NASA Impacts and Benefits Assessment from Improved Streamflow Forecasts

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TABLE OF CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

ACRONYMS

AF	acre feet
BLM	Bureau of Land Management
BOR	Bureau of Reclamation
CBRFC	Colorado Basin River Forecast Center
cfs	cubic feet per second
CPW	Colorado Parks and Wildlife
DRBA	Dolores River Boating Advocates
DW	Denver Water
DWCD	Dolores Water Conservancy District
ESP	Ensemble Streamflow Prediction
FRE	Farm and Ranch Enterprise (Ute Mountain Ute)
FSA	Full-Service Area
kaf	thousand-acre feet
MVIC	Montezuma Valley Irrigation Company
NRCS	National Resources Conservation Service
RFC	River Forecast Center
RTI	Research Triangle Institute
SNODAS	Snow Data Assimilation System
SNOTEL	Snow Telemetry
UCRB	Upper Colorado River Basin
UMU	Ute Mountain Ute
USFS	United States Forest Service
WWA	Western Water Assessment

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1 KEY MESSAGES

The "Value" of forecast information and improved skill has different qualitative and quantitative interpretations

Direct measures of value include hydropower generation or storage volumes, but value can come in a range of social, environmental, and economic forms. Value includes improved trust between operators and end-users; value is fish habitat sustainability; value is farm production and economic gains; value is reduced risk and dam safety; value is sustainable water for rituals and ceremonies. Assessing the value from improvements in forecast skill is a multi-perspective and not necessarily quantitative approach.

Conservative bias in reservoir management reduces the potential value from improved forecast information

Historical poor performance of reservoir metrics from errors in forecasts has resulted in issues with downstream stakeholders, including irrigators, flood managers, and recreational groups – those directly affected by reservoir management decisions. To limit the risk of over-promising, operators act conservatively to maintain an, 'under-promise and over-perform' approach to operations. This conservatism helps limit complaints from end-users but is sub-optimal and reduces the potential value achievable from the system. Efforts to improve forecasts and the resulting utility of the system may not be fully realized due to operator conservatism. To realize greater benefits, both improved forecast skill in addition to end-user confidence in best utilizing this information is required.

Legal or contextual parameters may override benefits from improved forecast skill

The western United States follows a prior appropriation doctrine of water allocation; thus, irrigation and water supply deliveries are prescribed by law, rather than what may 'optimize' production. Increasing forecast skill can support improved decision-making, but laws, agreements, or other constraints may limit the potential benefits from the improved forecast skill.

Reduction in ensemble streamflow bias provides significantly better outcome metrics over ensemble dispersion when evaluated in an optimization framework

Using an optimization framework based on the Stochastic Sampling Dynamic Programming algorithm, which explicitly uses all members of a forecast ensemble, can result in much better outcomes when bias is reduced compared to reductions in dispersion of the ensemble. Therefore, effortsto improve forecast skill that reduce bias should provide much greater value to the end-user community.

Optimization tools nearly match historical performance only when using perfect foresight, indicating real-time assimilation of data beyond ensemble members

Optimization models provide an unbiased means of directly comparing performance metrics using a range of variable ensemble forecast quality but can only match historical performance levels when using perfect foresight – information not available to operators in real-time. This is an indication that even though operators are using the same probabilistic information to inform decisions, they are supplementing with additional data beyond the ensemble streamflow forecasts. These data include either qualitative or quantitative assimilation of weather forecasts, opinions of Nation Weather Service operators, real-time ground based hydrometeorological observations, or operator experience and domain knowledge – information not easily ingested into an optimization framework.

Water supply forecast errors are associated with reduced farm yields and economic returns for irrigators

An analysis of annual irrigation and production data for farms receiving water from Dolores Water Conservancy District (via McPhee Reservoir on the Dolores River) indicates that seasonal (April-July) water supply forecasts provide tangible economic value to producers. Alfalfa and other hay producers must make early season planning decisions before total water supplies and allocations for the year are known with certainty. As a result, they must rely at least in part on projections based on streamflow forecasts. Using an ex-post analysis that allows us to control for actual full-season water supply levels, we find that larger forecast errors are associated with lower annual production levels. Therefore, improved forecasts with lower error can measurably increase farm revenues and income.

Higher confidence in the timing and size of excess reservoir inflows in wet years would result in higher economic value for recreational rafting

Because the Dolores project’s main priority is to supply water for agricultural users, planned spills from the reservoir for whitewater rafting are only contemplated in years when there is high confidence of excess water supplies – i.e., when inflows are expected to be greater than reservoir storage capacity. Even then, uncertainty regarding the timing and size of these excess flows often means that dam operators are unwilling to make spill announcements with the advance notice that boaters prefer for planning multi-week trips. When, for example, a 10-day spill on the Dolores River is fully utilized for rafting, we estimate that it can provide recreational benefits of $1M to $2M. Therefore, in wetter years improved forecasts can result in meaningful benefits for rafters; however, these benefits are primarily associated with improved shorter-term streamflow forecasts based on weather conditions rather than on seasonal forecasts based mainly on snowpack estimates.

