Uncertainty in Seasonal Runoff Forecasts Affects Water Management Decisions

Timbo Stillinger[1,1], Christopher Costello[1,1], Roger C. Bales[2,2], and Jeff Dozier[1,1]

[1]University of California, Santa Barbara
[2]University of California, Berkeley

November 30, 2022

Abstract

Heterogeneous snow accumulation in the mountains introduces uncertainty to water-supply forecasting in much of the world. Water managers' awareness of the challenge may account for forecast errors in management decisions. We assess the impact of uncertainty in seasonal-water-supply forecasts on reservoir management using the western slope of the Sierra Nevada of California as a case study. We find that higher forecast uncertainty decreases the volume of water released from reservoirs between April and July, suggesting that water managers hedge against the possibility of lower-than-expected runoff. We modeled April-July water releases as a function of corresponding runoff forecasts, their reported uncertainty, and available storage capacity. An unbalanced (n=416) panel data model with fixed effects suggests that if uncertainty goes up by 10 units, water managers reduce releases by about 6 units, even holding the mean forecast constant. The forecast volume, its uncertainty, available storage capacity, and the interaction between forecasted volume and uncertainty were all statistically significant predictors ($p < 0.005$) of releases. Increased forecast uncertainty and increased available storage were significantly and inversely associated with April-July release volume, whereas forecast volume and the interaction between forecast uncertainty and forecast volume were significantly and positively associated with release volume. These results support the hypothesis that water managers behave as if they are risk-averse with respect to the possibility of less runoff than forecasted. Thus, reducing operational forecast uncertainty may result in more water being released, without the need for direct coordination with water managers.

Uncertainty in Seasonal Runoff Forecasts Affects Water Management Decisions

Timbo Stillinger[1,2], Christopher Costello[2], Roger C. Bales[3], Jeff Dozier[2]

[1]Earth Research Institute, University of California, Santa Barbara, USA.

[2]Bren School of Environmental Science & Management, University of California, Santa Barbara, USA.

[3]Sierra Nevada Research Institute, University of California, Merced, USA.

Corresponding author: Timbo Stillinger (tcs@ucsb.edu)

Key Points:

- Forecast uncertainty is a statistically significant predictor of water releases from reservoirs.
- A measure of uncertainty, known at the time of the forecast, can be used as a metric to inform and improve decisions.

Abstract

Heterogeneous snow accumulation in the mountains introduces uncertainty to water-supply forecasting in much of the world. Water managers' awareness of the challenge may account for forecast errors in management decisions. We assess the impact of uncertainty in seasonal-water-supply forecasts on reservoir management using the western slope of the Sierra Nevada of California as a case study. We find that higher forecast uncertainty decreases the volume of water released from reservoirs between April and July, suggesting that water managers hedge against the possibility of lower-than-expected runoff. We modeled April-July water releases as a function of corresponding runoff forecasts, their reported uncertainty, and available storage capacity. An unbalanced (n=416) panel data model with fixed effects suggests that if uncertainty goes up by 10 units, water managers reduce releases by about 6 units, even holding the mean forecast constant. The forecast volume, its uncertainty, available storage capacity, and the interaction between forecasted volume and uncertainty were all statistically significant predictors ($p < 0.005$) of releases. Increased forecast uncertainty and increased available storage were significantly and inversely associated with April-July release volume, whereas forecast volume and the interaction between forecast uncertainty and forecast volume were significantly and positively associated with release volume. These results support the hypothesis that water managers behave as if they are risk-averse with respect to the possibility of less runoff than forecasted. Thus, reducing operational forecast uncertainty may result in more water being released, without the need for direct coordination with water managers.

Plain Language Summary

Over a billion people around the world rely on snow and ice for their water supply, and in many areas, reservoirs store the water once the snow melts. Deciding when to let water out of the reservoirs depends on forecasts of how much more rain and snowmelt will flow into the reservoirs. Often these forecasts express uncertainty, reporting a wide range of possible flows. As a case study, we use the historical record of past forecasts and water releases in California's Sierra Nevada to examine how the people responsible for releasing water from reservoirs respond to forecasts. Results suggest these water managers hedge their bets against the possibility of less water than forecasted. Greater uncertainty in a forecast was significantly associated with a reduced amount of released water. Reducing forecast uncertainty can support data-driven decisions in water-resource management by increasing water managers' confidence in upcoming inflows. Our results suggest that reduced uncertainty could allow more water to be released from reservoirs earlier in the year.

Index Terms

1816, 1990, 6309, 1857, 1863

Keywords

'Forecast uncertainty', 'water management', 'snow', 'reservoir management', 'decisions under uncertainty', 'runoff forecast'

1 Introduction

Mountain snowmelt is the primary water supply for over a billion people, and recent estimates place the annual value of snow globally at $1 trillion (Sturm et al., 2017). Despite snow's economic significance, the harsh weather and terrain of the mountain environment constrain our understanding of the volume of water in the snowpack each year. This crucial water supply varies from year to year and place to place, which adds uncertainty to water resource management because decisions rely on predictions of future snowmelt runoff. Forecasts of runoff, derived from measurements, models, and climatology, are uncertain and often wrong. Through years of experience, water managers know that these forecasts contain errors. A pressing question arises, applicable to both the gauged and ungauged regions of the world: How consequentially does the uncertainty of forecasts affect water management? The traditional approach to answering these questions involves running hydrologic and decision-optimization models, tuning parameters, and then observing modeled changes in operations (Ajami et al., 2008). In theory, accurate forecasts have value. In practice, forecasts have operational value only if water managers respond to them. In this paper we empirically examine how water managers respond to forecasts by analyzing a historical record of operational water supply forecasts and the corresponding water management decisions.

To optimally manage reservoirs in headwater basins during the snowmelt season, water managers must balance the benefits of filling reservoirs with water for drier months with the opportunity cost of not sending water down the river for other uses. Forecasts help water managers decide when and how much water to release. The tradeoff between the value of an early forecast versus the value of a later but more robust and accurate forecast has been explored within optimal stopping theory known as the "commitment" problem under forecast uncertainty: decisions on allocations of water and ensuring available storage space for incoming runoff must be made before the runoff has occurred (Krzysztofowicz, 1986). The longer the decision maker waits for improved information, the greater the opportunity cost of not acting, especially if the desired actions require mobilization of resources or coordination with institutions or individuals. This tradeoff applies to water resource mangers' daily decisions of holding or releasing water, since the key decision-making variable—the "quantity of seasonal snowmelt"—is available only after release decisions must be made.

Water infrastructure, water rights, and institutional frameworks for managing water pre-date many of the recent advances in hydrologic prediction that improve forecasts. Historically, when forecast accuracy was typically low, the benefit of extra time afforded by setting water allocations early in the winter outweighed the cost of waiting until spring to make major decisions. This precedent is visible in current policy and regulation. For example, in California the annual allocations set in early winter for State Water Project (SWP) and Central Valley Project (CVP) contractors precede most of the snowfall and the availability of an operational or research forecast based on measurements (CADWR, 1963-2019; USBR, 1992-2019). The decision-making environment for water operators during the spring runoff season is marked by the need to fulfill water contracts by making decisions with imperfect hydrologic information.

Our empirical analysis of the historical record examines how water managers respond to operational forecasts. A first principle, which we test, is that water managers will release more water if they anticipate higher runoff, all else equal. This hypothesis seems uncontroversial, and indeed we confirm it. A more nuanced question, and the one on which we focus, is how forecast uncertainty affects water releases. Holding the expected forecast constant, does a more uncertain forecast cause managers to release more, or less? Or does the degree of forecast uncertainty have no effect? To test these hypotheses, a fixed-effects panel regression model is used in a case study of basins on the western slope of the Sierra Nevada to determine the association between April-through-July runoff forecasts, their uncertainty, and volumes released from the reservoirs.

