spring recession and dry season baseflow
Low	Yes	(B) Watershed filling from a low storage level, with muted response to new precipitation	Fall pulse flow or small/slow post-dry-season flow increase
High	No	(C) Watershed draining from a high storage level	Winter baseflow and early spring recession
High	Yes	(D) Watershed spilling from a high storage level, with rapid response to new precipitation	Winter stormflow

Table 10: Schematic of watershed behavior and functional flow types occurring during the transition from the dry season to the wet season in a Mediterranean climate; the categories are illustrated in an example annual hydrograph in Figure 1. 'Storage level' refers to the overall water content of soil moisture storage and the aquifer, which are the two reservoirs in the Scott River watershed that are hydraulically connected to the surface water system.

in a slowly declining or flat hydrograph, with a flowrate that has decreased for several months (Figure 21, first period A). As the dry season ends, the watershed begins receiving rain, and enters a condition of "filling from a low storage level". In this catchment, much of the earliest water entering the system is routed as recharge through the soil or the streambed to occupy space in the aquifer. Because groundwater moves more slowly through the watershed than surface water, the hydrograph at the Fort Jones gauge demonstrates a muted or delayed response to early rain events (Figure 21, period B).

At the onset of a new wet season, under average conditions, the flowrate of filling is greater than the flowrate of draining, and so the "filling from a low storage level" condition at the beginning of a rainy season is transient, lasting only until the filling process occupies enough aquifer and soil storage volume to produce a "full" condition. After the water storage in the basin reaches "full", if no more rain occurs, the watershed returns to its default "draining" condition, though from a higher storage baseline than during the dry season, and with a higher draining flowrate (Figure 21, first period C). If there is additional precipitation, the hydraulic response is much more rapid, reflecting a "spilling" condition (Figure 21, intermittent events D).

The precipitation and winter temperatures during the wet season produce an accumulation of snowpack, though in some years this can be reduced by warm periods and rain-on-snow events. Melting snowpack contributes subsurface flow and tributary streamflow to the lower watershed, producing a spring flow recession typically lasting from the last major precipitation event into the summer (Figure 21, second period C and second period A).

Many of the phenomena described in the above paragraphs have been characterized as various types of functional ecosystem flow (Table 10). Winter stormflow is the obvious functional flow metric corresponding to a "spilling" watershed. The spring recession can last for three to six months and its steepness is moderated by snowmelt. Because it bridges the high-storage and low-storage states, the early and late spring recession appear in two different flow behavior categories (Table 10). Conversely, the flows classified under "watershed filling from a low storage level" are somewhat ambiguous and dependent on year-to-year conditions, since a discrete fall pulse flow does not occur in every water year, and no distinct metric has been proposed for the small or slow post-dry-season flow increases that constitute the watershed's response to minor precipitation at the end of the dry season.

Given the regular behavior observed during the dry season-to-wet season transition in the Fort Jones hydrograph, and the physical structure of this highly inter-connected basin, we expect to find a flowrate threshold at the Fort Jones gauge approximately defining the lower limit of the "full" or "spilling" basin condition. This flowrate, Q_{spill}, was estimated to be 100 cfs based on visual inspection of annual September-March hydrographs (Figure 24, panel A).

Stream-aquifer interaction

In the groundwater basin portion of the watershed, the alluvial aquifer is the largest storage reservoir. Groundwater-surface water interactions drive Scott River flow behavior towards the end of the dry season, before the next rainy season begins, when snowpack is depleted and streamflow in many areas is sustained by groundwater discharge alone. Discharge to streams from the alluvial aquifer occurs along the thalweg of the Scott River. In this highly-interconnected system, groundwater discharge in one reach of the river is typically approximately balanced out by infiltration through the streambed to the aquifer, much of it occurring on the upper alluvial fans of the tributary streams (see discussion below).

We can use the Scott Valley Integrated Hydrologic Model (SVIHM; Tolley, Foglia, and Harter 2019) to obtain the estimated volume of water exchanged monthly, in water years 1991-2018, between the surface stream network and the underlying aquifer. All positive fluxes and all negative fluxes (corresponding to gaining and losing stream reaches) were summed independently and then added to create a net value for each month in the simulation period (Figure 25, upper panel). These net monthly groundwater-to-stream flux values were then compared to simulated monthly flow volumes in the Scott River, measured at the Fort Jones gauge (Figure 25, lower panel).

3.3.2 Observed response variables ($V_{min,\ 30\ days}$ and P_{spill})

The Scott River is an undammed watershed, in which estimates of annual precipitation are an order of magnitude greater than the estimated combined volume of water stored in surface water bodies or aquifers and water pumped or diverted for agriculture (Tolley, Foglia, and Harter 2019). In this study we test whether fundamental hydrologic characteristics, specifically dry-season draining behavior and hydraulic response to early wet season cumulative precipitation, can be predicted using observable hydroclimate data. The first step is quantification of the two response variables.

Dry season baseflow quantities ($V_{min,\ 30\ days}$) and timing

Multiple numerical summaries of dry season baseflows were evaluated for suitability as the response variables in this prediction exercise (e.g., monthly flow volumes in Figure 26). Monthly flow volumes were preferred over a minimum daily flow value to represent durable conditions at the end of a dry season, and to reduce the influence of individual events that might affect flow on one or a small number of days, such as groundwater pumping or surface water diversions.

Historically, the rainy season in California tends to begin in October, and so by convention each water year begins on October 1st of the previous calendar year, and ends on September 30th. Matching this convention, in most years, the minimum-flow month for the Scott River is September; however, uncommon September storms can elevate flow volumes, and in some years with a late rainy season onset, the October flow volume may be lower. To capture these dynamics, for each calendar year, we calculated a rolling 30-day sum of daily flow volumes in the period July-December to identify the 30-day period with the minimum flow, referred to as $V_{min,\ 30\ days}$ (Figure 26). For consistency, each annual $V_{min,\ 30\ days}$ value was assigned to the water year ending in September of that calendar year, even if the minimum flow window included days in October of the following water year.

Cumulative precipitation P_{spill}

P_{spill} was calculated for each water year as the cumulative rainfall at the end of a dry season, starting September 1st, recorded on the first day that the Fort Jones gauge measured flow greater than Q_{spill} (Figure 26, lower panel). As stated above, conceptually, it is the amount of rainfall needed to "fill" the watershed such that it responds rapidly to new precipitation.

A dry season can have negative effects on an aquatic ecosystem if it produces extraordinarily low flows or if it lasts for an extraordinarily long time (e.g., delayed salmon habitat access documented in CDFW 2015a).

The quantity P_{spill} is correlated with both a lower minimum flow volume and a later river reconnection (Figure 22). If predicted in advance, a forecasted value of P_{spill} would be an indicator of the risk of a severe dry season. The timing of the increase in dry season baseflows has trended later over the past several decades (see Siskiyou County 2021, and Chapter 1 of this dissertation), and there could be demand for seasonal predictions of onset of the coming rainy season. However, predicting the timing of the onset of the rainy season or of Q_{spill} would likely rely on uncertain long-term weather forecasts and is beyond the scope of this paper. In other words, due to randomness in rainfall timing, the exact dry season baseflow extension caused by a higher P_{spill} is highly variable and, hence, uncertain.

3.3.3 Potential predictors and selected formulations

To evaluate candidate predictors of dry season baseflows, Pearson's correlation coefficient, R, was calculated between observed response variables $V_{min,\ 30\ days}$ and P_{spill}, and the following categories of observed predictor data (Figure 27):

1. Spring (March-May) water level observations in each of 74 individual wells (Figure 28).
2. Annual maximum snowpack water content at each individual snow monitoring station at 8 CDEC stations (Figure 23).
3. Cumulative precipitation, October-April, at each weather station within the watershed, and five outside the watershed (total of 17 NOAA stations). In these records, missing values (i.e., days with no recorded observation) are assumed to have 0 precipitation. Water years with more than 5 missing days are excluded from the predictor dataset (Figure 23).
4. Cumulative precipitation, October-April, of a composite precipitation record with no missing values, representing the mean of the Callahan and Fort Jones NOAA weather stations (located at the southern and northern ends of the valley, respectively), and referred to as "cal_fj_interp". To generate the composite record, missing values in the Callahan and Fort Jones were interpolated based on observations at neighboring stations (see method in Foglia et al. 2013).
5. The flow volumes observed at the Fort Jones gauge (USGS ID 11519500) during the preceding March and April (Figure 23).
6. Cumulative reference evapotranspiration (ET_0), October-April, using observations from the Scott Valley CIMIS station, Station No. 225 (2015-2021), or Spatial CIMIS estimates of ET_0 at the location of Station 225 (2002-2015) (Figure 23).
7. The timing (in Julian days) of the date of maximum snowpack measurement.

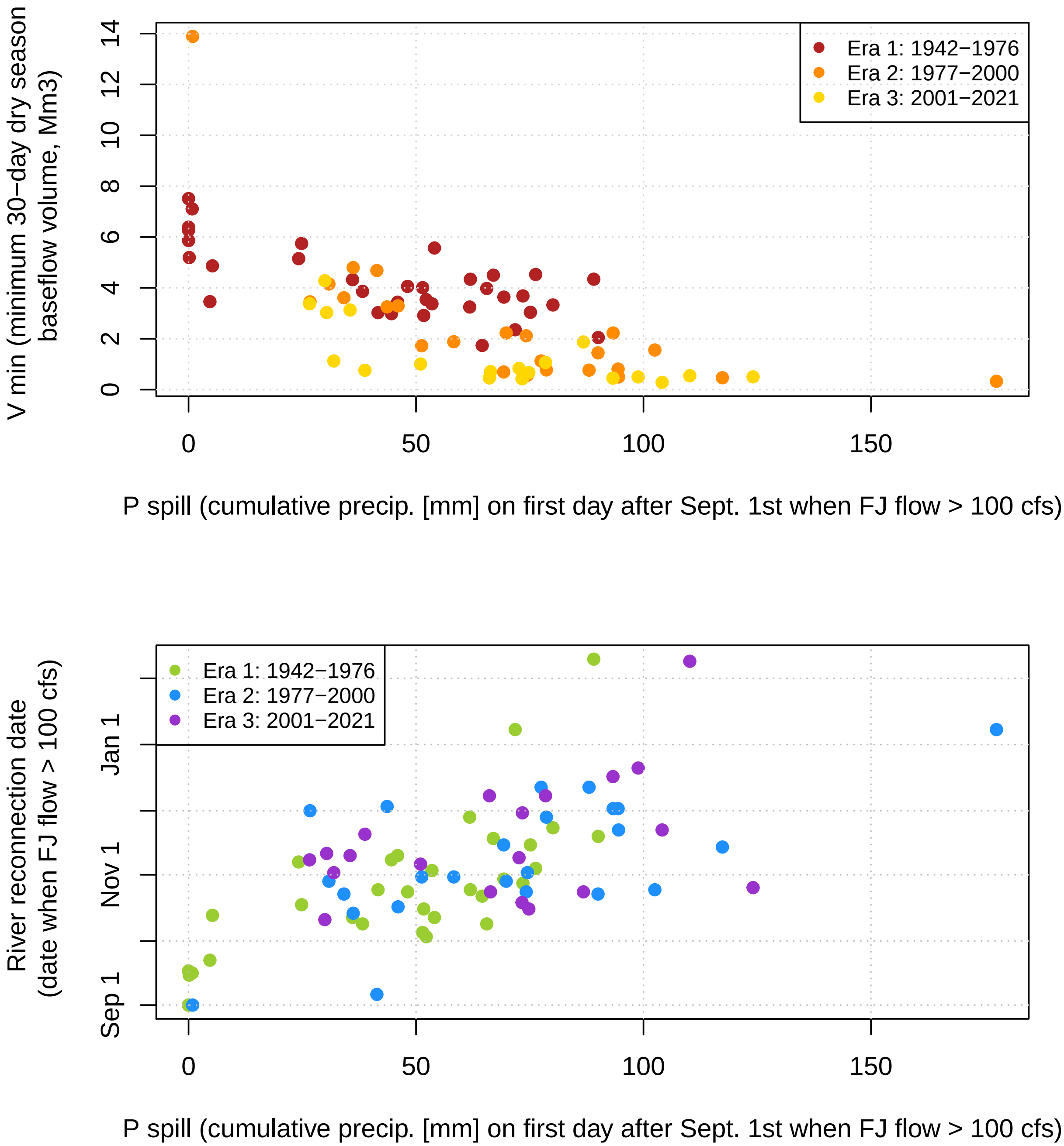


Figure 22: The quantity P spill (i.e., the amount of rainfall needed to 'fill' the watershed such that it 'spills', or responds rapidly to new precipitation) is correlated with both a lower minimum dry season baseflow volume (top panel) and a later date of river reconnection (lower panel).