2 INTRODUCTION

The Upper Colorado River supplies water for agricultural, municipal and industrial, recreation and ecological services for about 20 million Americans living in the Western United States covering a watershed area of 111,700 square miles across four states [1]. The Upper Colorado River Basin (UCRB) receives most of its precipitation in the form of snow that falls above 9,000 feet, with 85% of the annual basin runoff produced from snowpack covering only 15% of the basin area [2]. Predicting the amount and timing of runoff is essential for the various stakeholders that not only use this water, but make economic, environmental, and social decisions based on the streamflow forecasts.

Forecasts developed by the Colorado Basin River Forecast Center (CBRFC) are used for a variety of decisions, including planning reservoir operations, flood-management decisions, drought declarations and disaster assistance, water and power purchases, Colorado River Compact planning, scheduling system maintenance, diverting flows through tunnels, and for public messaging [3]. Creating accurate river forecasts is challenging due to uncertainties in snow conditions, complex physical processes in hydrologic models, the need for assimilation of ground- and space-based observations, and inclusion of weather and climate forecast information in probabilistic forecast products.

The ability to increase the skill of hydrologic forecasts was the focus of an initial investigation led by Research Triangle Institute (RTI) under this program. New spatially distributed hydrologic models were calibrated for 27 basins across the UCRB, which used a new snow data assimilation approach integrating remotely sensed data with ground observations [4] (In Review). This approach did improve forecast skill in a majority of basins, although improvements over the well-calibrated and manually tuned CBRFC models were marginal, and end-users may not immediately see the skill improvements. Nonetheless, these forecasts provided a base for enquiring about how they are used in the UCRB, and how end-users could benefit from any improvements of forecast skill.

Previous studies have assessed the value of weather forecasts [5], long lead-time forecasts [6], or the value of forecasts for flood control [7]. Here, we focus on the value provided not by the forecast, but rather how users can benefit from improved forecasts – what is the marginal gain in value from improved forecasts, and what is the potential value of this marginal improvement?

To study this question, we engaged with two unique water management groups in the UCRB and utilized a range of elicitation and modeling processes to understand how decisions are currently made, and more importantly, how those decisions may change when given forecasts of increased skill. Further, what are the economic, environmental, or social ramifications of these 'improved' decisions, and what are potential constraints from fully utilizing this improved forecast information?

The study starts with a review of these two main water management agencies (Chapter 3), followed by a study using an interactive game to elicit changes in decisions (Chapter 4) with one stakeholder. A review using an interview-style approach of eliciting information with extensive document review was completed with the other stakeholder, including many details of impacts on downstream users (Chapter 5). To assess numerically how decisions may change with varying forecast skill, an optimization model was used with varying synthetic probabilistic forecast skills (Chapter 6), followed by an assessment of the potential economic values from improved forecasts (Chapter 7).

3 STAKEHOLDER PROFILES

The range of stakeholders managing water, and affected by water, is both expansive and diverse, especially in the western United States with greater demand for a limited supply of water. We can divide stakeholders into two main groups – those that make direct water management decisions, and those that are affected by water management decisions. The latter may be making decisions in response to either forecasts or water availability, whereas the former is directly operating and managing the water resources.

For this study, we focus on two unique groups managing water in the mountain west – Denver Water, a water supply utility for the front-range of Colorado, and Dolores Water Conservancy District, a group providing water supply and irrigation water in southwest Colorado. Each of these groups has a unique set of stakeholders directly affected by their water management decisions, which have social, environmental, and economic ramifications.

Focusing on these two groups has allowed us a more detailed assessment of how forecasts are used, how the systems are managed, and how improved forecasts could affect a range of stakeholders. Each component of the study pulls from one of these water management groups, and thus a high-level overview of each is provided in this section.

3.1 DENVER WATER

Denver Water (DW) is the major utility providing raw and treated water to the Colorado front-range, including the Denver metropolitan area. They operate three major systems – the South Platte system, Moffat system, and the West Slope system – each with a series of reservoirs and diversions. In total, DW operates and maintains eleven reservoirs that are highly interconnected and require careful planning to balance storages, limit spilled water, and limit the unnecessary inter-basin transfer of water to the front range from the western slopes feeding the Colorado River Basin (Figure 3-1).

This delicate balance of managing reservoir storage, moving water through tunnels and natural rivers, and meeting other water rights obligations relies heavily on seasonal spring forecasts provided by CBRFC.

To keep any assessment of the value of forecasts tractable, all studies completed herein are focused on Dillon Reservoir, the largest reservoir in the DW system. Dillon Reservoir is within the Blue River watershed – a snowmelt dominated basin with unregulated flows upstream – and is one of the major forecast locations for the CBRFC. Flows can be diverted out of Dillon Reservoir through the Roberts Tunnel towards the front range, otherwise flows may be released downstream to the Green Mountain Reservoir.