2 Methods and Data

2.1 Study Area

California's Sierra Nevada provides an ideal case study location due to both the economic importance of water in the state and the extensive historical record of publicly available water data to model the relationship between operational forecasts and water management decisions. Figure 1 portrays the study location. The high-elevation watersheds are located along the interior of the state with the highest, snow-dominated watersheds to the south and the lower-elevation watersheds more influenced by rain to the north. The basins comprise a mix of geologic and hydrologic characteristics: granitic watersheds mainly in the Southern Sierra, watersheds with a mix of metamorphic and granitic base rock in the Central Sierra, and the northern Sacramento dominated by volcanic soils. The 14 watersheds within this study cover a mix of water management institutions, geology, hydrology, and climatology.

Water management links California's highly variable annual precipitation, limited surface water storage, and economy. With a 2017 gross state product of $2.58 trillion (U.S. Bureau of Economic Analysis, 2018), over 39 million residents, and production of one third of all vegetables and two thirds of all fruits and nuts consumed in the United States, California depends on a mountain snowpack for water supply. Either diverted from seasonal runoff or extracted from groundwater, Sierra Nevada rain and snowmelt from higher elevations provide a continuous source of water for the state that experiences larger interannual fluctuations in precipitation than any other U.S. state (Dettinger et al., 2011). Water management decisions matter every year, as there is both limited year-to-year carryover storage and a limited time each spring to capture surface water in reservoirs; the median total spring flows are similar in magnitude to the total storage capacity of the reservoirs in the Sierra Nevada (Rittger et al., 2016).

With dry summers and highly variable wet winters, the annual flows of winter rain and melting snow from the Sierra Nevada fill surface reservoirs and extend surface water availability into the dry summer months when demand rises, providing about 60% of the annual water supply and replenishing the 40% that comes from groundwater extraction (California Natural Resources Agency, 2018). Statewide, energy harvested from water as hydroelectricity contributes on average 15% of the State's electrical generation, ranging from 6% in drought years to over 20% of the power mix in wet years (California Energy Commission, 2018). Runoff from the Sierra Nevada and associated groundwater storage fuel California's valuable agriculture industry, with exports exceeding $20 billion in 2016 and gross revenues in excess of $50 billion in 2017 (U.S. Bureau of Economic Analysis, 2018). Urban water supplies in California are also tied to annual seasonal flows and storage volumes in the reservoirs. Most urban water districts that deliver water to 28 million urban residents rely on annual runoff from the Sierra Nevada and Colorado River, alongside groundwater and local surface sources; the diversity of their water sources buffers against the impacts of drought (Palazzo et al., 2017).

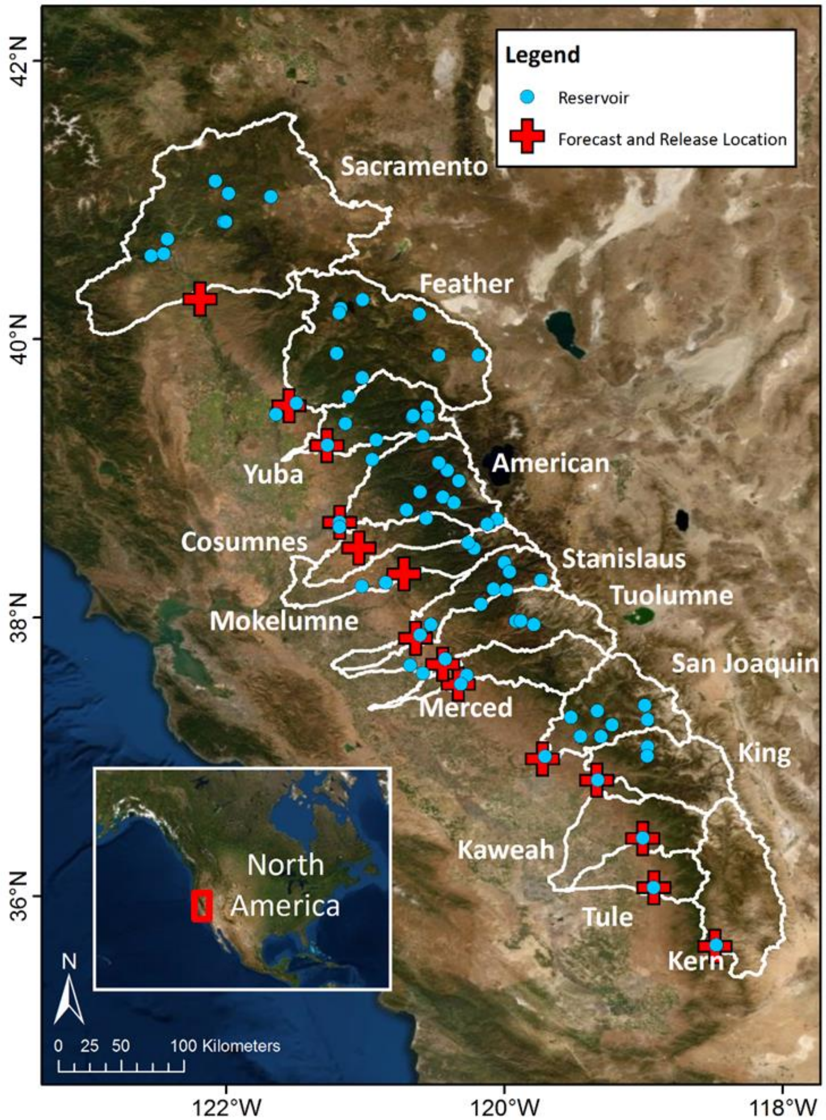

Figure 1. Map of the study area. There are 14 high-elevations basins, with 74 reservoirs (blue dots) operated by 18 different water managers. Table S1 in the Supplement contains the full list of reservoirs and their characteristics. 416 decisions from 34 years of data from 1985-2018 are analyzed. The forecasts and the releases are from the red locations.

California has some of the best-instrumented rivers and monitored watersheds in the world. The Sierra Nevada are safe and accessible, water in the state is such a valuable good with no substitutes, and there is limited storage space available, all suggesting a high value of information from forecasts. California has a century-long history of observing and measuring the snowpack in the Sierra Nevada (Church, 1914). Starting in 1930, the California Department of Water Resources began publishing the official Bulletin 120 of forecasted snowmelt runoff for each basin of the Sierra Nevada, February through May of each year (California Cooperative Snow Survey, 1930-2019). These forecasts use multivariate linear regressions that predict annual spring runoff based on estimated year-to-date rain and snow and expected precipitation (Huber & Robertson, 1982). Snow courses, linear transects of measured snow water equivalent, provide the oldest form of field data used for the forecasts (Church, 1933). Eventually, the field data were expanded to include snow pillows, 123 telemetered stations scattered around the Sierra Nevada in largely flat clearings at mid elevations. California has consistently invested in the effort needed to collect snow data for spring flood and water supply forecasts: in 2019 inflation-adjusted US dollars, $220,000 per year in 1930, over $560,000 per year by 1954 (Strauss, 1954), to the latest published estimate in 2003 of $5.5 million (Roos, 2003). These forecasts comprise the baseline of information available to water managers for making informed decisions on storage and releases from reservoirs in preparation for the upcoming summer.