8. The timing (in Julian days) of the date of the volumetric center of the rainy season, calculated as the day the cumulative precipitation crossed 50% of the total.
9. The 1-year-lagged metrics of maximum snowpack, October-April cumulative precipitation, and April water levels (e.g., the October-April cumulative precipitation measured a full 17-23 months prior to a September minimum flow).

Individual measuring locations, such as wells or weather stations, were evaluated for sample size (i.e., years of data) and degree of relatedness with the two response variables. Relatedness of the monitoring locations with the highest R values in each category of monitoring observation are shown in Figure 27.

Prediction formulae for $V_{min,\ 30\ days}$ and P_{spill}

With a sample size of 80 years of dry season baseflow volumes, a one- or two-predictor model is best to avoid overfitting (James et al. 2013). To predict $V_{min,\ 30\ days}$, a set of six one-predictor models were generated using the observation location from each category with the highest R, and model fit was evaluated using Leave One Out Cross Validation (LOOCV; James et al. 2013) (Figure 29). For a dataset with n observations, the LOOCV error of a predictive model is obtained by recalculating the model coefficients n times, each time leaving out one observation, and comparing the resulting prediction to the single left-out observation. The root mean square of these n errors is the LOOCV error used to evaluate model performance in Results.

The single predictors with the lowest LOOCV error (excluding Reference ET, due to insufficient observation record length) were used to produce a set of four two-predictor models (Figure 30) for $V_{min,\ 30\ days}$, including two that incorporate a partial one-year holdover term, to test the validity of the DWR Water Year Type index method in this local setting. A similar approach was used to assess two-predictor models for P_{spill}, though no one-year holdovers were included, and several additional two-predictor combinations were evaluated. In both cases, the best-performing model took the following form:

$$Predicted_i = Int. + m_A * obs_{A,\ i} + m_B * obs_{B,\ i}$$

Where:

- $Predicted_i$ is the predicted value (either $V_{min,\ 30\ days}$ or P_{spill}) in calendar year i (i.e., at the end of water year i).
- $obs_{A,\ i}$, $obs_{B,\ i}$ are the observed predictor values in October-April in water year i (millimeters).
- $Int.$, m_A, m_B are the coefficients of the selected linear model.

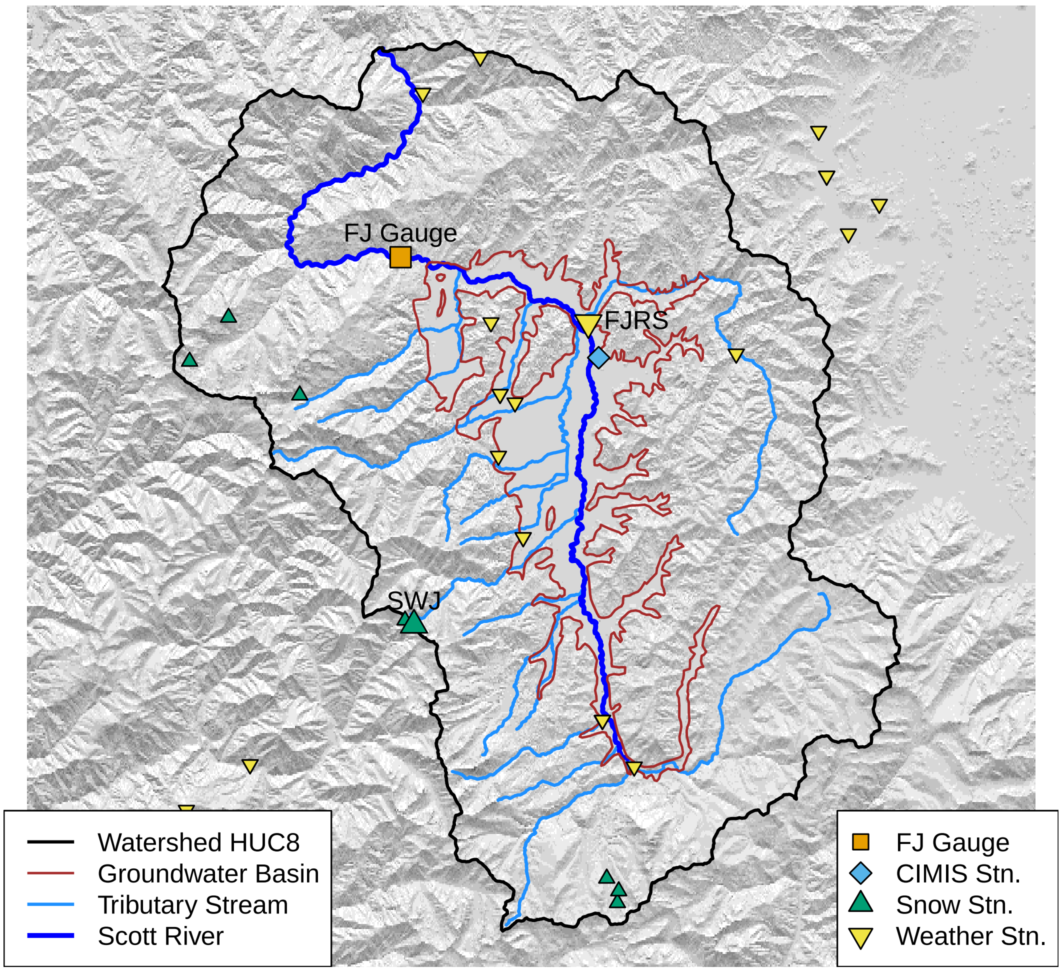


Figure 23: Scott River HUC8 watershed and groundwater basin boundaries, stream network, and key monitoring locations: the Fort Jones stream gauge (USGS ID 11519500), weather stations, snow observation locations, and CIMIS station. Selected locations are highlighted with an enlarged symbol and an abbreviated label.

3.4 Results

3.4.1 Scott River precipitation-runoff behavior

Visual inspection of 80 years of Fort Jones hydrograph behavior during the transition from the dry season to the rainy season indicate that there are two distinct domains of flow: one in which flow is relatively flat (dry season baseflow), and one in which the flowrate is an order of magnitude higher, and it is highly responsive to rain events (wet season baseflow and stormflow; Figure 24, panel A). By visual inspection, and corroborating local observations (see discussion below), the approximate boundary between these domains, denoted as Q_{spill}, is 100 cfs (approximately 7.5 Mm^3 per month). The intermediate hydrologic state, "filling from low storage", is visible in some fall-winter hydrographs (Figure 24, panel A), but tends to last a relatively short time before the filling rate overwhelms the draining rate and produces a responsive "full" condition.

Monthly volume of stream-aquifer exchange, estimated using SVIHM (Tolley, Foglia, and Harter 2019), can be used to further investigate baseflow generation and the boundaries between the draining and spilling flow domains. In most months, the aquifer discharge and stream leakage components of the exchange tend to be of equivalent volume, and net stream-aquifer exchange near 0 (Figure 25, upper panel). Exceptions to this tend to happen only at high Scott River flowrates; all net groundwater-to-stream flux volumes of >0.25 Mm^3 / 30 days (approximately 3.3 cfs) occur at simulated Fort Jones flowrates of >20 Mm^3 (approximately 267 cfs; Figure 25, lower panel).

Additionally, net monthly stream-aquifer exchange volume tends to be an order of magnitude lower than the flow simulated at the Fort Jones gauge. Clear seasonal trends in the net exchange volume suggest that in the winter and spring, precipitation events can temporarily produce large pulses in groundwater discharge. In the summer growing season, when flows are high (e.g. > 10 Mm^3/month, during the early summer snowmelt period), the result tends to be net aquifer recharge, but at low flowrates, the surface water flow is sustained by groundwater discharge. Similarly, very low dry season flows (e.g., < 1 Mm^3/month) are largely composed of groundwater discharge, but when flowrates are higher the direction of net stream-aquifer exchange is more variable, responding to the elevation of the proximate groundwater (Figure 25, lower panel).

3.4.2 Observed response variables

Dry season baseflow quantity and timing, and Scott River eras

Minimum 30-day dry season baseflow volumes, denoted here as $V_{min,\ 30\ days}$, have ranged from 0.3 to 7.5 Mm^3 / 30 days, with one outlier value of 13.9 Mm^3 / 30 days in 1984, when an early September storm