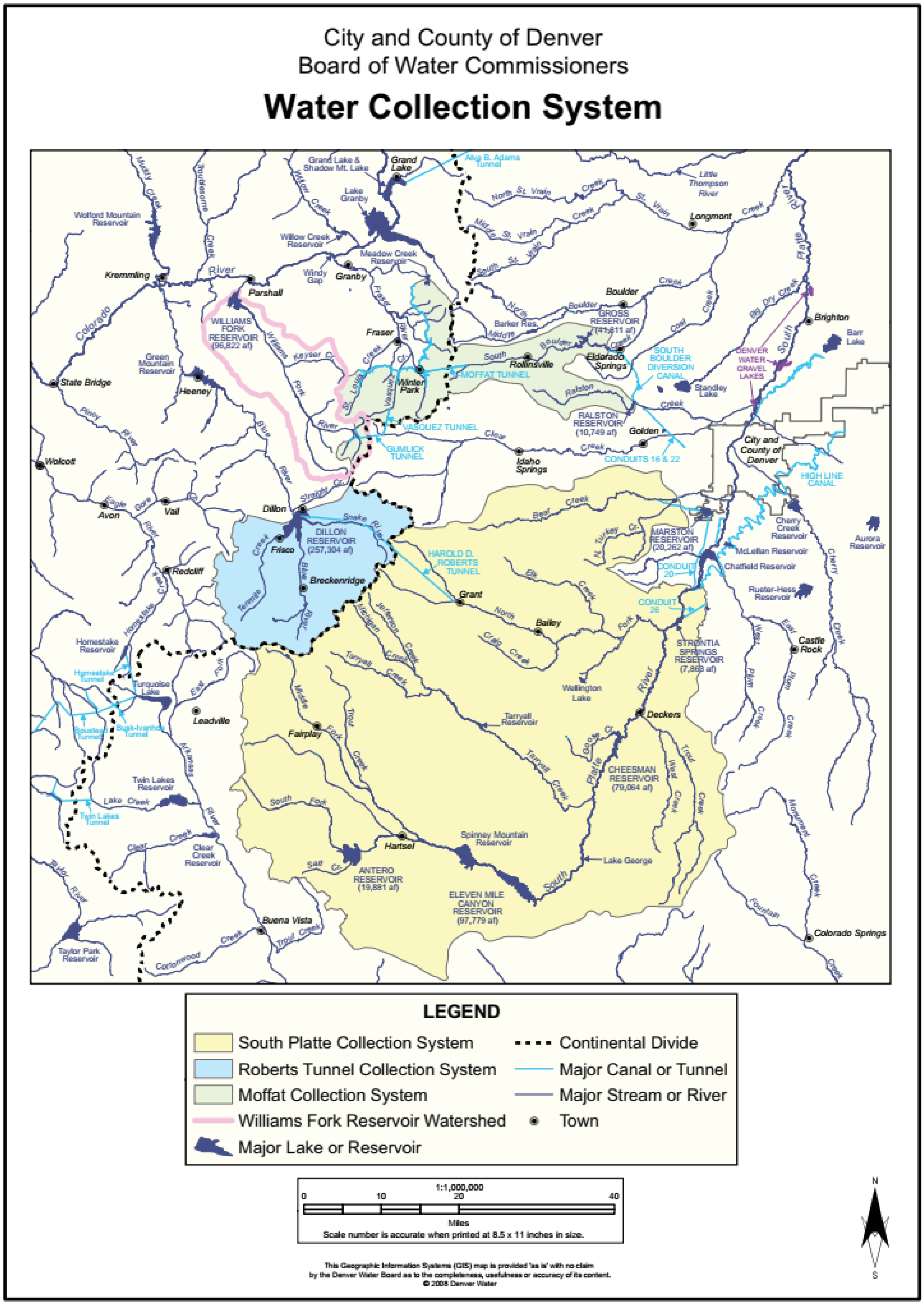

Figure 3-1 - Schematic of Denver Raw Water Distribution System (courtesy of Denver Water)

3.1.1 Operational Objectives

Objectives specific to the Dillon Reservoir were elicited through interviews and discussions with DW, and are highlighted below. As with most reservoir management systems, explicit rules and targets can be difficult to define due to the many potential exogenous influences, such as storage in other reservoirs, maintenance outages, wildfires, water quality, environmental targets, or many other factors. The list here represents generalized targets for this system.

Denver Water Operational Priorities for Dillon Reservoir

- Balance system-wide storage to maximize a) total storage and b) equal distribution across the system for increased flexibility.
- Minimize required trans-basin diversions to the front-range through Roberts Tunnel.
- Minimize downstream flooding – limit total discharge to less than 1800 cfs.
- Fill Dillon Reservoir to El. 9012’ and maintain near this level for upstream recreation and marina access.
- Maintain releases for downstream recreation for fishing (100-400 cfs) when possible and rafting (500-1700 cfs) for a period of 21-days to support rafting companies.
- Maintain releases between 50 and 100 cfs to maximize hydropower generation.

Other operating constraints include a regulated target maximum flow rate of 1,900 cfs for downstream safety and flood control. Certain large rain events may make this target impossible in the spring if the reservoir is full resulting in uncontrolled releases through the morning glory spillway.

For downstream water quality and habitat, the project must meet a minimum flow rate of 50 cfs at all times. Further, DW is obligated to release certain volumes of water to Green Mountain reservoir as part of existing water rights agreements.

The Dillon Reservoirs incudes a hydropower plant that operates from 50 - 100 cfs but is not a primary operational objective – rather, it takes advantage of the available head with the required releases downstream as an ancillary benefit. Further downstream at the BOR’s Green Mountain facility, where they operate in a range from 100 and 1,400 cfs, hydropower is a significant objective.

3.1.2 How forecasts are used

Denver Water relies heavily on the CBRFC streamflow forecasts in their reservoir operation planning during both flood and drought conditions. Given the current state of system storages, DW considers a range of scenarios from low, average, and high flow conditions to determine operational strategies. The likelihoods of each scenario are adjusted over time using the CBRFC forecasts.