The accuracy of operational seasonal runoff forecasts has been thoroughly documented in the western United States. Pagano et al. (2004) evaluated snowmelt runoff forecasts, and Harrison and Bales (2016) comprehensively analyzed the full history of California's Sierra Nevada seasonal outlooks of runoff. As anticipated, forecast skill increases as the season progresses. Areas like California with a wet winter followed by a dry melt season show forecast improvement through the season as the forecast shifts from a precipitation prediction challenge to a snowpack measurement challenge. Predictions made on 01 April of each year of the April-through-July flows in all Sierra Nevada rivers, published in Bulletin 120 by California's Department of Water Resources (CADWR), show forecasts exceeding runoff by 50% or more in one year in ten and 100% or more in one year in fifty (Figure 2).

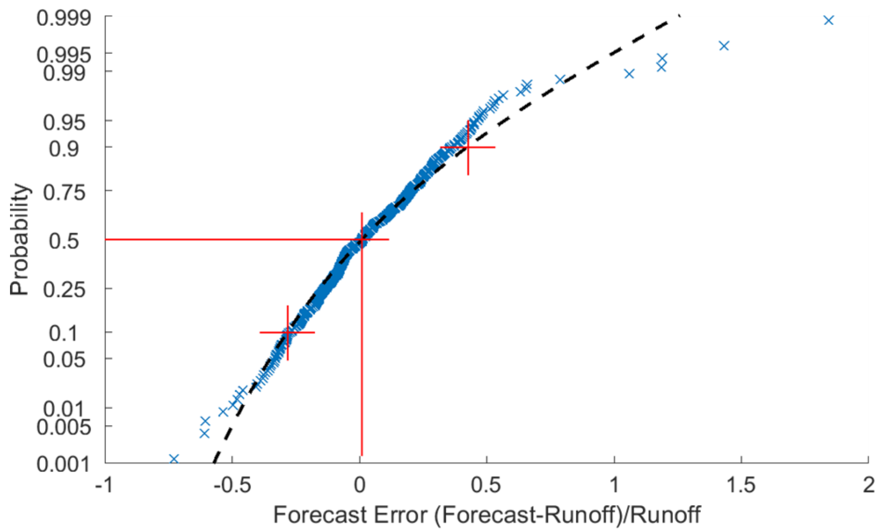

Figure 2. Cumulative distribution of errors for historical 1st April Bulletin 120 forecasts of April-through-July full natural flows (FNF) in Sierra Nevada rivers (1985-2018, n = 442). The black dashed line represents a generalized-extreme-value-distribution fit to the data. The red lines indicate the median error, near 0%. The red crosses indicate the errors at the 10th and 90th probability threshold, and the intersecting red lines indicate the median error. On the negative end, errors can never be worse than –100%. On the positive end, one forecast in ten shows errors of +50% or more, and one forecast in fifty shows errors of +100% or more. Negative errors indicate an under forecast, there was more flow than expected; positive errors indicate an over forecast, less flow than expected.

Reservoir managers rely on a combination of operational forecasts, predetermined allocations of water, and flood risk management rules for guiding operations and determining water releases. In the Central Valley of California, below the Sierra Nevada, as is common among many water projects, delivering contracted water to customers mainly drives decision making. The largest water systems in the state, California's state water project (SWP) and the U.S. Bureau of Reclamations Central Valley Project (CVP), provide water to 279 contractors which supply water to more than 30 million people and over 6 million hectares of farmland. Delivering allocated water supplies drive these major water operations in the spring, summer, and fall.

Water management decisions should relate to operational forecasts of water supply. Measured accumulated precipitation and spring runoff forecasts in the Bulletin 120 likely influence the decisions to increase or decrease the annual allocations of water within these major water systems. Prior to the accumulation of winter precipitation, SWP receives requests for annual water allocations from the 29 contractors it supplies. In November, still prior to any significant annual precipitation, SWP determines the fraction of each contractor's requested water to be allocated for the coming water year. These allocations are updated in public notices to SWP contractors, up to a few times a year, usually before 01 April (CADWR, 1963-2019). In a similar manner, the Central Valley Project issues initial water supply allocations for its 250 contractors between January and April of each year (USBR, 1992-2019).

Based on the monthly Bulletin 120 forecasts, managers also prepare for required environmental releases dictated by the official water year classification. Bulletin 120 forecasts are used to set annual mandated environmental flows and are the foundation for the official water year type classifications in the Sacramento and San Joaquin rivers, the two largest rivers that drain the Central Valley of California. Monthly, February through May, the Bulletin 120 forecast is used in a linear equation to calculate an index value that categorizes each water year as one of five types (critical, dry, below normal, above normal, wet). The water year type calculated on 01 May is used to set strict minimum flows below reservoirs through the dry summer months (State Water Resources Control Board, 1978, 1999).

Aside from delivering water to customers, surface reservoirs also provide protection against floods, reducing flooding in the communities and irrigated lands below these mountainous watersheds. During the winter months, maximum stored volumes in each reservoir are independent of forecasted flows, allocated water supplies, or anticipated environmental releases required in the summer. Maximum stored volumes through the end of March are fixed lower than the available space to store water in each reservoir to reduce the risk of flooding from rain during large winter storms. After the risk of flooding from winter rain subsides, flood-pool storage is reduced, and is available to store additional late season runoff, and the focus of water managers shifts to delivering the contracted allocations of water, generating hydroelectricity when possible, and meeting environmental flow requirements. Within the constraints of these predetermined allocations of water and available winter storage, water managers have the freedom to make subjective decisions about when to release water and how much to release.

2.2 Data

To assist water supply management, California has an expansive network of field measurements and a record of all operational forecasts. Sensors monitor rain and snow in the mountains, stream gauges monitor runoff, and recordings monitor the volume of water stored in each reservoir. Not only has the state invested in measuring snow, rain, runoff, and reservoir storage, it has devoted resources to the care of statewide hydrologic data and prioritized public access to these comprehensive hydrologic records. CDEC, the California Data Exchange Center (http://cdec.water.ca.gov/) houses these public data as an example of databases essential to the "Fourth Paradigm" of environmental informatics (Frew & Dozier, 2012; Hey et al., 2009). Using these data, we assembled a panel dataset of 34 years of water data from the 14 high elevation basins. Figure 3 gives an example from the Tuolumne River in 2011 of the data used in the panel data model, and Figure 4 displays a conceptual overview of actions within the watershed that lead to monthly release volumes. Each component of the system in the conceptual model is explained in detail in the following subsections. Table 1 gives an overview of the datasets used in the panel analysis and the variability in characteristics between the 14 basins.