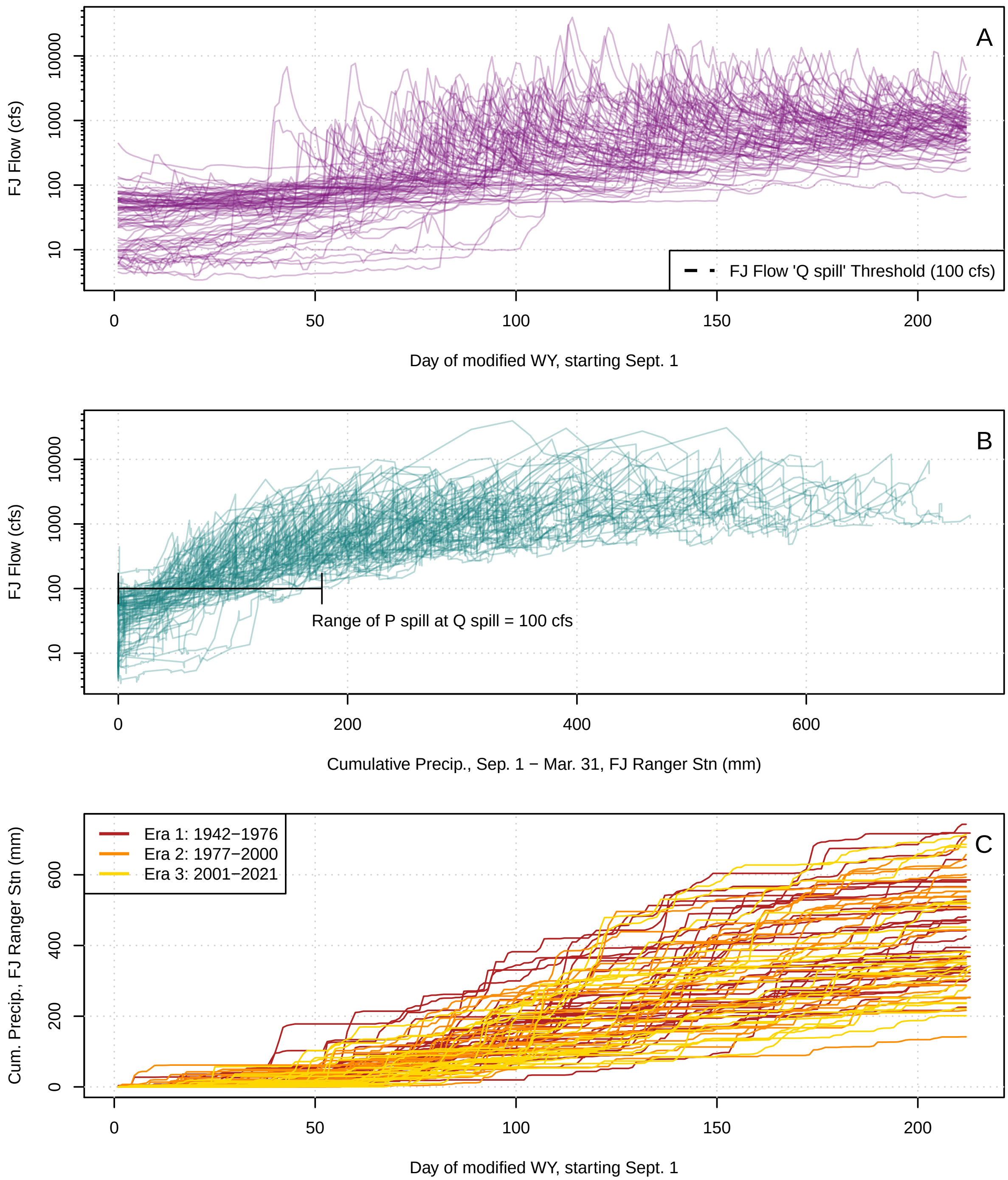


Figure 24: In all three panels, 80 years of data series from September 1 to March 31 are overplotted to illustrate dynamics during the transition from the dry to the wet season: observed Fort Jones hydrographs in Panel A; cumulative rainfall and Fort Jones flow values on fall and winter days in Panel B; and cumulative rainfall over time in Panel C.

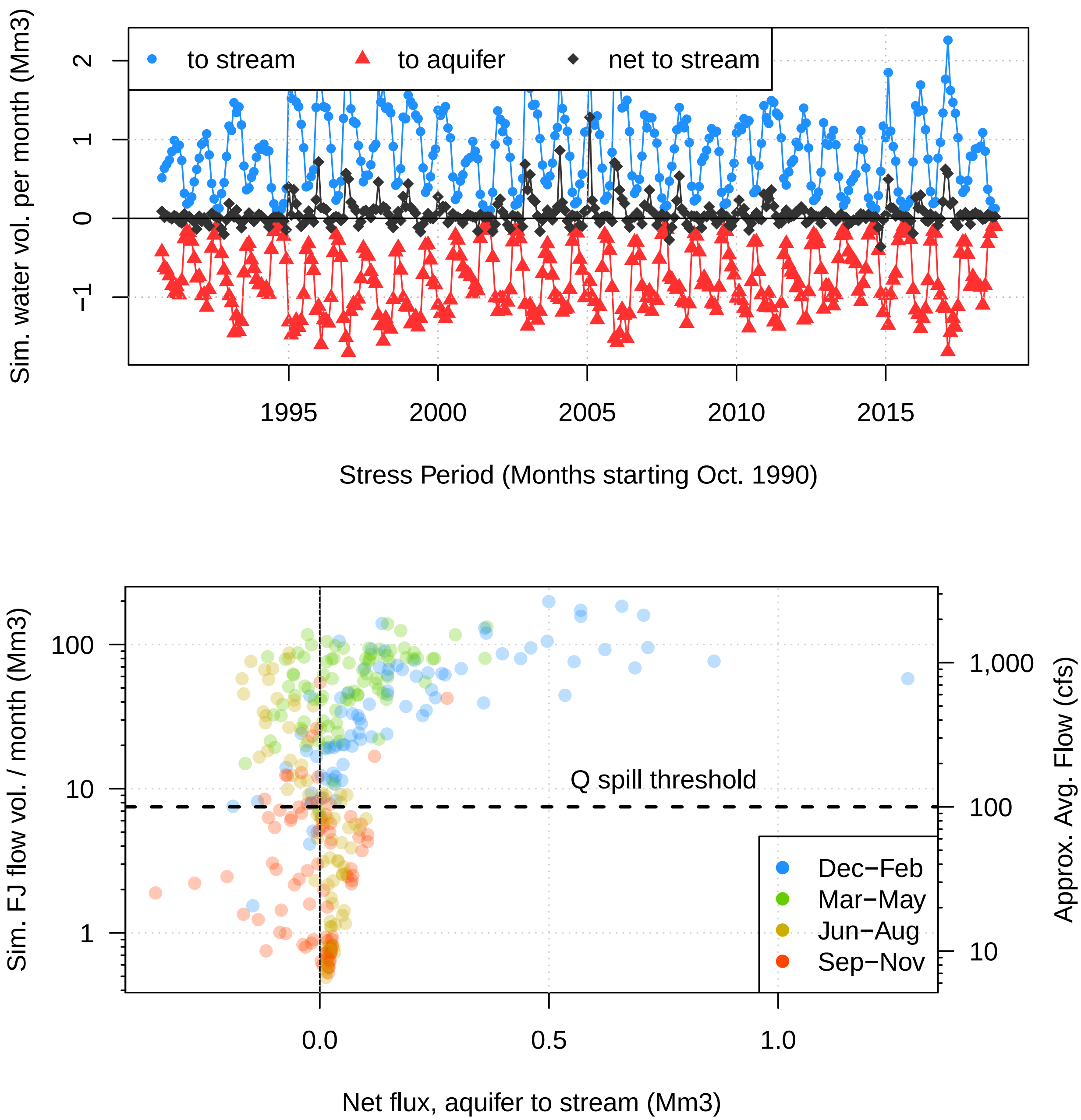


Figure 25: Both stream leakage and aquifer discharge increase in the rainy season, while net flux to the stream remains relatively close to 0 (top panel). Strong seasonal trends are evident in net flux to the stream (lower panel; described further in text).

followed a wet year in 1983 (Figure 26).

Three periods of water use and climate forces have been proposed for the Scott River (e.g., by Pyschik 2022): Eras 1, 2, and 3, ranging from 1942-1976, 1977-2000, and 2001-2021, respectively. These eras are separated by the low minimum flow in the year 1977, which corresponds to the widespread installation of groundwater pumps, and by the onset of a two-decade abnormally dry period in 2000.

Matching other long-term declining flow trends in this watershed, the flows in August and September are relatively steady in Era 1, and they become more variable with significantly lower lows in Eras 2 and 3 (minimum of 2.1 Mm^3 / 30 days [28.6 average cfs] in 1942-1976 and 0.3 Mm^3 / 30 days [4.4 average cfs] in 1977-2021; Figure 26, upper panel).

The timing of the midpoint of the 30-day minimum-flow period falls most commonly in September, though it has fluctuated over the last eight decades (Figure 26, middle panel).

Cumulative fall precipitation and watershed response

In some water years prior to the 1980s, the Fort Jones flowrate exceeded Q_{spill} on September 1st (Figure 24, panels A and B), indicating that even under persistent dry season draining conditions, under the climate and water use conditions of wet years in the mid-20th century, the Scott River remained responsive to new precipitation year-round. As a result, the range of P_{spill}, the cumulative precipitation necessary to reach Q_{spill}, is wide (0 to 178 mm, or 0 to 7 inches) (Figure 26, lower panel). Mean P_{spill} values were 45, 70, and 68 mm in Eras 1, 2 and 3, respectively.

3.4.3 Predictor comparison for $V_{min.\ 30\ days}$ and P_{spill}

The observations of spring flows, snowpack, valley floor precipitation, and groundwater elevation are positively correlated both within each category and to each other overall, which is unsurprising: wet years are associated with higher values in all of these categories. Groundwater wells with highest predictive power tend to have long records (e.g., n of 10 or greater years) and to be close to the Scott River (Figure 28); these results focus on two wells proximate to the river, with long records (well IDs 415635N1228315W001 and 416295N1228926W001).

Both response variables are strongly correlated with four categories of observations: spring flowrates, maximum snow water content, cumulative precipitation recorded at weather stations or or near the valley floor (October-April), and March-May water levels in some wells. Observations in these categories are positively correlated with $V_{min.\ 30\ days}$ and negatively correlated with P_{spill}. The correlation coefficient, R, of these

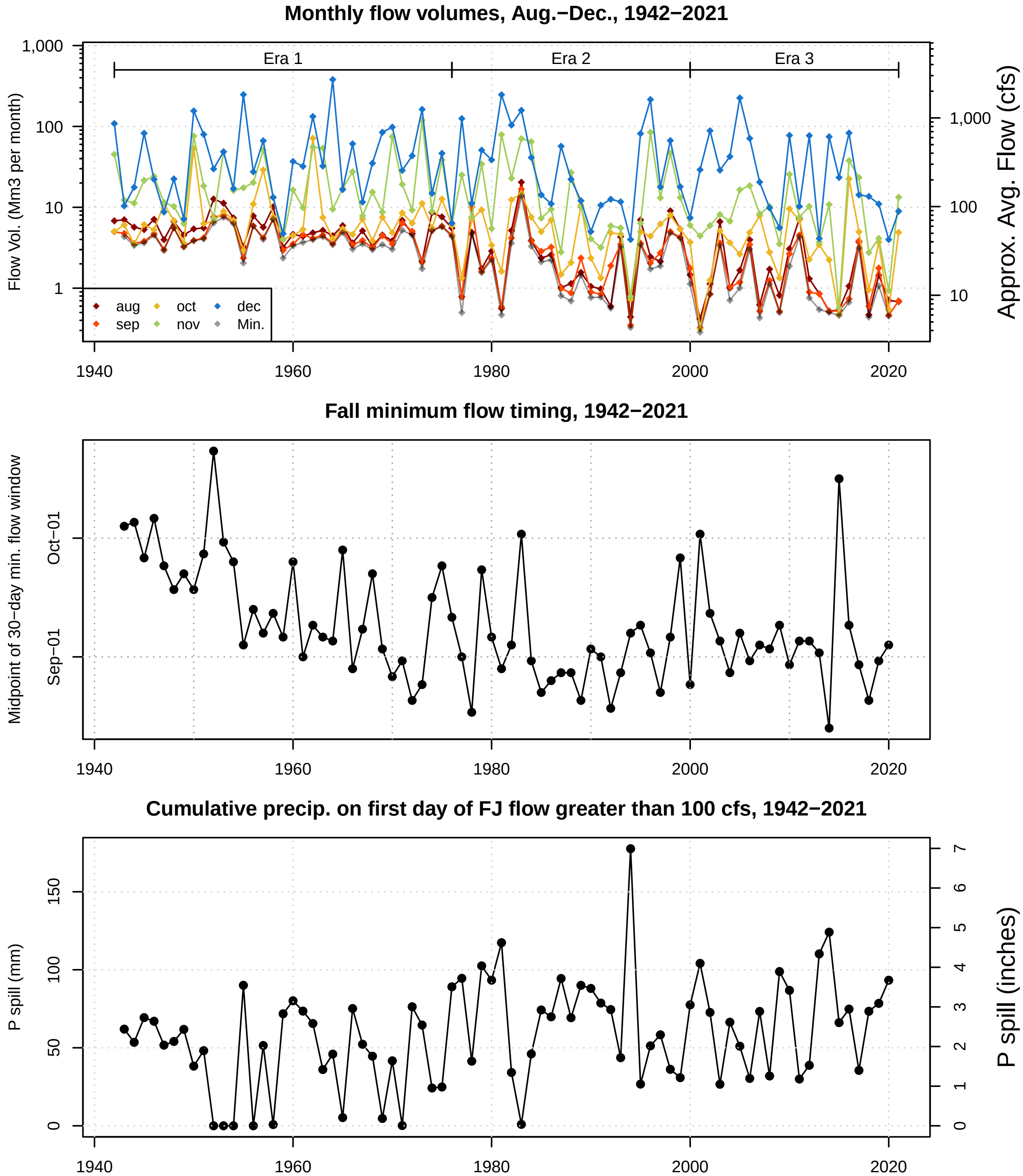


Figure 26: FJ Gauge flow volume, by year, aggregated to monthly time windows in the late summer, fall, and early winter. Eras are noted that correspond to various management and climate forces (e.g., the widespread installation of groundwater wells in the late 1970s, and the onset of a two-decade abnormally dry period in 2000). 0.1 Mm3 per 30 days is equal to 1.4 cfs