DW also utilizes the CBRFC ensemble traces, not just the exceedance probabilities for volumes, in operational modeling tools. This process results in ‘spaghetti plots’ of different scenarios given a range of potential ensemble members. The reservoir filling season is roughly from April 1st to July 4th with the ablation of the seasonal snowpack.

Currently, DW is also experimenting with assimilating the NASA Airborne Snow Observatory (ASO) data through an empirical correlation approach with observed runoff volumes. This approach is intended to supplement the CBRFC forecasts and provide another data point rather than replace these forecast products.

3.2 Dolores Water Conservancy District

The Dolores Water Conservancy District (DWCD) is located in southwest Colorado, where the Dolores Project is comprised of McPhee Dam and Reservoir on the Dolores River. This project provides water to approximately 12,000 people in the towns of Cortez, Dove Creek, and Towaoc, as well as irrigation water to approximately 63,000 acres of farm and range land in Dolores and Montezuma counties and the Ute Mountain Ute Indian Reservation. The DWCD is the operational manager of McPhee and is in charge of delivery of municipal water and irrigation water to 122 individual users in the Full-Service Area (29,000 acres) and the Ute Mountain Ute Farm and Ranch Enterprise (7,700 acres). The Montezuma Valley Irrigation Company (MVIC) has senior water rights on the Dolores River, and although it cooperates with the DWCD, it is a private business operation that owns and operates diversion tunnels, canals, and ditches which deliver irrigation water to shareholders on 26,300 acres in Montezuma County (Figure 3-2).

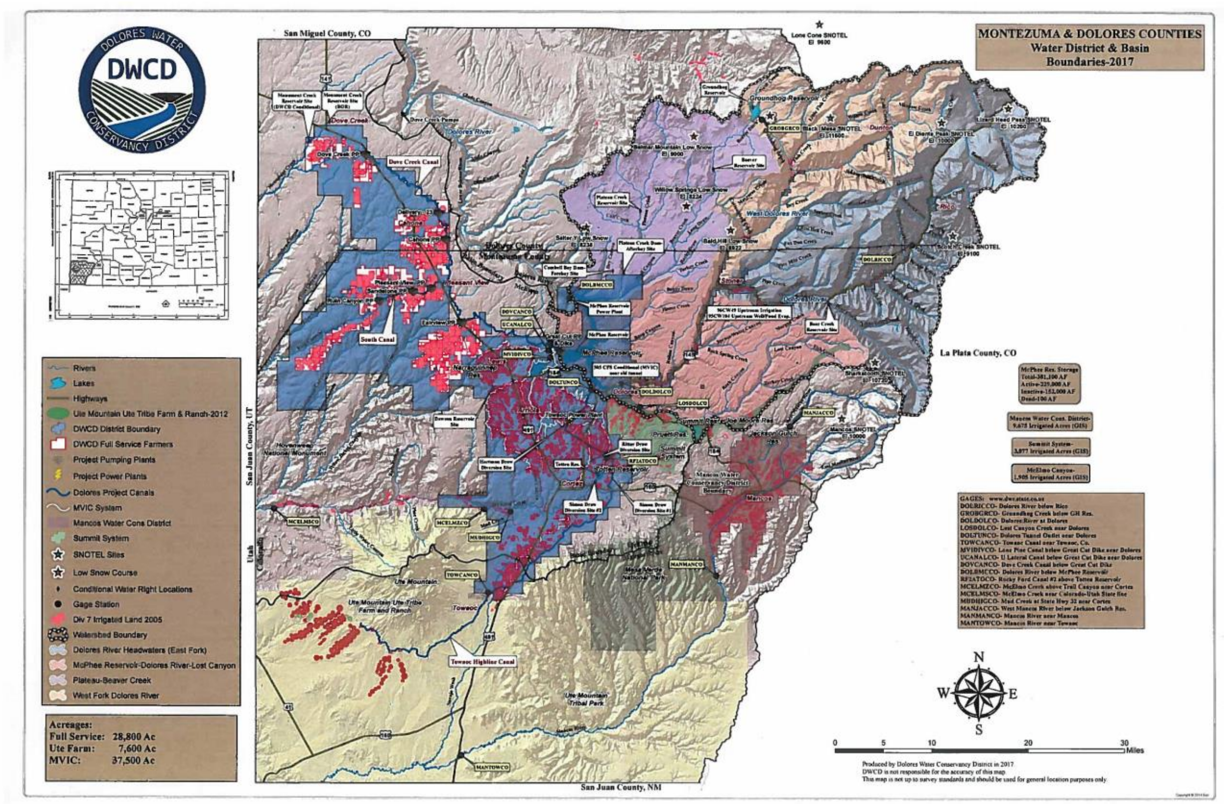

Figure 3-2 - Map of DWCD Irrigation Districts

The agriculture and recreation sectors are important water stakeholders in the Dolores, where agricultural uses constitute the majority of allocated of Colorado River water. Recreational water users are highly dependent upon water supply and are a powerful constituency group in DWCD water management decisions. Anglers and boaters directly depend on water levels for recreation, and stream ecology depends on the seasonal flow regime for spawning and benthic stream quality. Improved or diminished stream ecology impacts direct users along with nonusers who may value the riparian ecosystem and its connection to the larger area ecosystem.