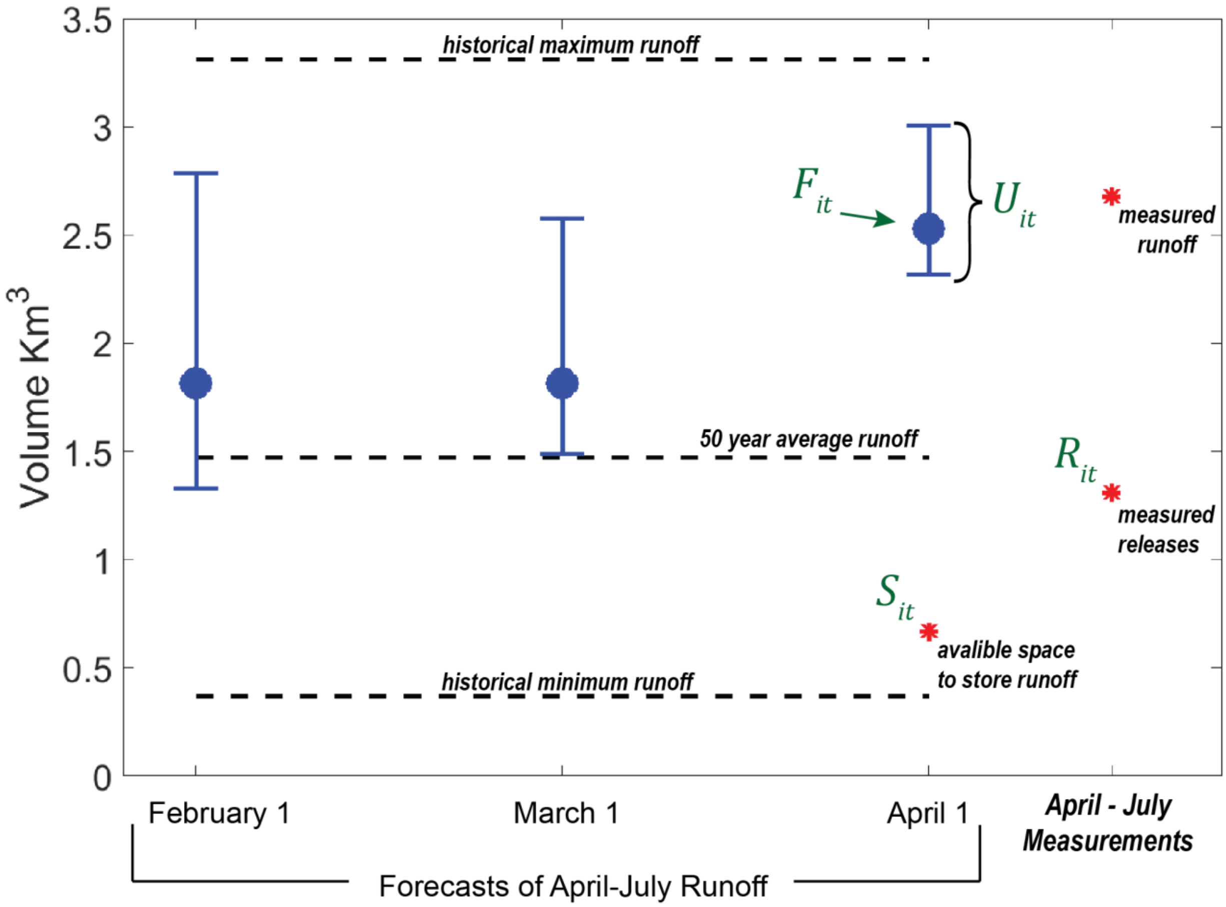

Figure 3. April-July forecasts and measurements from 2011 for the Tuolumne River at La Grange Reservoir. The upper bound of the forecast is the 10% exceedance probability forecast, the lower bound of the forecast is the 90% exceedance probability forecast, and the forecast (F_{it}) is the 50% exceedance probability. The forecast uncertainty (U_{it}) is the difference between the 90% and 10% exceedance probabilities. As the season progresses the forecast uncertainty decreases. The red asterisks detail the conditions in the watershed: the available space to store runoff on 31 March in all reservoirs above the forecast point (S_{it}), the actual measured runoff at the end of the season and then measured release volume from the watershed (R_{it}). The difference between runoff and releases is variable from year to year (Figure 5) and is the product of human actions in the watershed. The variables used in the panel data model in equation 1 ($F_{it}, U_{it}, S_{it}, R_{it}$) are labeled.

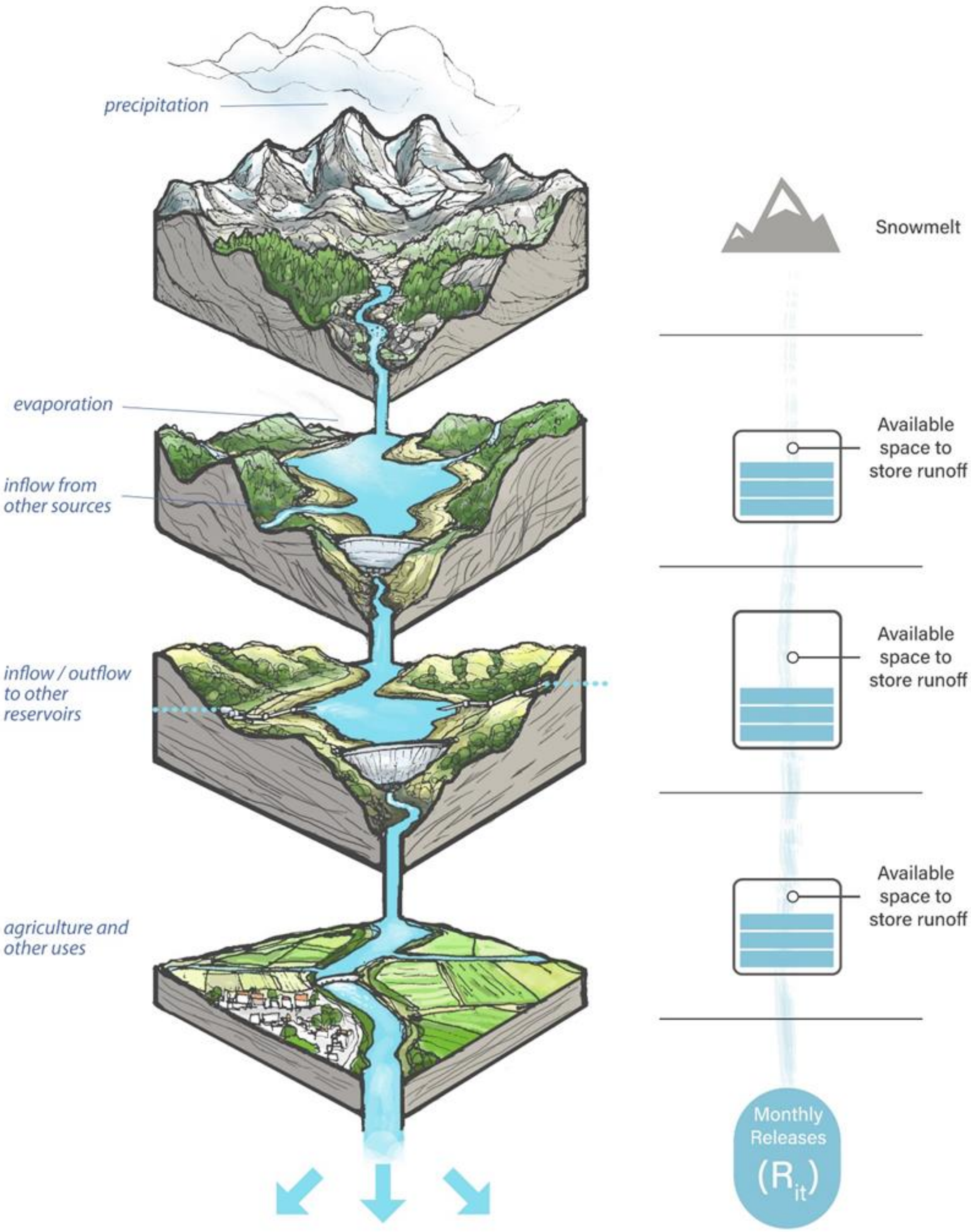

Figure 4. Conceptual model of the general conditions under which forecasts and decisions are made. Monthly releases are the result of changes in reservoir storage volumes, interbasin transfers, and the diversions for and return flows from consumptive uses with the basin. The measured releases from the basin each month are the integrated result of human decisions to use, hold, or release water. The fixed effects panel data model predicts monthly releases (R_{it}).

Table 1. Overview of the surface water system on the west side of the Sierra Nevada used in the panel analysis. Basins are sorted north to south.