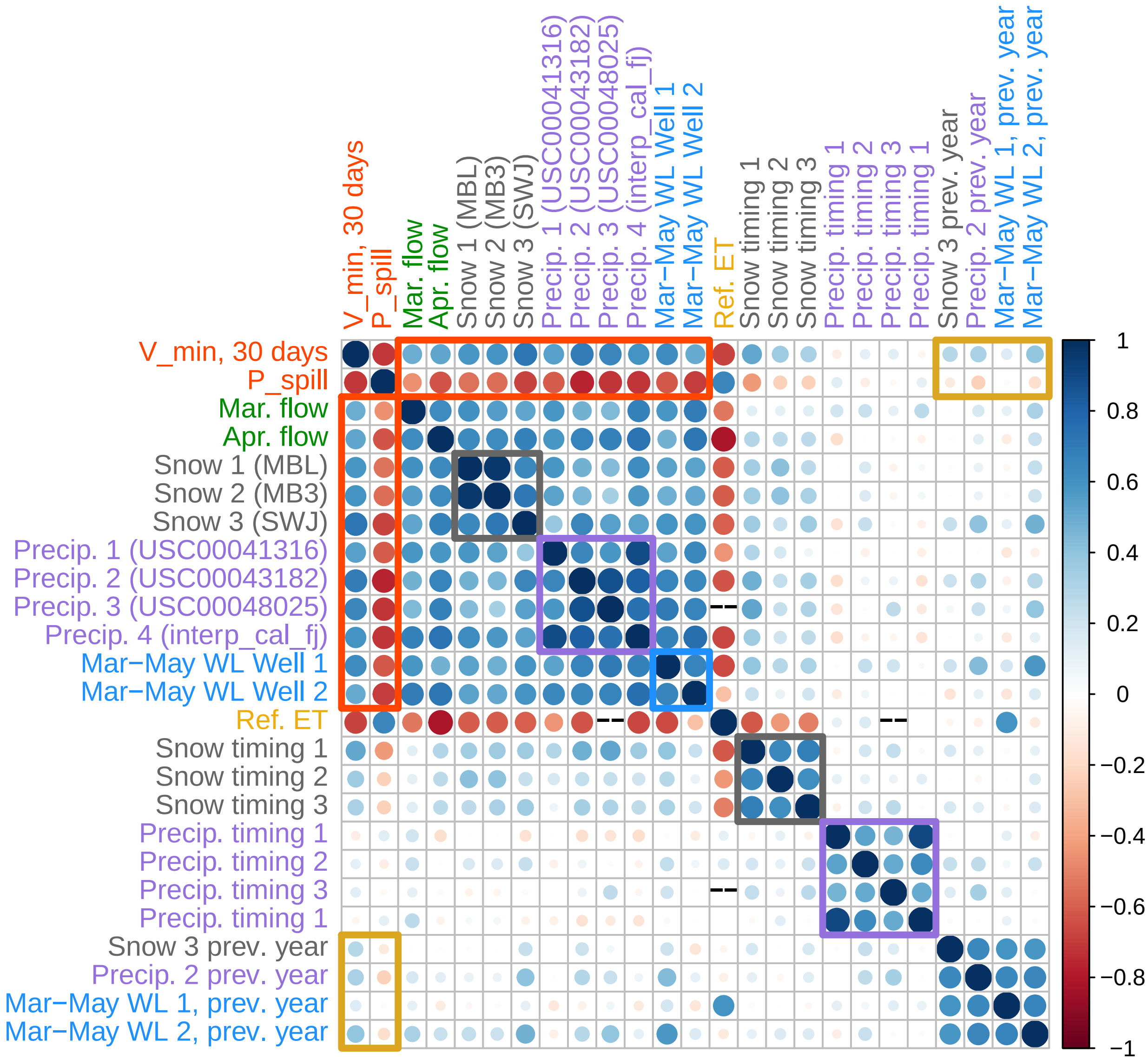


Figure 27: Correlation coefficient matrix of two response variables, minimum 30-day dry season baseflow volumes (V min) and cumulative precipitation necessary to produce 100 cfs in the Scott River (P spill), with various possible predictor metrics. Gray, purple, and blue squares highlight the inter-category correlation coefficients of snowpack metrics, Oct-April cumulative precipitation, and March-May groundwater elevation measurements. Red and yellow rectangles highlight the predictors with the greatest absolute correlation coefficient values with V min and P spill, respectively.

response-predictor relationships range from 0.5 to 0.73 for $V_{min.\ 30\ days}$ and from -0.45 to -0.76 for P_{spill} (Figure 27).

Conversely, cumulative ET_0, October-April is negatively correlated with $V_{min.\ 30\ days}$ and positively correlated with P_{spill} (R of -0.68 and 0.65 for $V_{min.\ 30\ days}$ and P_{spill}, respectively). October-April cumulative ET_0 is also negatively correlated with snow, precipitation, and groundwater level indicators. While ET can remove a significant volume of water from the watershed, this correlation reflects the fact that years with more rainy or stormy days accumulate less total insolation and atmospheric water demand, rather than indicating that high ET is driving low flows. Additionally, the relatively high absolute values of R for between ET_0 and the two response variables may be due to a small sample size, as all available ET_0 observations or estimates were collected in 2002 or later (i.e., in Era 3; Figure 29).

Both response variables are also somewhat correlated with snow timing (i.e., the Julian day of the maximum measured snowpack in a given year; R of 0.33 to 0.52 and -0.24 to -0.42 for $V_{min.\ 30\ days}$ and P_{spill}, respectively), but no significant correlation is evident between the response variables and precipitation timing (Figure 27).

A subset of observations from the previous water year were included in the correlation matrix to test for multi-year influence on the response variables. These previous-year metrics had a slight positive correlation with $V_{min.\ 30\ days}$ (R of 0.29 to 0.33), and an even slighter negative correlation with P_{spill} (R of -0.11 to -0.24), providing moderate evidence for an "echo" effect of the previous year's hydroclimate conditions on a given fall season.

3.4.4 Predicted values of $V_{min.\ 30\ days}$

Predictor assessment and prediction formula

In each of six high-R categories, the monitoring location in each category with the highest R value with observed $V_{min.\ 30\ days}$ values was selected for further analysis (Figure 29). Out of this set of six, the maximum snowpack and October-April cumulative precipitation produce the lowest model errors (LOOCV errors of 2.74 and 2.72 Mm^3, respectively; Figure 29, top two panels). In combinations of two predictors, a linear combination of maximum snowpack and cumulative precipitation improved on the best single-predictor model, with an LOOCV error of 2.29 Mm^3 (Figure 30, upper left panel).

Among the two-predictor models evaluated was a combination of maximum snowpack water content and the timing of the maximum measurement (Figure 30, top right panel). This produced a slightly worse error (2.78 Mm^3) than the single-predictor model with maximum snowpack water content alone (2.74 Mm^3;

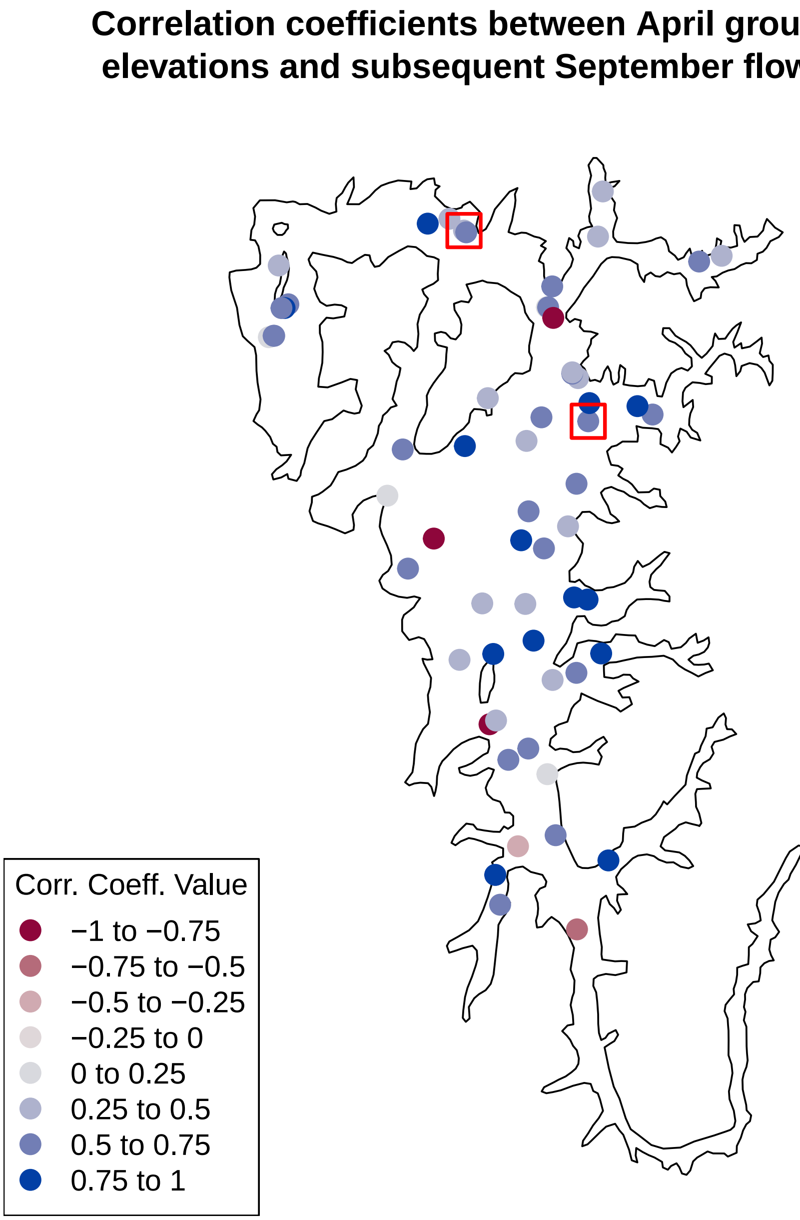


Figure 28: Boundary of the groundwater basin (corresponding approximately to the extent of the flat valley floor in the Scott River watershed) and selected well locations. Colors correspond to the correlation coefficients between April groundwater elevations and September flow volume. The wells included in the predictor comparison are highlighted with a red outer square.