Because the Dolores Project is a trans-basin project that removes water from the Dolores River Basin into the San Juan River Basin, the project poses additional challenges to recreational users and for stream ecology below the dam. Managers at the DWCD work with the recreation sector and with Colorado Parks and Wildlife, the Bureau of Land Management, and the US Forest Service to provide year-round flows below the dam for ecological purposes, including maintaining stream habitat. In years with high enough run-off, DWCD works with recreational and ecological interests to provide spills that provide recreational opportunities for boating and rafting as well as flows to improve stream habitat.

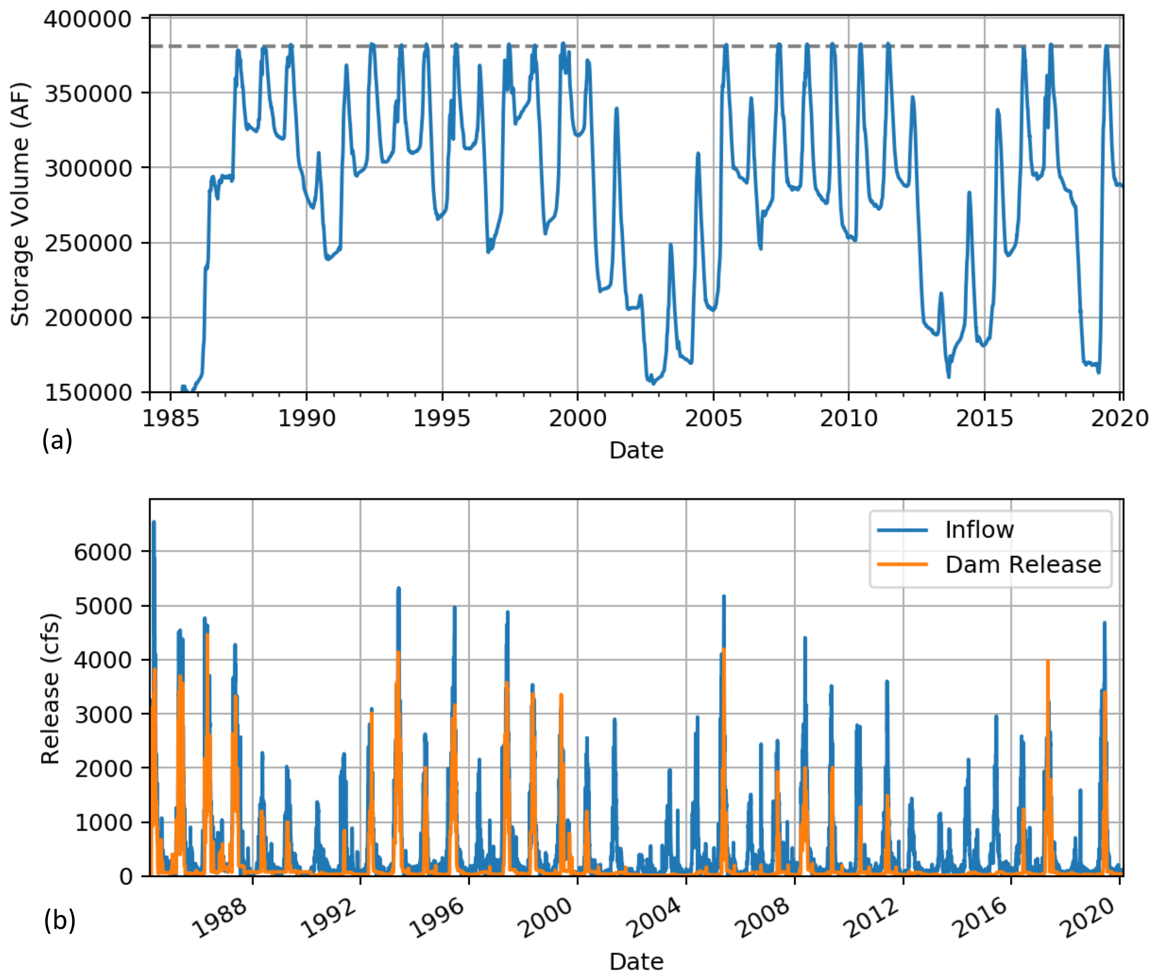

Figure 3-3 - McPhee Reservoir Historical Operations (a) storage volumes with full pool shown as dashed line, (b) daily inflow and outflow via dam releases to downstream channel (source: USBR)

3.2.1 Operational Objectives

The primary objective for operation of McPhee Reservoir is water storage for meeting downstream or trans-basin diversion requirements by filling the reservoir each year. As seen in Figure 3-3(a), the dashed line represents full storage of 381,195 ac-ft, but this level is not achieved each year due to insufficient yield. Figure 3-3(b) represents the inflow hydrograph (blue) and the releases to the downstream channel as 'excess' flow (orange). In this case, variability can be observed in downstream spring releases with some obtaining levels suitable for rafting, and other years experiencing no spill event.

DWCD Operational Priorities for McPhee Reservoir in order of priority

- Maintain safe operating levels of McPhee Reservoir for dam safety
- Fill McPhee Reservoir to allow full water allocations
- Maintain acceptable environmental flows downstream
- Time any 'excess' volume releases in a manner beneficial to the rafting community downstream
- Generate hydropower from downstream releases

3.2.2 How forecasts are used

Forecasts are mainly used to a) position the reservoir storage and time and downstream releases, and b) determine early-season announcement levels or shortages for irrigation allocations.