River basin	Forecast and release location	Latitude	Longitude	Basin storage capacity (Km^3)	Reservoirs	Operators	Drainage area above reservoirs (Km^2)	Precipitation stations	Snow courses	Snow pillows
Sacramento	Bend	-122.186	40.289	6.10	8	2	17262	8	12	10
Feather	Oroville	-121.547	39.522	6.70	11	3	9342	8	22	10
Yuba	Smartville	-121.274	39.235	1.85	8	3	2849	10	20	5
American	Folsom	-121.183	38.683	2.17	12	6	4882	10	28	17
Cosumnes	Michigan Bar	-121.044	38.500	0.06	1	1	122	7	8	0
Mokolumne	Pardee	-120.719	38.313	1.07	4	2	1603	8	19	10
Stanislaus	Melones	-120.637	37.852	3.50	8	4	2331	9	17	10
Tuolumne	Don Pedro	-120.441	37.666	3.44	6	3	3994	9	21	10
Merced	Exchequer	-120.331	37.522	1.28	2	1	2686	7	13	11
San Joaquin	Friant	-119.724	36.984	1.42	8	3	4338	8	21	16
Kings	Pine Flat	-119.335	36.831	1.53	3	2	4002	8	25	14
Kaweah	Terminous	-119.003	36.412	0.23	1	1	1453	10	16	8
Tule	Success	-118.922	36.061	0.10	1	1	1018	10	7	3
Kern	Isabella	-118.484	35.639	0.70	1	1	5372	8	24	12

Characteristics of the individual basins. The precipitation stations, snow courses and pillows represent the data points that are used in the creation of the runoff forecast. The mix of operators within each basin is unique. For a full list of individual reservoirs and operators within each basin see TableS1 in the supplement.

2.2.1 Monthly Full Natural Flow

The calculated Full Natural Flow (FNF) represents the unimpaired flow in a river. Measured flow is adjusted to FNF by accounting for six ways that human actions and natural processes alter that unimpaired flow as Figure 4 shows: changes in reservoir storage, reservoir evaporation, exports to other basins, imports from other basins, and diversions minus return flows from consumptive uses within the basin. We use the monthly values. The California Department of Water Resources, water operators on each river, and the US Army Core of Engineers are responsible for the calculations. Monthly FNF data are from the same stations for which the seasonal runoff forecasts are produced for each of the 14 basins in Figure 1. These monthly FNF data are used to calculate the forecast error of the CADWR April through July runoff forecasts in Figure 2.

2.2.2 California Department of Water Resources April 1st Forecast and Uncertainty

The California Department of Water Resources publishes the April through July runoff forecasts in Bulletin 120 each month from February through May. The forecasts of the monthly Full Natural Flow for these 14 Sierra Nevada Basins are the longest running forecasts in California of water resources from the Sierra Nevada, in some watersheds dating back to the 1930s. The forecast of spring runoff used in this study is the Bulletin 120 seasonal volume forecast, which includes a confidence range (90% to 10% exceedance probabilities, as Figure 3 shows). These forecasts are based on regression analyses from measured snow water equivalent, rain, and streamflow. We use the forecasts made on 01 April because they are the final, and most accurate, forecasts available before the start of the forecasted time period so they represent the information available to water managers at the start of spring runoff. The median (50% probability) forecast is used as the forecast value, and the uncertainty in the forecast is calculated as the 10% exceedance forecast minus the 90% exceedance forecast (Figure 3). This measure represents the level of uncertainty available to water managers at the time of the forecast and varies from year to year as seen in the individual box plots for each basin's uncertainty range in Panel b of Figure 5.

2.2.3 Monthly Basin Releases

The high elevation basins in the Sierra Nevada offer a diverse mix of water management conditions and management actions determine the amount of water released April through July. Basin releases—defined as the measured monthly flow below the terminal reservoir for the 14 basins in Figure 1—are the volumes of water released by water managers. Panel a in Figure 5 shows the variability in the relationships between the basin releases April through July and the Full Natural Flow from the basins during the same time period across all study years and basins. Because the overall storage capacity of the basins about equals the mean annual flow, most water that flows out of the basins results from water management decisions.

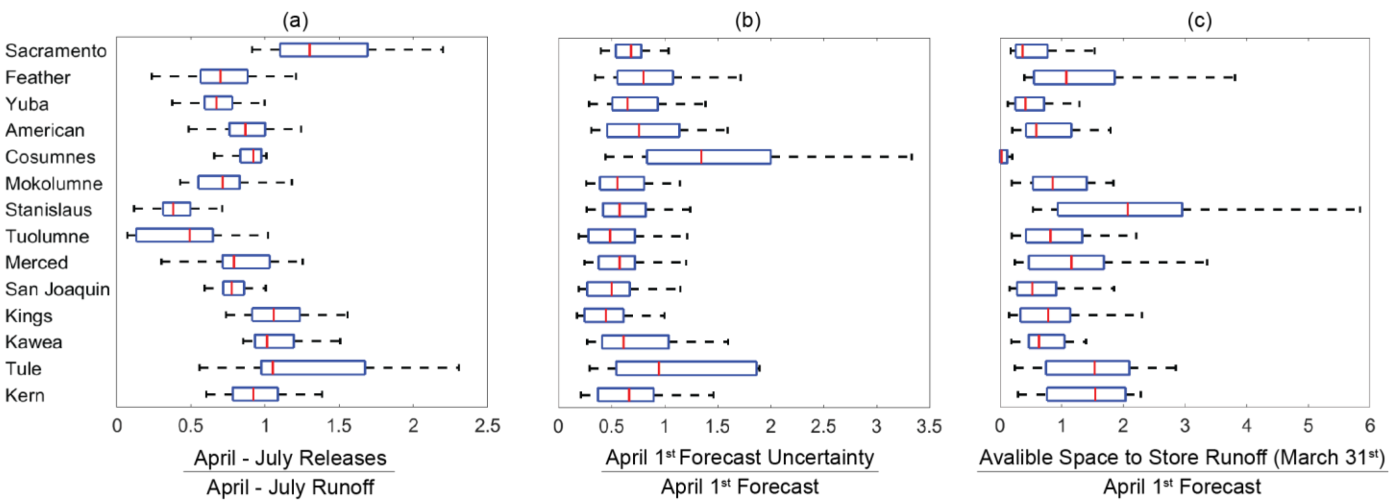

Figure 5. Panel (a) shows the ratio of releases from a basin to its runoff across the study period. Panel (b) shows the ratio of forecast uncertainty to forecast volume. Panel (c) shows the ratio of the available space in a basin to store runoff on 31 March to the forecasted April through July Full Natural Flow on 01 April. For each boxplot in all panels, the central red mark indicates the median, and the left and right edges of the blue box indicate the 25th and 75th percentiles. The black whiskers extend to data up to 1.5 times the spread between the 25th and 75th percentiles. Outliers are not plotted.

2.2.4 Available Space to Store Runoff at the End of March

Our measure of the real time conditions water managers make decisions within is their total available reservoir space to store incoming flows. Each year there are variable amounts of available space to store runoff in relation to how much runoff is expected in the forecasted period. Panel c in Figure 5 shows the variability in available space to store runoff at the end of March in relationship to the forecasted volume of runoff to enter the basin during the spring melt season. For our panel data model, all reservoirs in a basin are treated as a single large reservoir because we are interested in the total available reservoir space to store incoming flows above the basin release point. Reservoir storage data from 31 March each year were available for 74 reservoirs within the 14 basins in our study area. The total basin storage capacity is the summed volume of all reservoir storage capacity, not adjusting for dead pool, the level at which the reservoir can no longer drain via gravity through its outlet, in each basin. Available space to store runoff on 31 March in each basin is calculated by subtracting measured stored volumes from the total storage capacity. These values represent the starting condition for water managers when they receive the 01 April forecast and begin active management of the spring runoff. Our calculated value, available space to store runoff on 31 March, is used instead of the direct measurement of stored volume in each reservoir, because available space directly represents the conditions managers must work with and avoids having to calculate lost storage capacity due to sedimentation or worry about the specifics of each reservoir's usable pool. The list of all reservoirs used in this analysis with information on their capacity, basin, and operating organization are in supplemental Table S1. The monthly reservoir storage data limited extending the study to before 1985; too many reservoirs had no available data in CDEC prior to 1985.