Figure 29, middle left panel), indicating that the timing of maximum snow accumulation is either relatively unimportant in generating dry season baseflows – perhaps because, regardless of the peak time, the melting snowpack becomes recharge, which moves slowly enough through the subsurface to buffer the timing of snowmelt – or that the actual timing of snowpack maximum is not captured in temporally sparse snow course measurements.

Additionally, two models featuring a partial one-year holdover were evaluated, to test the validity of this component of the methodology of DWR's Water Year Type index. In both cases, the addition of the climate data from the previous year produced a very small change in model error (Figure 30, two lower panels), indicating that in the Scott Valley context, the previous year's climate may have a minor influence on dry season flows relative to the immediately preceding rainy season.

Based on these results, the model selected as the $V_{min.\ 30\ days}$ prediction formulation was a linear combination of snowpack maximum from the Swampy John (SWJ) snow station (with data collected by CDEC) and cumulative October-April precipitation from the Fort Jones Ranger Station (FJRS) weather station (with data collected by NOAA) as follows:

$$V_{min.,\ 30\ days,\ i} = -1.33 + 0.00525 * FJRS_{Oct-Apr,\ i} + 0.00267 * SWJ_{max,\ i}$$

Where:

- $V_{min.,\ 30\ days,\ i}$ is the predicted value of minimum 30-day dry season baseflows in calendar year i (i.e., at the end of water year i) (million m^3 or Mm^3)
- $SWJ_{max,\ i}$ is the maximum snow water content recorded at the Swampy John snow course (CDEC station ID SWJ or 285) in water year i (millimeters)
- $FJRS_{Oct-Apr,\ i}$ is the cumulative precipitation, recorded October-April of water year i, measured at the Fort Jones Ranger Station (NOAA station ID USC00043182) (millimeters)

Predicted and observed $V_{min.\ 30\ days}$ over time

The $V_{min.\ 30\ days}$ formulation proposed above predicts minimum 30-day dry season baseflows with a model error of 2.3 Mm^3 (31.3 cfs), and a root mean squared error of 1.4 Mm^3 (19.4 cfs).

Matching the historical trends of decreasing snowpack, the observed and predicted $V_{min.\ 30\ days}$ values show a downward trend over time (Figure 31, top panel). An outlier in the year 1984 reflects extremely high

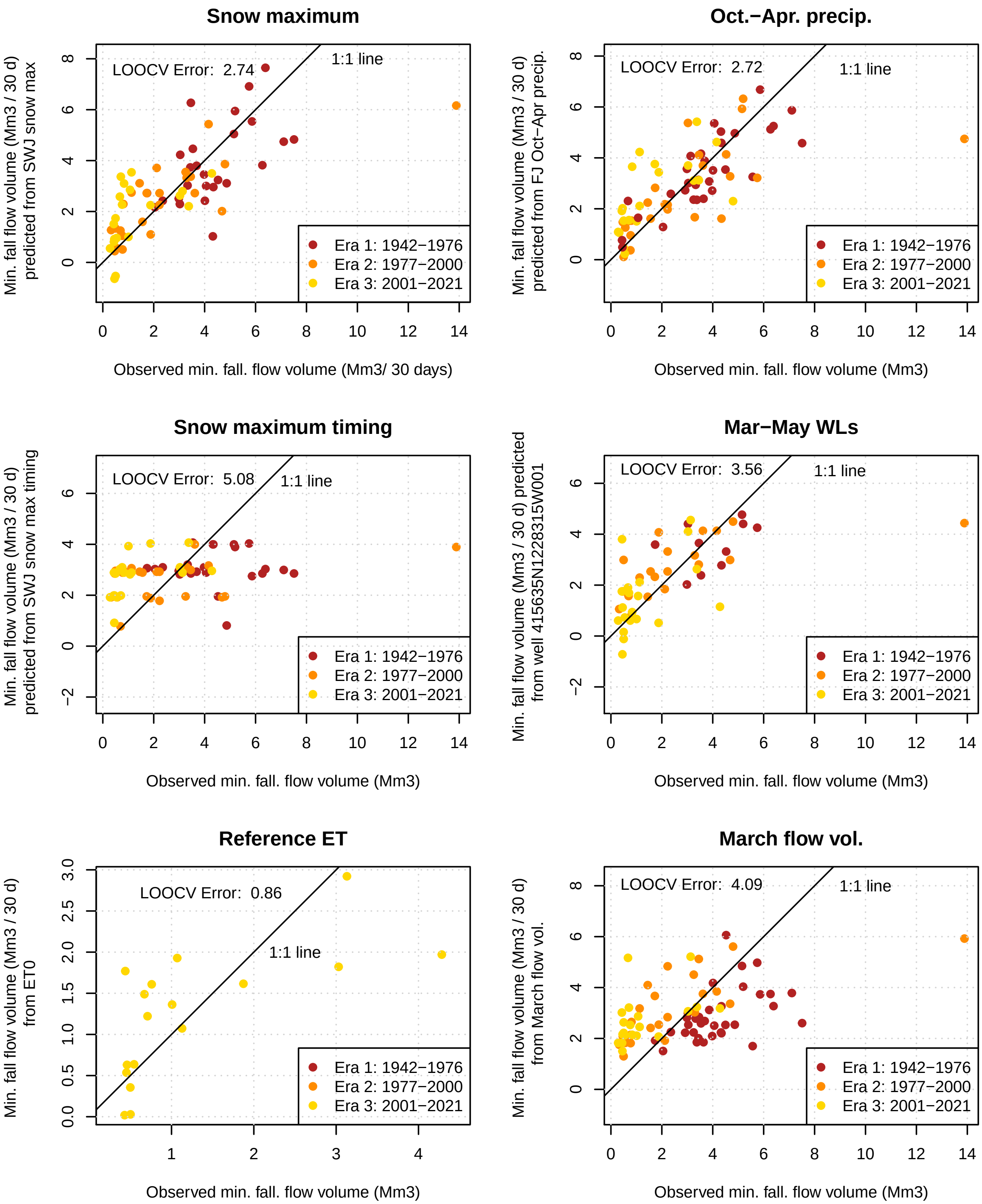


Figure 29: Single-predictor models of minimum 30-day dry season baseflows in the Scott River.

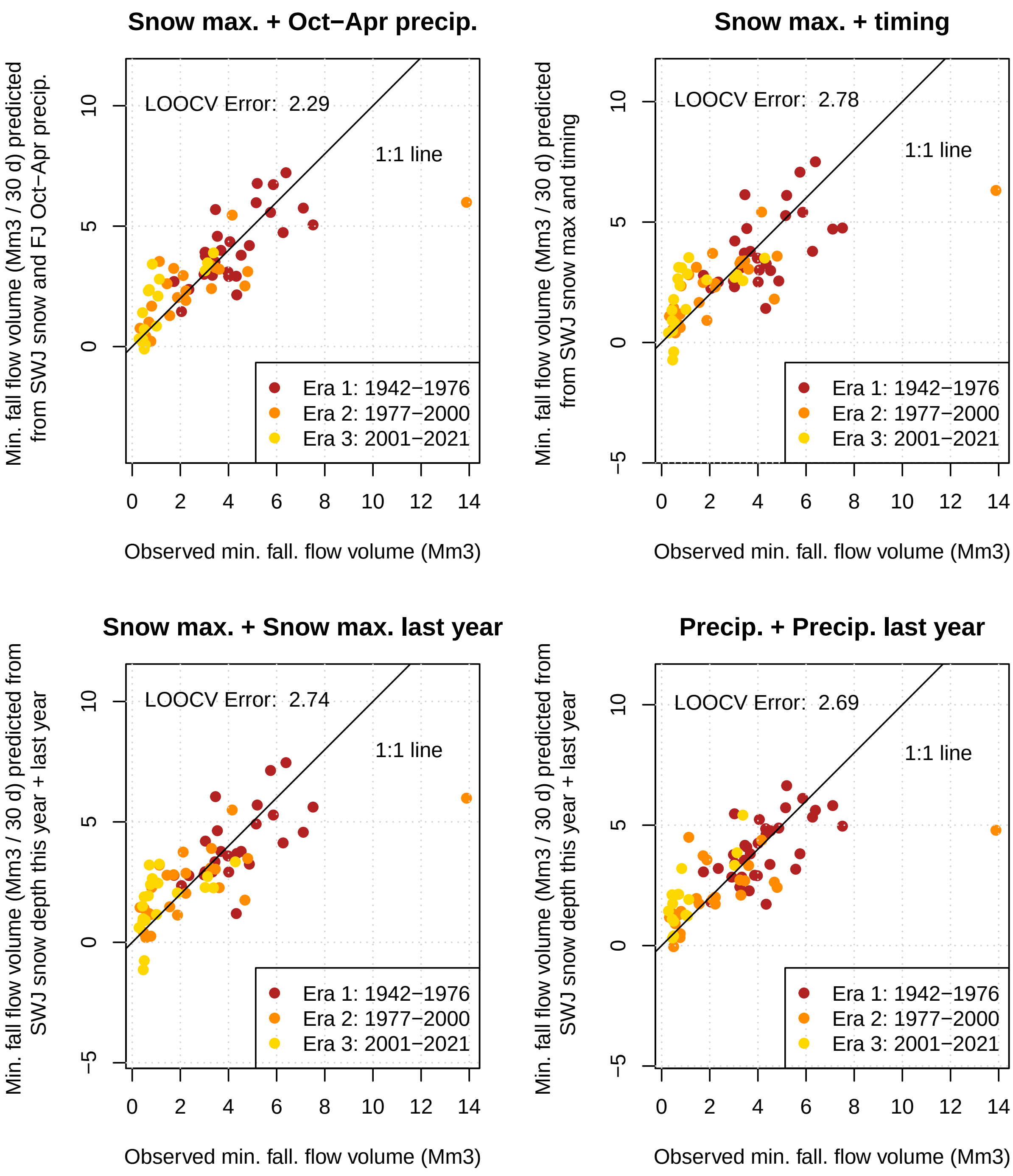
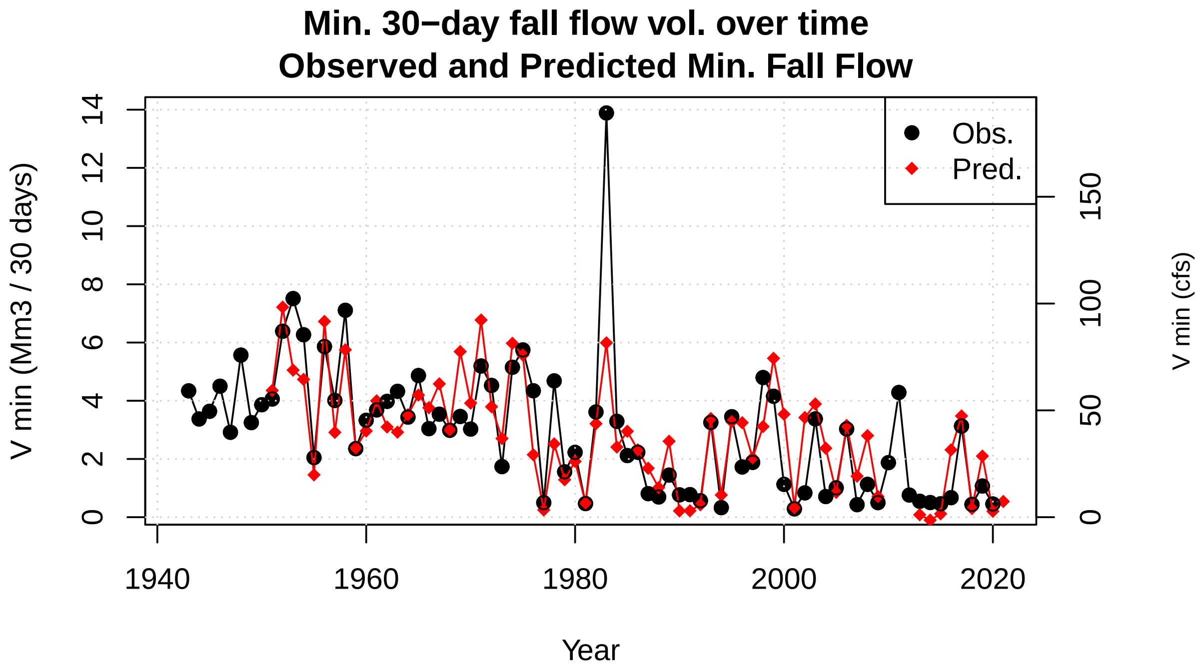


Figure 30: Two-predictor models of minimum 30-day dry season baseflows in the Scott River.