DWCD relies heavily on the CBRFC forecasts to inform their short- and long-term operations of the McPhee Reservoir. Shorter term real-time operations also rely on a larger set of both observational hydrometeorological data and forecasts, including SNOTEL stations, weather stations, USGS stream gages, weather forecasts, and even snow albedo to help estimate dust-on-snow effects that may impact melting rates. This information goes above and beyond the CBRFC forecasts and is assimilated subjectively using expert knowledge, rather than through numerical estimates.

DWCD also retains both an internal bias in its responses to the forecasts, and a learned conservatism in operations to limit the false-alarm rate or over-promised conditions. For example, allocations are determined using the 70% exceedance level (P70) to limit the potential for overly committed allocations. As we'll discuss using different approaches, this may lead to sub-optimal utilization of water resources and benefits. The combination of improved forecast skill with improved decision-maker confidence in forecasts could increase potential benefits from the use of streamflow forecasts.

4 VALUE OF FORECASTS USING GAME ELICITATION

The objective is to assess how decisions change, and how metrics improve, with improved forecast skill. There are several methods to elicit this information and infer effects directly or indirectly, one of which is the use of simulation models using a 'gaming' approach. Here, we interact with one of the stakeholders using a simulation game where input, actions, and responses are recorded, from which the impacts of improved forecasts can be inferred.

4.1 APPROACH

Our team created a custom web-based game to compare operational decisions made with different forecast information (e.g., "scenarios"). This allowed us to elicit decision differences in response to both realized forecast improvements (e.g., RTI ESP) and/or synthetic improvements (for both bias and uncertainty). Each scenario consists of a specific year (e.g., where DW had flow measurement data available) and a forecast scenario. The scenario game presented participants with an ESP volume forecast, similar to the information available through CBRFC, including the 10%, 30%, 50%, 70%, and 90% exceedance probabilities and the SNOTEL information for the area beginning on March 1 (Figure 4-1). The participant was then asked to make a water management plan for the month of March including when and how much water they would choose to release and/or divert.

Within the gaming interface, participants used slider widgets to change diversion or release amounts for a given month, and there is a window that allowed them to see how these changes would impact the overall elevation of the reservoir (Figure 4-1 and Figure 4-2). Once the participant finalized a plan for the month and decisions were submitted without recourse, the game advanced to the following month. This process repeated until July 1, representing the end of the runoff season, and the game advanced to the next scenario year (different water year and different forecast skill level).

The scenarios game was built on a simple water balance model using reservoir storage volumes that respond to both realized and predicted inflows and user-defined diversions. To perform the elevation prediction, daily reservoir volumes were calculated by subtracting user-defined outflows and observed evaporation volumes from the daily volumetric ESPs of inflows. This volume was associated with an elevation based on volume-elevation relationships derived from available records.

The game recorded daily water diversions and shortages to downstream water users—a timescale that is compatible with agricultural production modelling—which is useful for a range of industries and sectors.

4.2 DENVER WATER

The reservoir management game was designed to simulate the decisions that the Denver Water managers make in response to Ensemble Streamflow Predictions (ESPs) of various forecast skill levels. In it, players were asked to make daily diversion schedules on a monthly decision increment according to target objectives that they set prior to the game. As elicited from engagement with Denver Water, targets were to:

1. *maximize* Denver Water runoff storage and water balance across their system,
2. *minimize* trans-basin diversions to the front-range through the Roberts Tunnel,
3. *maximize* the number of days between 500 and 1,400 cfs for rafters and 100 and 400 cfs for fishers, and

4. *maximize* the number of days above El. 9,012’ for marina boating access.

Model developed forecast volumes were converted to exceedance probabilities to recreate the information typically available to managers. These probabilities were calculated using a lognormal cumulative probability function derived from streamflow records between 1989 to 2010. A lognormal distribution was chosen to align with the methodology outlined in Day, 1985 [8], allowing volumes for the 10, 30, 50, 70, and 90% exceedance probabilities to be presented.

The RTI Data-Assimilated ESP product for Dillon Reservoir inflows was found to have similar forecast skill as the CBRFC forecast methodology. Therefore, ESP predictions were synthetically improved by a simple reduction in bias and uncertainty. Bias was improved by reducing the difference between the 50% exceedance probability prediction (P50) and the historically realized streamflow. All other ESP values were adjusted by the same amount and the ensemble spread is initially maintained. Uncertainty was then adjusted by reducing the difference between the P50 and each other exceedance probability according to the same percentage as with bias.

In an attempt to recreate the informational context in which the ESPs influence decision-making, a small suite of additional information was made available to players within the gaming interface:

a) SNOTEL data (precipitation, temperature, and snow water equivalent) for one or more sites surrounding the reservoir acquired from the National Resource Conservation Service’s Water and Climate Center web service.
b) Summary statistics of historical flows from Denver Water’s own streamflow records, volumetric estimates of remaining inflows
c) Time series of observed inflows, diversion, evaporation and reservoir elevations up to the decision-making period
d) Predicted future reservoir elevations were all provided.

To help keep track of user decisions, a “water score” portal was made available to show each player their progression towards the pre-defined goals.

The historical year of the current scenario is hidden from the user and, because the same year will be played multiple times with different ESPs, inflow figures are slightly perturbed (+- 0.15 kaf) to help anonymize the specific year. All streamflow decisions for all players, game years, and ESP forecast “skill levels” are recorded and stored in a database as the game is played.