2.3 Analysis Methods

To examine how releases are related to forecasts, we built a panel regression model and applied it to the 14 western Sierra Nevada watersheds described above. This regression model allows us to empirically estimate how the predicted flow, uncertainty in flow, and other variables are associated with releases, while allowing for basin-level fixed effects that control for unobserved differences across basins that do not change over time (for example geomorphology or environmental flow requirements). The model ensures that standard errors are robust to heteroskedasticity and adjusted for 14 clusters (Álvarez et al., 2017).

The unit of analysis is the basin and the time steps are annual from 1985-2018. The starting year of 1985 is the first year when data were available for all parameters in the panel data model. Because a few data points are missing from CDEC, the model was run as an unbalanced panel with n = 416 and 398 degrees of freedom. The main advantage of the fixed effects panel model is that it controls for unobserved heterogeneity in each basin. The form of the model is:

$$R_{it} = \beta_0 F_{it} + \beta_1 S_{it} + \beta_2 U_{it} + \gamma_1 F_{it} U_{it} + \mu_i + \epsilon_{it} \tag{1}$$

R_{it} is the release of water from basin *i* in year *t*, which we take to be the manager's decision, F_{it} is the forecasted flow, $S_{it}$is the available reservoir space to store runoff the day before the forecast arrives, $U_{it}$is the uncertainty in the forecast, and $F_{it}U_{it}$ interacts the forecast with its uncertainty. This interaction term allows for the possibility that a manager reacts differently to a forecast depending on its uncertainty and its magnitude. The fixed-effect μ_i accounts for basin-specific unobservable variables that do not change over time. The error term ϵ_{it} has a mean of zero and no autocorrelation:

$$E[\epsilon_{ti}] = 0 \; with \; i.i.d\left(0, \theta_\mu^2\right) \tag{2}$$

This setup enables modeling the relationship between water supply management and spring runoff forecasts by evaluating the associations of forecasts with basin releases and forecast uncertainty.

5 Results

Table 2 summarizes the results of the fixed-effects panel data model in equation (1), which tests the association of basin releases and water supply forecasts. The model coefficients estimate the marginal change in basin releases from a unit change in each of the predictors, controlling for the heterogeneity between groups. By analyzing associations at the basin scale, the preferred model captures 70% of the variability in the outcome of April-July basin releases (adjusted $R^2 = 0.70$, F-Test, $p \ll 0.001$). The 01 April forecast, forecast range, available storage capacity, and the interaction between forecasted volume and uncertainty are all statistically significant predictors ($p \ll 0.005$) of basin releases. The sign of each estimated coefficient is consistent with first principles. Increased forecast uncertainty and increases in available storage are both negatively associated with April-July basin release volume, whereas forecast volume and the interaction between forecast uncertainty and forecast volume are both positively associated with release volume. The estimated interaction term, γ_1, is positive, which requires interpretation. Its sign implies that the effect of uncertainty on releases also hinges on the magnitude of the forecast. The fact that $\gamma_1 > 0$ implies that when flows are forecast to be higher, the net effect of uncertainty is weakened (the marginal effect of uncertainty on releases is $\beta_2 + \gamma_1 F_{it}$, and $\beta_2 < 0$) . When forecasted flows are high enough, the influence of uncertainty on releases disappears, above about 5 km^3. Table 3 lists the individual fixed-effects, μ_i from equation (1), for each basin in the study. These are estimates for the unobserved time invariant variables specific to each basin. The fixed effects estimates account for heterogeneity that does not vary with time, so can be interpreted as baseline flow levels for each basin.

Our main result is that all else being equal, basins with larger forecast uncertainty on 01 April release less water.

Table 2. Results of the fixed-effects panel regression models with the outcome April through July basin release volume (N=14, T=34; n =416).

Variable		Coefficent	Robust standard error	t-Statistic	p value
April 1st forecast	(β_0)	0.703	0.061	11.55	0.000
Available space to store runoff on March 31st	(β_1)	-0.229	0.067	-3.401	0.005
April 1st forecast uncertanty	(β_2)	-0.598	0.147	-4.082	0.001
Forecast x uncertainty interaction	(γ_1)	0.119	0.050	2.378	0.033

Weighted statistics	
R^2	0.712
Adjusted R^2	0.700
TSS / ESS	803.580
RSS	38.473
Wald F	333.695
p value (Wald F)	0.000

Dependent variable: Basin Release
Sample: 1985-2018
Cross-sections included: 14
Total Panel (unbalanced) observations: 416
Standard errors robust to heteroskedasticity

Table 3. Fixed effects μ_i for the 14 basins in the study sorted from North to South.

Basin	Individual fixed effect (μ_i)	Robust standard error	t-Statistic	p-value
Sacramento	2.540	0.369	6.883	0.000
Feather	0.931	0.364	2.558	0.024
Yuba	0.451	0.323	1.394	0.187
American	0.810	0.329	2.461	0.029
Cosumnes	0.125	0.296	0.422	0.680
Mokolumne	0.273	0.305	0.895	0.387
Stanislaus	0.289	0.335	0.863	0.404
Tuolumne	0.207	0.334	0.620	0.546
Merced	0.396	0.305	1.301	0.216
San Joaquin	0.538	0.322	1.669	0.119
Kings	0.818	0.326	2.512	0.026
Kawea	0.236	0.396	0.597	0.561
Tule	0.066	0.385	0.172	0.866

6 Discussion

Water managers have significant discretion about how much water to release, and we find evidence that they make decisions based on the forecasts. When higher flows are forecasted and when reservoirs are already quite full, water managers release substantially more water. The more nuanced question is: Do these operators also respond to the uncertainty in forecasts?

Holding the forecast volume fixed, a risk-averse water manager facing a more uncertain forecast releases less water, hedging against the possibility of lower-than-expected inflows. When the forecast is more precise, water managers have higher confidence that additional inflow will refill reservoirs, so they release more water earlier in the year. These early releases may enable additional beneficial uses of the water not available had it been released later. By including an interaction in the analysis between forecast volume and forecast uncertainty, we find that the effect of uncertainty on releases is mediated as the forecast volume goes up: Hedging one's bets becomes less important.

While our analysis focuses on snowmelt runoff in California, the diversity of operational structures, geology, hydrology, and climatology among the 14 analyzed basins suggests that our findings can inform water management in other locations. Principally, reducing uncertainty in runoff forecasts can beneficially affect water management.

6.1 Water Operations and their Relationship to Hydrology

Our results empirically confirm water manger behavior predicted by reservoir-operation models. Models predict forecasts to return the most value to water managers when reservoir storage capacity is between 25-100% of the mean annual flow of the river and that managers will not respond to improved forecasts if storage capacity is significantly greater than the mean annual flow (Barnard, 1989; Ødegård et al., 2019). Consistent with but distinct from previous literature, we show that releases across 14 Sierra Nevada basins, which have reservoir storage capacity similar to annual flow volumes, are sensitive to uncertainty in runoff forecasts.

We find that uncertainty plays the largest role when forecast volume is low. This effect decreases, and eventually disappears when there is more water expected than room to store it. The high variability of flows in California implies that only rarely do flow volumes eliminate the influence of uncertainty on reservoir releases.