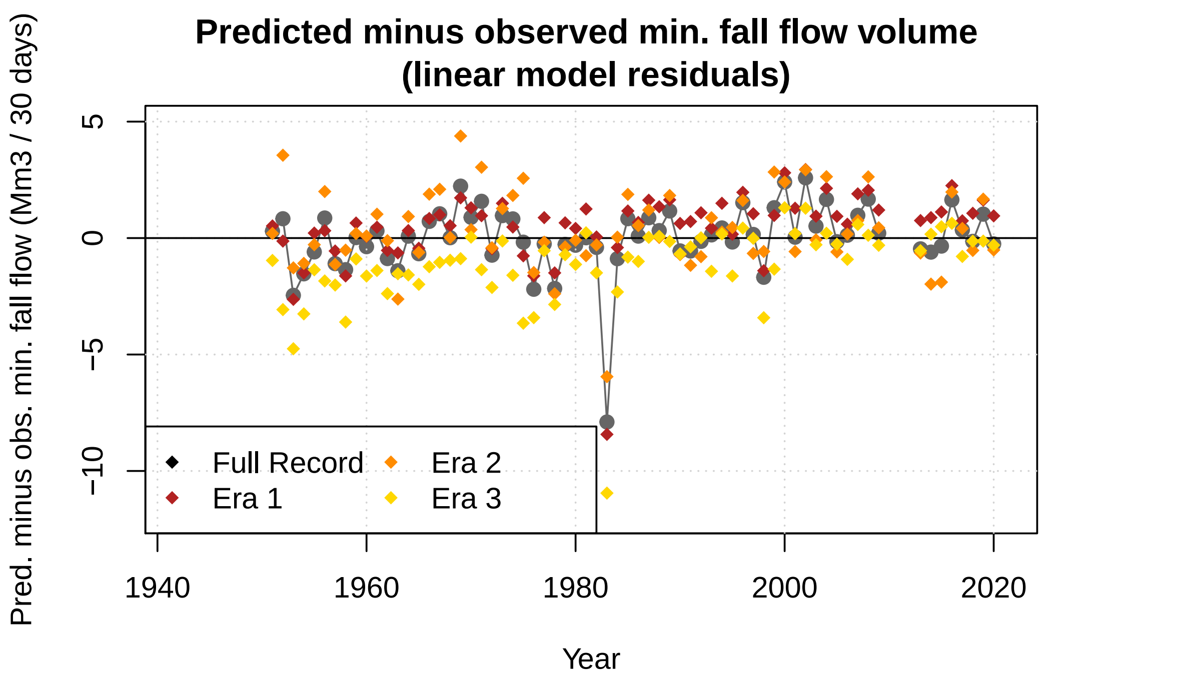


Figure 31: Observed and predicted minimum 30-day dry season baseflows both trend downward between the three eras of the period of record (top panel). The predicted-minus-observed difference (residual) over time also reflects this trend, underpredicting minimum flows pre-1977 and overpredicting them post-2000 (middle panel). The predictive model is based on observations from the full record, but three additional models were generated based on only the observations from Eras 1, 2, and 3. Residuals based on Era 1 data are similar to those of the full record; Era 2 residuals tend to overpredict more than the full record; and Era 3 residuals show better performance post-2000 than the full record, but significant underprediction pre-2000.

minimum dry season baseflows, relative to the predicted values and the overall distribution. In that year, a relatively high-baseflow season was followed by an early September storm. The model residual (predicted minus observed flow volumes) for this year is also an outlier, indicating that the model has a sufficient sample size to not be overwhelmed by this extreme value produced by an extremely uncommon sequence of events (Figure 31, middle panel).

The predictive $V_{min.\ 30\ days}$ model is based on observations from the full record, but three additional models were generated based on only the observations from each period: Eras 1, 2, and 3, respectively. Residuals based on Era 1 data are similar to those of the full record, with a slight but systematic overprediction in Era 3; Era 2 residuals tend to overpredict in Era 1 more than the full record; and Era 3 residuals offer better performance in Era 3 than the full record, but produce significant systematic underpredictions pre-2000 (Figure 31, middle panel).

3.4.5 Prediction of P_{spill}

Predictor assessment and prediction formula

The results of the predictor assessment for the P_{spill} prediction formula were similar to those for $V_{min.\ 30\ days}$, in that the two best single predictors were October-April cumulative precipitation and maximum snowpack (Figure 32, top two panels), with LOOCV model errors of 695 and 496 mm, respectively. (Reference ET was once again excluded from consideration based on a short record length.) Again similar to $V_{min.\ 30\ days}$, the best two-predictor model was the combination of the two best single predictors, with an LOOCV error of 461 mm (Figure 33, upper left panel).

Several combinations of correlated observation categories produced comparable model results, such as spring water levels with maximum snow, maximum snow timing, and cumulative precipitation (Figure 33, upper right and two middle panels). However, not all combinations of co-correlated data produced reasonable predictors; a model with a linear combination of maximum snowpack timing and March flow volumes performed relatively poorly (LOOCV error of 1,005 mm; Figure 33, lower right panels).

Based on these results, the model selected as the P_{spill} formulation for a given water year was a linear combination of the same observation records as $V_{min.\ 30\ days}$: snowpack maximum from the SWJ snow station (with data collected by CDEC) and cumulative October-April precipitation from the Fort Jones Ranger Station weather station (station ID USC00043182, with data collected by NOAA).

$$P_{spill,\ i} = 123 - 0.111 * FJRS_{Oct-Apr,\ i} - 0.0274 * SWJ_{max,\ i}$$

Where:

- $P_{spill,\ i}$ is the predicted value of cumulative rainfall at the end of the dry season, starting Sep. 1, on the first day that the Fort Jones gauge records flow greater than or equal to 100 cfs in calendar year i (i.e., at the end of water year i) (millimeters)
- $SWJ_{max,\ i}$ is the maximum snow water content recorded at the Swampy John snow course (CDEC station ID SWJ or 285) in water year i (millimeters)
- $FJRS_{Oct-Apr,\ i}$ is the cumulative precipitation, recorded October-April of water year i, measured at the Fort Jones Ranger Station (NOAA station ID USC00043182) (millimeters)

Predicted and observed P_{spill} over time

The P_{spill} estimate formulation proposed above predicts P_{spill} values with a model LOOCV error of 461 mm (18.1 inches), and a root mean squared error of 20.7 mm (0.8 inches).

Matching the historical trends of decreasing snowpack, the observed and predicted P_{spill} values show an upward trend over time (Figure 34, top panel). A high outlier in calendar year 1994 (in early water year 1995) was caused by a dry water year 1994 followed by a series of small storms in November and December, none of which produced 100 cfs of flow, followed by a much larger storm on January 8th-9th of 1995 in which the river flow jumped to 600 and then 7,500 cfs in two days.

The predictive P_{spill} model is based on observations from the full record, but three additional models were generated based on only the observations from each period: Eras 1, 2, and 3, respectively. Residuals based on Era 1 tend to underpredict Eras 2 and 3 more than the full-record model; Era 2 residuals tend to overpredict in Eras 1 and 3 more than the full record; and Era 3 residuals have a slightly higher tendency to underpredict than the full record, but overall are fairly similar to the full-record residuals (Figure 31, lower panel).

3.4.6 Comparison with California DWR Water Year Type (WYT) category

The DWR water year type categories map fairly well onto the two proposed hydrologic indices $V_{min.\ 30\ days}$ and P_{spill} (Figure 35, upper two panels), which is to be expected, as both DWR WYT and the two proposed indices are based in part on cumulative precipitation data. However, there is less of an ability to identify a long-term trend in the DWR WYT index time series than in the time series of observed or predicted $V_{min.\ 30\ days}$ or P_{spill} values. Likely causes include the information lost when binning water years into five categories, and the 30-year ranking window that would prevent a direct comparison of post-2000 WYTs with pre-1950s WYTs (Figure 35, lower panel).

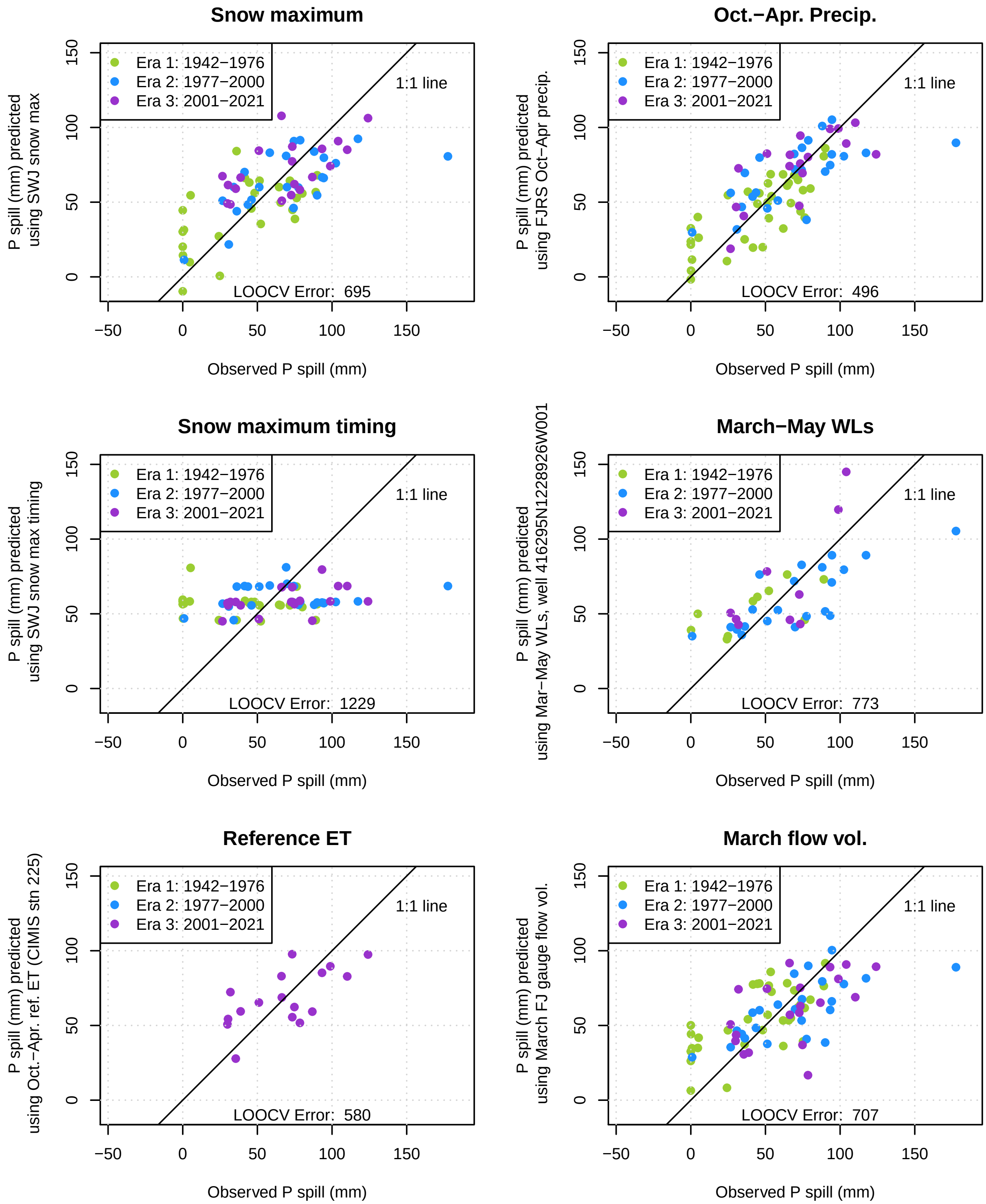


Figure 32: Single-predictor models of P spill, the cumulative precipitation after the dry season needed to generate 100 cfs of flow in the Scott River.