For the DW participants, the game consisted of sixteen scenarios: four years (2006, 2007, 2008, 2009) each with four treatments (CBRFC forecast, two systematically improved forecasts, and the climatological average (1989-2010)). The synthetically improved scenarios were developed by decreasing the bias and uncertainty by 10% and 30%. We selected 10% and 30% improvements to test decision-making sensitivity and threshold about bias and uncertainty. To reduce bias in responses, the scenarios were ordered to minimize the chance the players would recognize the different treatments for a year that they had already seen (Table 4-1).

Table 4-1 - Order for the DW game scenarios

	F_1= CRBFC	F_2= Climate	F_3= Small Imp (10%)	F_4= Larger Imp (30%)
Y_1	1	12	7	4
Y_2	3	8	10	6
Y_3	5	11	9	2
Y_4	13	16	14	15

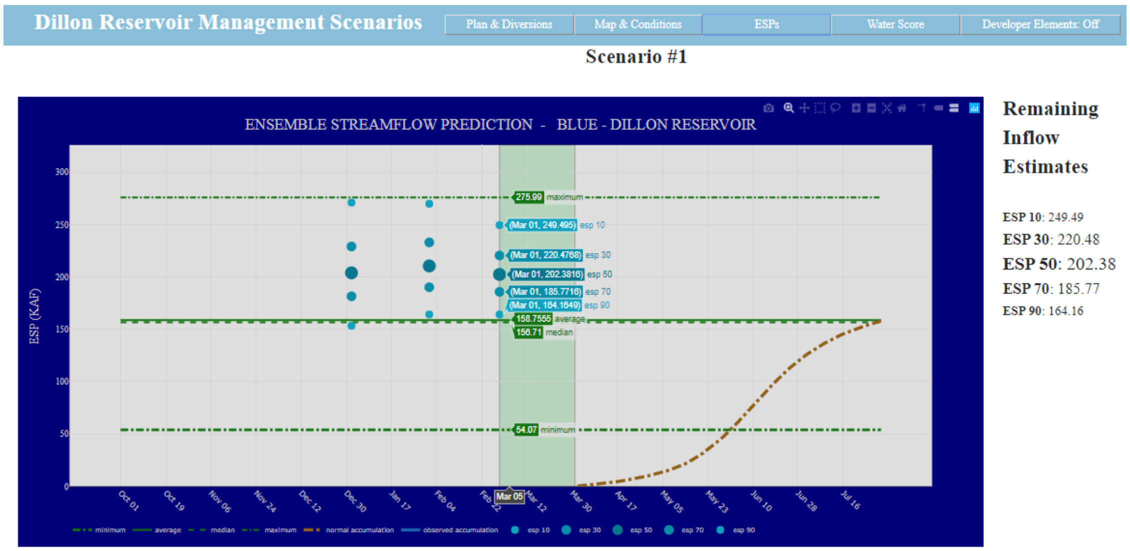

Figure 4-1 - Sample screenshot of the scenario game showing the ESP forecast for March 1

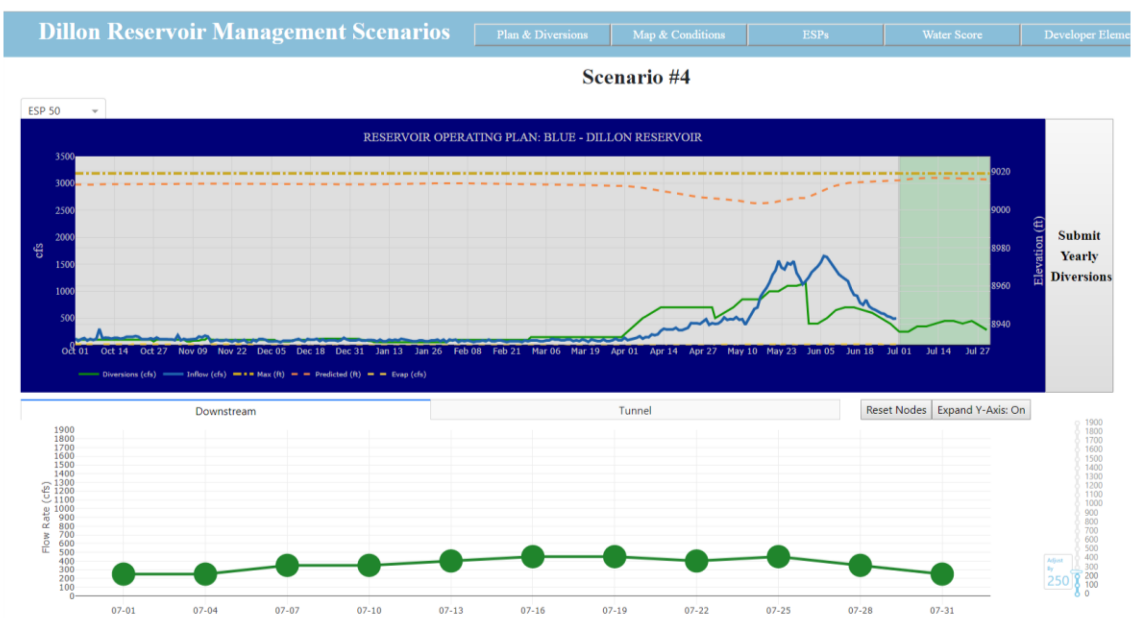

Figure 4-2 - Sample screenshot of the scenario game showing the diversion input portal with the "drag and drop" plan (bottom) and the graph showing the elevation based on the participant's decision at the 50% exceedance probability level (top)

4.3 RESULTS OF GAME ELICITATION

The interface developed for this process worked very well for the operators at DW and was designed specifically to mimic the information available to operators in real-time. Future values are hidden from the users, and thus they must make decisions based on probabilistic information. Decisions are no-recourse, thus the state is updated based on their decision and realized inflows at the next timestep. Feedback from the operators and engineers at DW was positive in using this interface to elicit decisions, even though the interface was entirely different than what they use normal day-to-day operations.