Previous analyses of the Bulletin 120 forecasts have focused on the forecast error itself and have not directly connected forecast performance to water management (Dozier, 2011; Harrison & Bales, 2016; Pagano et al., 2004). We show room for improvement in the relationship between operational forecasts and water management. Reducing uncertainty in the forecast can lead to more optimal water operations. Recent advances in forecasting that incorporate distributed hydrologic sensor networks (Zhang et al., 2017), remotely sensed data (Painter et al., 2016), or adaptive flood-control measures (Jasperse et al., 2017) all improve forecasts. These methods provide operational products in only a few basins. We provide evidence to support the connection between improved forecasts and actual water supply operations.

As a legacy network, snow pillows and snow courses provide statistical power to forecasts from their long historical record. But with climate change, as the past becomes less representative of the future, the power of these forecast may be reduced as their uncertainty increases. Current work on improved sensor networks that accurately measure the spatial and temporal variability of precipitation, snow depth, wind, temperature, and humidity (Molotch &

Bales, 2005; Zhang et al., 2017) could help improve the operational network and contribute to an effort towards making forecasts robust to secular trends.

Prior work in the Sierra Nevada that focused on hydropower revenues used models to see how better forecasts may lead to increased income, with values of $1 million calculated for the Yuba-Bear hydropower system (Rheinheimer et al., 2016). Those results, explicit to hydropower on a single basin of the Sierra Nevada, showed that reducing uncertainty has significant value. Our study complements prior work by establishing the behavioral responses of managers to uncertainty across basins that have diverse operations ranging across hydropower, water supply for cities and agriculture, flood control, and environmental flows for aquatic habitats.

Managers' behavioral responses to uncertainty likely strive to meet promised allocations of water set in contracts before knowing the volume and timing of future runoff. Since many commitments are made prior to knowing the annual water supply, reducing forecast uncertainty is a measurable goal that may improve the timing of releases and avoid the more difficult task of postponing the timing of major water management decisions.

6.2 Unavoidable Uncertainty

Some error and uncertainty in runoff forecasting are inevitable. The uncertainty related to precipitation can be divided into two broad categories: uncertainty in measurement of rain and snow that have already fallen and uncertainty in expected future precipitation. In early winter before much seasonal snow has fallen, operational decisions are being made based on predictions of the water that might accumulate in the coming year. These predictions rely mostly on historical medians of seasonal precipitation (Roos, 2003) but also to some extent on climate indices such as El Niño and the Pacific Decadal Oscillation (McCabe & Dettinger, 2002; Williams & Patricola, 2018) or later in the season the Madden-Julian Oscillation (Guan et al., 2011). However, the timing and spatial distribution of storms can cause median assumptions to misguide projections of the effect of additional precipitation on runoff volume and timing. For example, atmospheric rivers which provide both natural hazards (Henn et al., 2020) and water resources (Dettinger, 2013). As the season progresses, the forecast fundamentally changes to an estimation of likely runoff based on knowledge of the snowpack and other hydrologic conditions (Cox et al., 1978) combined with expected precipitation to come. When communicating forecasts to water managers, it may be valuable to separate forecast uncertainty into these two categories: measurement uncertainty and prediction uncertainty. Knowing where the confidence lies in the predictions of upcoming runoff may give water mangers more confidence in making a decision that would be too risky if the uncertainty were distributed differently between these two sources.

6.3 Strengths and Limitations of the Analysis

We focused on releases that occurred in the Spring, not on the actions of the water managers from August through March. Although our results show that less water is released during the spring melt season when forecast uncertainty is greater, we did not identify if these releases are delayed outside the April-July timeframe. We focused on April through July because most of the annual runoff occurs then, forecasts are available at the start of the time period for the expected flows, and water managers are actively controlling the volumes and timings of basin water releases.

In principle, it is possible to test our hypotheses at a finer resolution by breaking the analysis down to the individual operating agencies or to the individual reservoirs themselves. We analyze at the basin level because doing so integrates behavior across all actors in a region and most of the data are at that scale. The significant findings at this coarse resolution give merit to a more detailed look at operators or individual reservoirs. While the hydrologic conditions each year significantly affect how much water they release from each basin, no variables perfectly correlate with releases. Some constraints on water supply operations are independent of river flow; flood control, environmental flows, and water rights dictate specific actions each year that may reduce the explanatory power of a forecast on actual basin releases.

These significant findings in California bolster the case to look at similar systems in other states or parts of the world where water management and the timing of decisions are different and may confirm our findings or lead to different outcomes.

7 Conclusion

Reducing uncertainty in runoff forecasts is a tractable objective that can drive forecast improvement, would not require reducing forecast error, and could lead to changes in amount and timing of water released from reservoirs. Our analysis shows that water releases across 14 Sierra Nevada basins are sensitive to the magnitude and uncertainty of runoff forecasts. Water managers effectively hedge against the possibility of lower-than-expected spring runoff. Increased forecast uncertainty and increases in available storage are both negatively associated with April-through-July basin releases, whereas forecast volume and the interaction between forecast uncertainty and forecast volume are both positively associated with releases. Results suggest that all else being equal, basins with larger forecast uncertainty on 01 April release less water from April through July. As forecasted flows increase, the effects of uncertainty are muted.

Narrowing the uncertainty of the forecast, independent of improving the forecast itself, could improve water operations. Moreover, changing the presentation of forecast uncertainty to a format that communicates uncertainty arising from the measurement of snow on the ground separately from the uncertainty in expected precipitation could guide water operations and open new opportunities for using surface water.

Acknowledgments and Data

The authors declare no real or perceived financial conflicts of interests. This work was supported by the University of California award LFR-18-548316. Special thanks to Blaze Skya for helping us communicate through his artwork in Figure 4. All water data used in our analysis are available with no restrictions on access from the California Data Exchange Center (https://cdec.water.ca.gov/), and the forecast data are in the monthly issues of Bulletin 120 (https://cdec.water.ca.gov/snow/bulletin120/index2.html). Because the data in our analysis are scattered throughout those sources, we have consolidated the datasets needed to reproduce our reported findings in two tables in a publicly accessible archive (Stillinger, 2020).

References

Ajami, N. K., Hornberger, G. M., & Sunding, D. L. (2008). Sustainable water resource management under hydrological uncertainty. *Water Resources Research, 44*. https://doi.org/10.1029/2007wr006736

Álvarez, I. C., Barbero, J., & Zofío, J. L. (2017). A panel data toolbox for MATLAB. *Journal of Statistical Software*, *76*, 1-27. https://doi.org/10.18637/jss.v076.i06

Barnard, J. M. (1989). *The value of inflow forecasting in the operation of a hydroelectric reservoir.* (Master of Applied Science), University of British Columbia, Vancouver, BC.

CADWR. (1963-2019). *Bulletin 132 Management of the California State Water Project*. Sacramento: California Department of Water Resources Retrieved from https://water.ca.gov/Programs/State-Water-Project/Management/Bulletin-132.

California Cooperative Snow Survey. (1930-2019). *Water Conditions in California Bulletin 120*. Sacramento: California Department of Water Resources Retrieved from https://cdec.water.ca.gov/snow/bulletin120/.

California Energy Commission. (2018). Total System Electric Generation: 2017. *California Energy Almanac*. Retrieved from https://www.energy.ca.gov/almanac/electricity_data/total_system_power.html

California Natural Resources Agency. (2018). *California Water Plan Update 2018: Managing Water Resources for Sustainability*. Sacramento: California Natural Resources Agency Retrieved from https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/California-Water-Plan/Docs/Update2018/Final/California-Water-Plan-Update-2018.pdf.