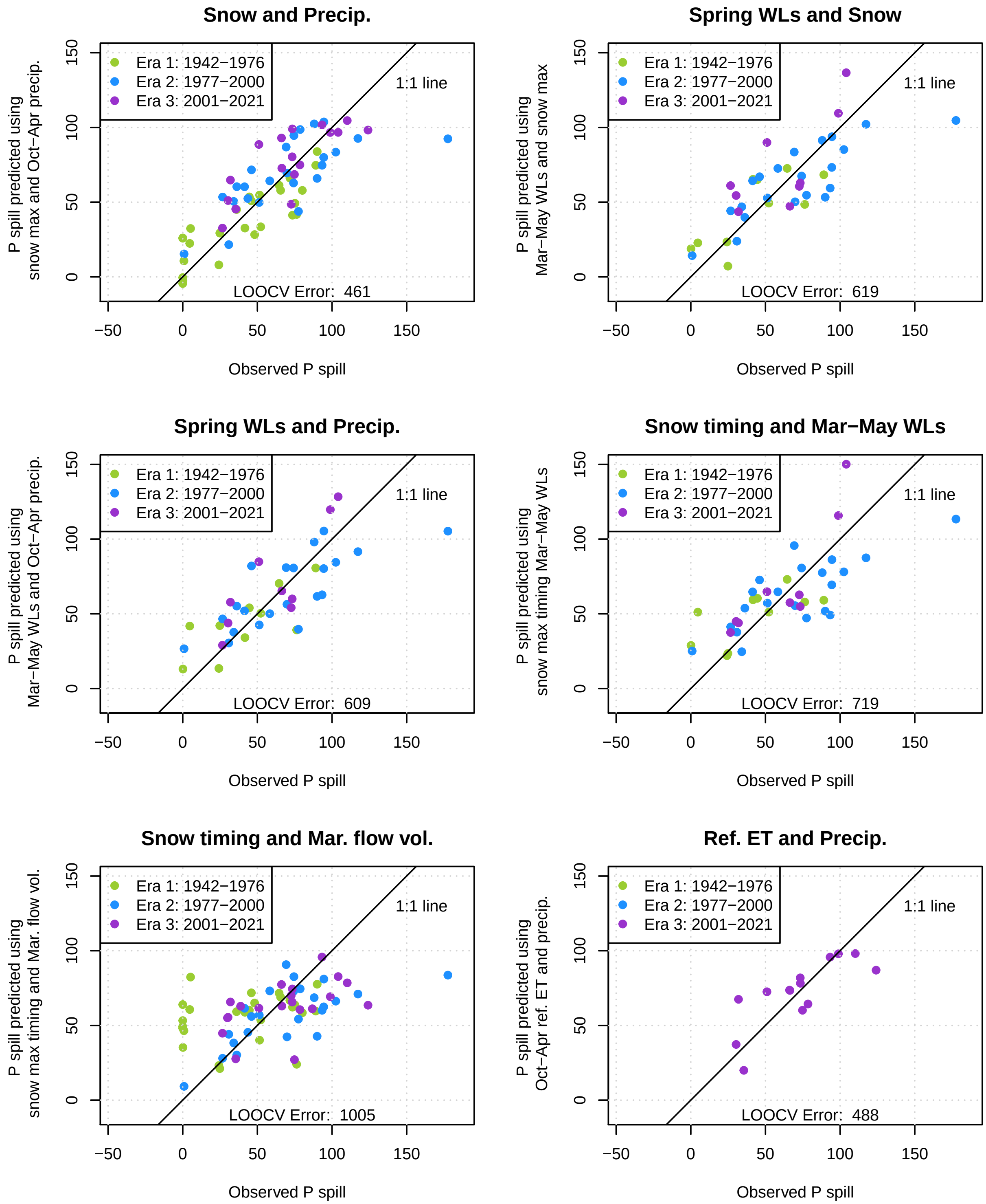


Figure 33: Two-predictor models of P spill, the cumulative precipitation after the dry season needed to generate 100 cfs of flow in the Scott River.

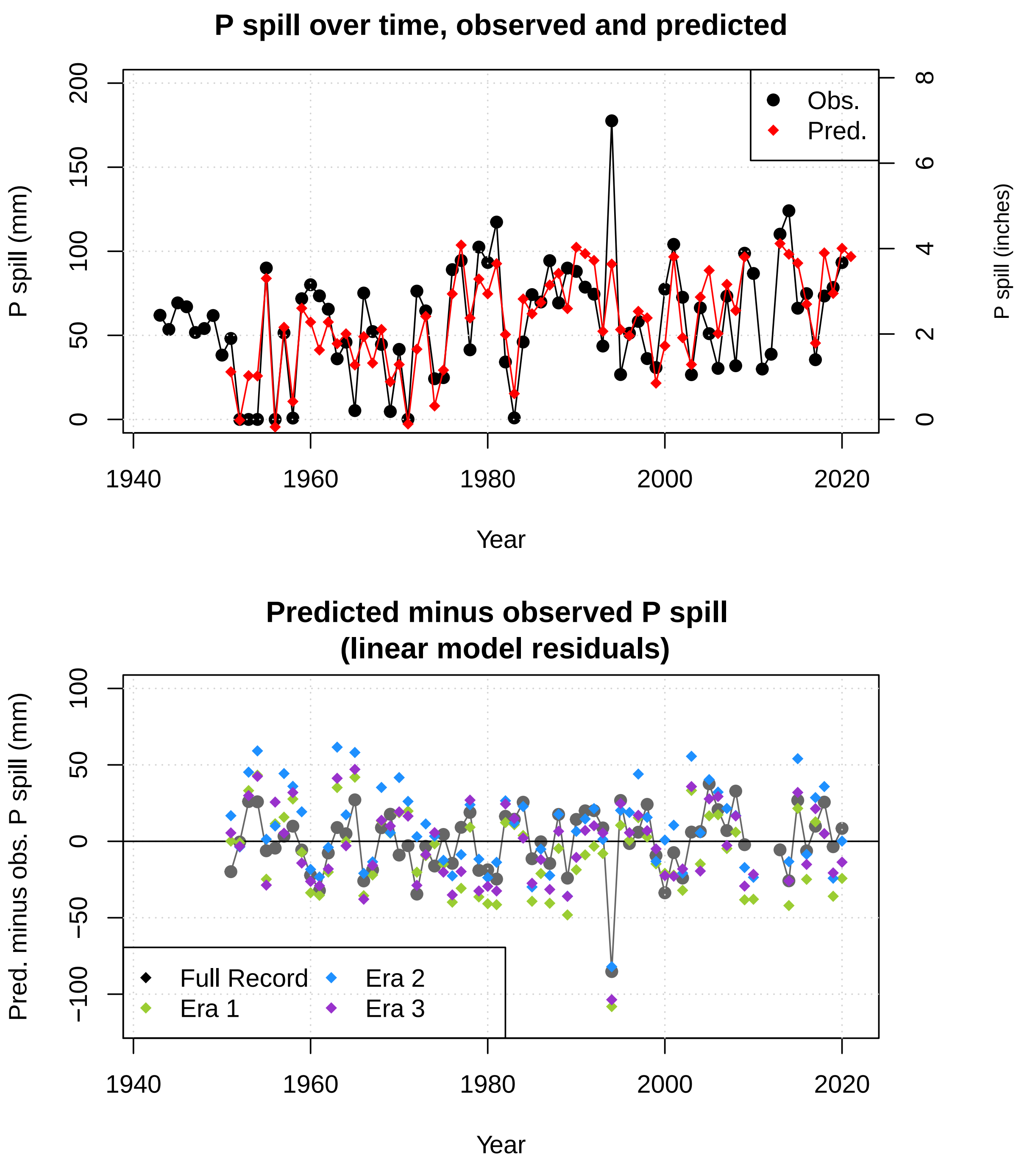


Figure 34: Observed and predicted values of P spill (top panel) indicate a worse model fit for the P spill prediction than for minimum 30-day dry season baseflows (Figure 9). Serious overprediction in Era 1 is followed by more mixed over- and under-prediction in Eras 2 and 3 (bottom panel). The overall P spill model is based on observations from the full record, but three additional models were generated based on only the observations from Eras 1, 2, and 3. Residuals based on Era 1 data are generally lower than those from Eras 2 or 3 or from the full record.