Church, J. E. (1914). Recent studies of snow in the United States. *Quarterly Journal of the Royal Meteorological Society, 40*, 43-52. https://doi.org/10.1002/qj.49704016905

Church, J. E. (1933). Snow surveying: Its principles and possibilities. *Geographical Review, 23*, 529-563. https://doi.org/10.2307/209242

Cox, L. M., Bartee, D., Crook, A., Farnes, P. E., & Smith, J. L. (1978). *The care and feeding of snow pillows*. Presented at the 46th Western Snow Conference, Otter Rock, Oregon. https://westernsnowconference.org/node/1109

Dettinger, M. D., Ralph, F. M., Das, T., Neiman, P. J., & Cayan, D. R. (2011). Atmospheric rivers, floods and the water resources of California. *Water, 3*, 445-478. https://doi.org/10.3390/w3020445

Dettinger, M. D. (2013). Atmospheric rivers as drought busters on the U.S. West Coast. *Journal of Hydrometeorology, 14*, 1721-1732. https://doi.org/10.1175/JHM-D-13-02.1

Dozier, J. (2011). Mountain hydrology, snow color, and the fourth paradigm. *Eos, 92*, 373-374. https://doi.org/10.1029/2011eo430001

Frew, J. E., & Dozier, J. (2012). Environmental informatics. *Annual Review of Environment and Resources, 37*, 449-472. https://doi.org/10.1146/annurev-environ-042711-121244

Guan, B., Waliser, D. E., Molotch, N. P., Fetzer, E. J., & Neiman, P. J. (2011). Does the Madden–Julian Oscillation influence wintertime atmospheric rivers and snowpack in the Sierra Nevada? *Monthly Weather Review, 140*, 325-342. https://doi.org/10.1175/MWR-D-11-00087.1

Harrison, B., & Bales, R. (2016). Skill assessment of water supply forecasts for Western Sierra Nevada watersheds. *Journal of Hydrologic Engineering, 21*. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001327

Henn, B., Musselman, K. N., Lestak, L., Ralph, F. M., & Molotch, N. P. (2020). Extreme runoff generation from atmospheric river driven snowmelt during the 2017 Oroville Dam spillways incident. *Geophysical Research Letters, 47*, e2020GL088189. https://doi.org/10.1029/2020GL088189

Hey, T., Tansley, S., & Tolle, K. (Eds.). (2009). *The Fourth Paradigm: Data-Intensive Scientific Discovery*. Redmond, WA: Microsoft Research.

Huber, A. L., & Robertson, D. C. (1982). *Regression models in water supply forecasting*. Presented at the 50th Western Snow Conference, Reno, Nevada. https://westernsnowconference.org/node/922

Jasperse, J., Ralph, M., Anderson, M., Brekke, L. D., Dillabough, M., Dettinger, M. D., Haynes, A., Hartman, R., Jones, C., Forbis, J., Rutten, P., Talbot, C., & Webb, R. H. (2017). *Preliminary viability assessment of Lake Mendocino forecast informed reservoir operations*. La Jolla, CA: Center for Western Weather and Water Extremes Retrieved from http://pubs.er.usgs.gov/publication/70192184.

Krzysztofowicz, R. (1986). Optimal water supply planning based on seasonal runoff forecasts. *Water Resources Research, 22*, 313-321. https://doi.org/10.1029/WR022i003p00313

McCabe, G. J., & Dettinger, M. D. (2002). Primary modes and predictability of year-to-year snowpack variations in the Western United States from teleconnections with Pacific Ocean climate. *Journal of Hydrometeorology, 3*, 13-25. https://doi.org/10.1175/1525-7541(2002)003<0013:PMAPOY>2.0.CO;2

Molotch, N. P., & Bales, R. C. (2005). Scaling snow observations from the point to the grid element: Implications for observation network design. *Water Resources Research, 41*, W11421. https://doi.org/10.1029/2005wr004229

Ødegård, H. L., Eidsvik, J., & Fleten, S.-E. (2019). Value of information analysis of snow measurements for the scheduling of hydropower production. *Energy Systems, 10*, 1-19. https://doi.org/10.1007/s12667-017-0267-3

Pagano, T., Garen, D., & Sorooshian, S. (2004). Evaluation of official western US seasonal water supply outlooks, 1922-2002. *Journal of Hydrometeorology, 5*, 896-909. https://doi.org/10.1175/1525-7541(2004)005<0896:Eoowus>2.0.Co;2

Painter, T. H., Berisford, D. F., Boardman, J. W., Bormann, K. J., Deems, J. S., Gehrke, F., Hedrick, A., Joyce, M., Laidlaw, R., Marks, D., Mattmann, C., McGurk, B., Ramirez, P., Richardson, M., Skiles, S. M., Seidel, F. C., & Winstral, A. (2016). The Airborne Snow Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo. *Remote Sensing of Environment, 184*, 139-152. https://doi.org/10.1016/j.rse.2016.06.018

Palazzo, J., Liu, O. R., Stillinger, T., Song, R., Wang, Y., Hiroyasu, E. H. T., Zenteno, J., Anderson, S., & Tague, C. (2017). Urban responses to restrictive conservation policy during drought. *Water Resources Research, 53*, 4459-4475. https://doi.org/10.1002/2016wr020136

Rheinheimer, D. E., Bales, R. C., Oroza, C. A., Lund, J. R., & Viers, J. H. (2016). Valuing year-to-go hydrologic forecast improvements for a peaking hydropower system in the Sierra Nevada. *Water Resources Research, 52*, 3815-3828. https://doi.org/10.1002/2015wr018295

Rittger, K., Bair, E. H., Kahl, A., & Dozier, J. (2016). Spatial estimates of snow water equivalent from reconstruction. *Advances in Water Resources, 94*, 345-363. https://doi.org/10.1016/j.advwatres.2016.05.015

Roos, M. (2003). *California's Cooperative Snow Surveys Program*. Presented at the 49th Annual Meeting of California Snow Survey Cooperators, Folsom, CA. http://cdec.water.ca.gov/snow/meeting/2003/Calif_Coop_Snow_Program.pdf

Water Right Decision 1485, State Water Resources Control Board Decision 1485 C.F.R. (1978).

Revised Water Right Decision 1641, State Water Resources Control Board Decision 1641 C.F.R. (1999).

Stillinger, T. (2020). *Water Management Panel Data (1985-2018) of California's Western Sierra Nevada High-Elevation Basins*. https://doi.org/10.5281/zenodo.3942600

Strauss, F. A. (1954). Forecasting water supply through snow surveys. *Journal American Water Works Association, 46*, 853-863. Retrieved from http://www.jstor.org/stable/41253116

Sturm, M., Goldstein, M. A., & Parr, C. (2017). Water and life from snow: A trillion dollar science question. *Water Resources Research, 53*, 3534-3544. https://doi.org/10.1002/2017wr020840

U.S. Bureau of Economic Analysis. (2018). Real Total Gross Domestic Product for California [CARGSP]. Federal Reserve Bank of St. Louis. Retrieved from https://fred.stlouisfed.org/series/CARGSP

USBR. (1992-2019). *Central Valley Project Water Allocations*. Sacramento, CA: United States Bureau of Reclamation Retrieved from https://www.usbr.gov/mp/cvp-water/allocations.html.

Williams, I. N., & Patricola, C. M. (2018). Diversity of ENSO events unified by convective threshold sea surface temperature: A nonlinear ENSO index. *Geophysical Research Letters, 45*, 9236-9244. https://doi.org/10.1029/2018gl079203

Zhang, Z., Glaser, S., Bales, R., Conklin, M., Rice, R., & Marks, D. (2017). Insights into mountain precipitation and snowpack from a basin-scale wireless-sensor network. *Water Resources Research*, *53*, 6626-6641. https://doi.org/10.1002/2016wr018825