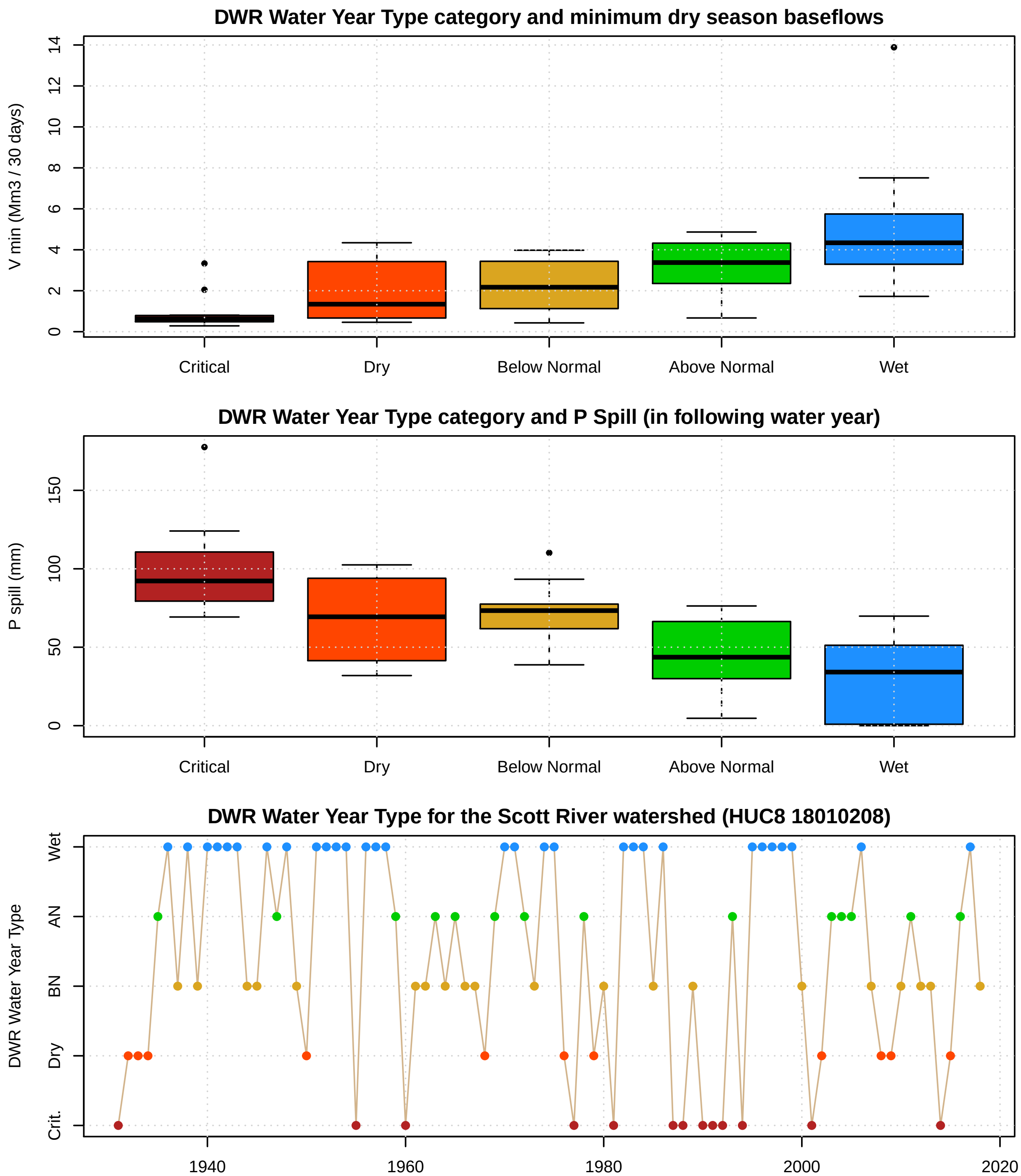


Figure 35: DWR Water Year Type indices over time and compared to the two metrics of hydrologic conditions developed in this study: minimum 30-day dry season baseflow volume (V min) and the amount of precipitation necessary to produce 100 cfs flow in the Scott River (P spill).

3.5 Discussion

3.5.1 Scott River watershed behavior

The degree to which these forward-looking seasonal predictions are accurate depends on fundamental hydrologic relationships between climate inputs and flow outputs, with some complications introduced by water evaporating or transpiring through native or cultivated vegetation.

The condition of a "full" watershed can be operationally defined as a state of being highly responsive to new precipitation. The condition is transient, and proximity to a full condition relies on the balance of slow draining and rapid filling flowrates in any given rainy season. However, in this Mediterranean climate, the general shape of the relationship between cumulative precipitation-runoff behavior is preserved in dry and wet water years (Figure 24, panel B).

Although a Q_{spill} of 100 cfs was identified by visual inspection of aggregate fall hydrograph behavior (Figure 24), it also matches information from local stakeholders. Many tributary streams on the valley floor run dry during the summer and fall, and some tributary streams respond more quickly to fall precipitation than others. Generally, the timing of all tributaries reaching flowing status corresponds with the Fort Jones gauge reaching 100 cfs (Sommarstrom 2020).

Simulated estimates of stream-aquifer exchange corroborates these precipitation-flow relationships. Dry season baseflow ($V_{min.\ 30\ days}$) and the onset of wet season flow (framed in terms of P_{spill}) are both influenced by net groundwater discharge from the aquifer. One interpretation of the high frequency of near-0 net monthly stream-aquifer flux values (Figure 25) is that the high degree of connectivity between the streams and the aquifer in the Scott River system produces balancing counter-forces in response to hydrologic stresses on the system, such as large recharge events. This balancing tendency can be temporarily overwhelmed by large precipitation pulses, but high-flow conditions quickly reduce the volume of water in the surface water system, returning the Scott River to a baseline of nearly-balanced stream-to-aquifer and aquifer-to-stream fluxes. This dynamic also reflects the small size of the available aquifer storage, relative to the amount of precipitation received by the watershed in a given water year (see water budget information in Chapter 2 of this dissertation).

The resulting water storage limitations mean that multi-year planning, such as the long-term GSP projects, may be impossible in the Scott River watershed without making assumptions about how much it will rain (i.e., the future climate predictions in Siskiyou County 2021). If those assumptions are not fulfilled by future climate, year-by-year adaptive management may be necessary to achieve management outcomes.

3.5.2 $V_{min.\ 30\ days}$ and P_{spill} prediction utility

Though various methods exist to qualitatively predict, in the spring, the severity of the coming low-flow season in the Scott River watershed, a quantitative short-term forecasting index could support more rigorous thresholds for adaptive management. To this end we developed two linear equations for predicting minimum dry season baseflows about five months in advance, effectively taking an inventory in each April of relevant hydrologic inputs. It could be used to support decisions made in the late spring timeframe regarding the growing season, such as potential regulatory actions and some farmer cropping decisions.

There are several methods in current use. Observations at existing monitoring locations, such as weather stations and long-term snow course records, have been used as ad-hoc hydrologic indices. Historical adaptive management decisions in the Scott River watershed, such as planning to purchase surface water rights leases, have relied on individual monitoring observations, such as percent of snowpack relative to average conditions, or the Fort Jones flow in the spring (e.g., Scott River Water Trust (SRWT) 2018). Additionally, DWR has effectively extended the methodology of the SVI and SJI metrics to all of California by publishing a categorical water year type (WYT) index for all its major watersheds (to the HUC8 level; California Department of Water Resources (DWR) 2021). This metric quantifies meteoric drought and relies only on precipitation data, so as to be comparable across the state. Matching SVI and SJI methodology, it can be calculated at multiple points in each spring, with a final determination in May, but in the case of Scott Valley it has been used to classify WYTs only retroactively through 2018. As previously mentioned it is a relatively complex metric with provisions including a partial one-year holdover (i.e., dry conditions in the previous year will make a dry-type categorization more likely the following year), and non-stationary index thresholds, with a 30-year ranking window.

The proposed quantitative prediction methods map well onto the existing DWR WYT index, but preserve more detailed information. The primary advantages of the proposed method over these and other previous methods of gauging near-term hydrologic conditions is that it is tailored to local hydroclimate data and is interpretable as a numeric prediction of fall conditions. This could be used to inform regulatory actions in an attempt to increase fall environmental flows, or for surface water diverters to plan for low-flow conditions.

Though it also serves as an indication of the severity of a water year, the additional specific utility of the second predicted metric, P_{spill}, may be less than for that of minimum dry season baseflows. Management decisions such as the last possible date to keep a temporary stream gauge installed in a river, without risk of it being washed out, could be informed by a P_{spill} prediction when combined with weather forecasts in the fall.

3.5.3 Management implications of best-performing predictors

As described in Results, the linear models that best predicted observed values of $V_{min.\ 30\ days}$ and P_{spill} were both based on the same two observation locations (the SWJ snow course and the FJRS weather station; Figure 23), both with lengthy observation records. One interpretation of these results is that the climate inputs produce a predictable fall watershed response, and that human management decisions have a negligible influence on fall river flow. However, model simulations suggest that the timing and magnitude of fall flow increases can be influenced by human water use (e.g., scenarios in Chapter 2 of this dissertation; Siskiyou County 2021).

Multiple possible explanations could reconcile these two pieces of seemingly contradictory evidence. First, random variability in human water use could be a contributing factor to the error of the predictive models of fall-season hydrologic behavior. Alternatively, human water uses could be so consistent in response to wet or dry season conditions that these water uses could be implicitly incorporated into the predictive models. If adaptive management actions (potentially including events as diverse as regulatory curtailments or individual cropping choices) are carefully recorded in the future, they could be compared to residuals of the climate-based predictive models to evaluate whether any signal of a response to human interventions can be observed.

3.5.4 Influences of climate change on predictive indices

Both predictions (using the full record of hydrologic data) assume some degree of hydroclimate stationarity, in that it uses historical snowpack- and precipitation-runoff relationships to predict modern runoff. In one sense, a longer-term record can be an asset, in that it provides context for the severity of the dry periods of the past two decades. In another sense it is a liability for prediction accuracy: for example, the predicted $V_{min.\ 30\ days}$ values based on the full record appear to systematically overpredict $V_{min.\ 30\ days}$ in the most recent era (2001-2021; Figure 30, top left panel, and Figure 31, middle panel). This suggests that factors not captured in these climate data, such as warmer air temperatures, changing upland vegetation and evapotranspiration dynamics, and possibly unknown changes in water use, may be altering the relationship between the spring water supply and dry season baseflow rates.

3.6 Conclusions

This study proposed two locally-tailored hydrologic decision-support metrics for the Scott River watershed in northern California. Both use snowpack and cumulative precipitation data from October-April to predict the quantity of interest: the first is the minimum 30-day flow volume in a given water year, referred to as $V_{min,\ 30\ days}$, which typically occurs in September or October. The second index is the cumulative rainfall needed to "fill" the watershed after the end of the dry season to a "spilling" condition that responds quickly to precipitation events, referred to as P_{spill}. Both indices can be calculated at the end of April to support near-term (seasonal) adaptive management regarding the growing season or the fall, similar to the SVI and SJI in California's Central Valley. However, climate change may reduce the predictive accuracy of indices based on long-term data records, and updates based on smaller numbers of more recent water years should be considered periodically.

The management choices facing local managers in this basin are difficult to quantify and summarize, as is the case in basins throughout California and arid regions globally. Locally-derived summary metrics, tailored to regional hydrologic dynamics, have provided and will continue to provide tools for supporting those choices and communicating them to diverse stakeholders and the general public.

Concluding Remarks

These three chapters are contributions to the extensive list of studies on water resources in Scott Valley. The central questions and analyses were made possible by an opportunity to deeply study one watershed for several years, building on the legacy of past investigators, including a modeling tool (the Scott Valley Integrated Hydrologic Model, or SVIHM) that was a decade in development. The dissertation has been greatly enriched by access to local data and expertise, and collaborations that began during development of the Scott Valley Groundwater Sustainability Plan (GSP) in 2018-2021. As described in the preceding chapters, concern about the impacts of farming practices on local environmental flows are longstanding, and have only been exacerbated by climate change, but many management actions designed to improve flows for fish risk reducing water supply reliability for farmers.

Rather than identify a single solution to this conflict, the three studies in this dissertation were designed to be responsive to some of the needs articulated during the public GSP development process. Chapter 1 is intended to mitigate (if not completely resolve) a key knowledge gap that arose consistently in public meetings: which flows are "good enough" for coho salmon? Chapter 2 is intended to provide clarity to the management alternative-consideration process by allowing all management scenarios to be plotted on the same three summary axes (i.e., agricultural and environmental benefit, and new infrastructure costs). Chapter 3 is intended to support seasonal adaptive management choices and complement existing information that has historically been used to inform those choices. Furthermore, a focus on summary metrics reflects a commitment to distill complex modeling results or observed data into clear tools for communicating scientific information to an audience, whether that audience is the reader of a scientific paper, a local stakeholder, or an interested member of the public.

The tools developed in these chapters may be of service in the future planning efforts of Scott Valley, and potentially in other communities facing similar local resource management trade-offs.

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