One of the challenges in working with the operations group was their limited availability – each simulation scenario, which includes decisions over multiple stages through a runoff season, takes 15-30 minutes or more. Ideally, each operator would complete hundreds of scenarios, but their ability to commit to the program and repeat trials was limited to only a few hours.

Figure 4-3 - Game deployment and engagement with Denver Water raw water reservoir operators, (September 2019)

A scenario is composed of the following:

1. A unique year, perturbed to anonymize the year of the data
2. A unique scenario of forecast skill [Climate, CBRFC, Improvement 1, Improvement 2]

In total, the elicitation process resulted in 67 unique and independent scenario runs completed by three separate DW operators. Although operators may be completing the same scenario (working independently), they may choose completely different approaches to manage the reservoir.

To attempt to understand if the operators were able to make better decisions with better forecast information the results were pooled into different groups as shown in Figure 4-4. One immediate observation is the consistent differences between all three users for the four different forecast improvement treatment groups – User 3 consistently has higher water elevations in June. Looking across forecast skill treatment groups, with lowest skill on the left to the highest skill on the right, there is no identifiable trend of higher storage levels in June (July, not shown, shows similar pattern).

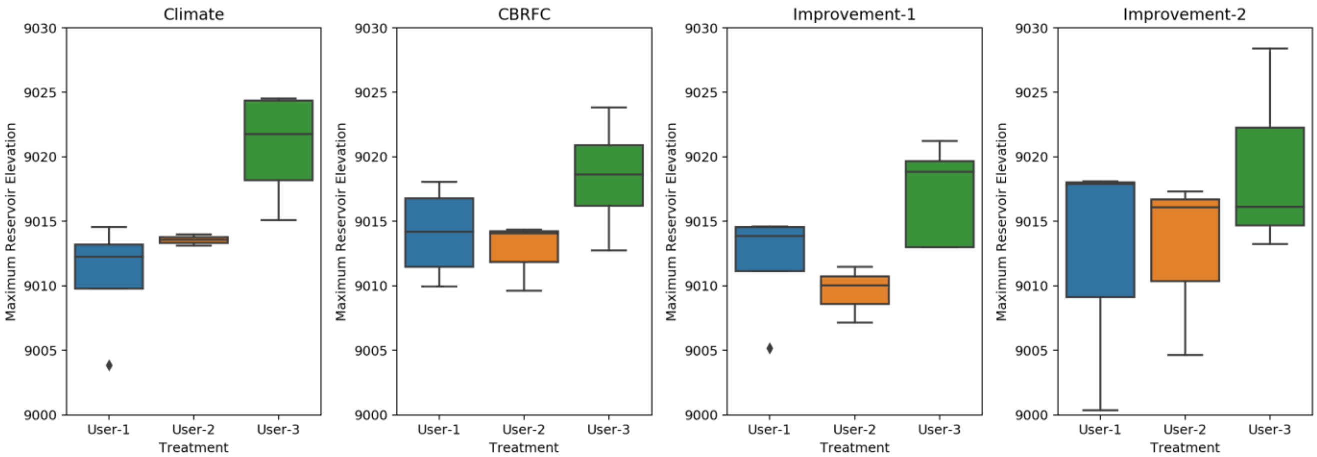

Figure 4-4 - Performance of users across years with variable forecast quality – water surface elevations in June

Alternatively, we can group all operators and assess impacts on various reservoir metrics for each forecast improvement treatment group (Figure 4-5). The maximum reservoir elevation for Dillon Reservoir is seen in Figure 4-5(a); with very little information, such as the *Climate* treatment, there is increased chance of an unforeseen large inflow causing greater than desired pool levels (i.e. upstream flooding). Conversely, with improved forecasts, preemptive measures can be taken to reduce any potential adverse peak storage levels – this improvement is not obvious in the mean across the treatments, but rather in the upper extremes across treatments.

Figure 4-5(b) shows tunnel diversions that move water from the western slope to the front range – a necessary but ideally minimized operational decision. With improved skill across treatments we can see a general reduction in the volume transferred, especially with respect to the improved forecasts over the *Climate* treatment, and well minimized for the most skillful forecast, *Improvement 2*.

Rather than considering annual maximum peak levels, we can look at quantiles to represent increased pool exceedance levels - Figure 4-5(c) shows the 85% quantile exceedance indicative of acceptable higher pool storage levels. There is no difference across treatments – improved forecast skill does not impact a more common pool level at the 85% exceedance level.

Finally, we can consider how much flow is diverted into the downstream channel across different treatment groups in Figure 4-5(d). Again, there is no change in how much is diverted across forecast skill treatments for this metric of diversion.

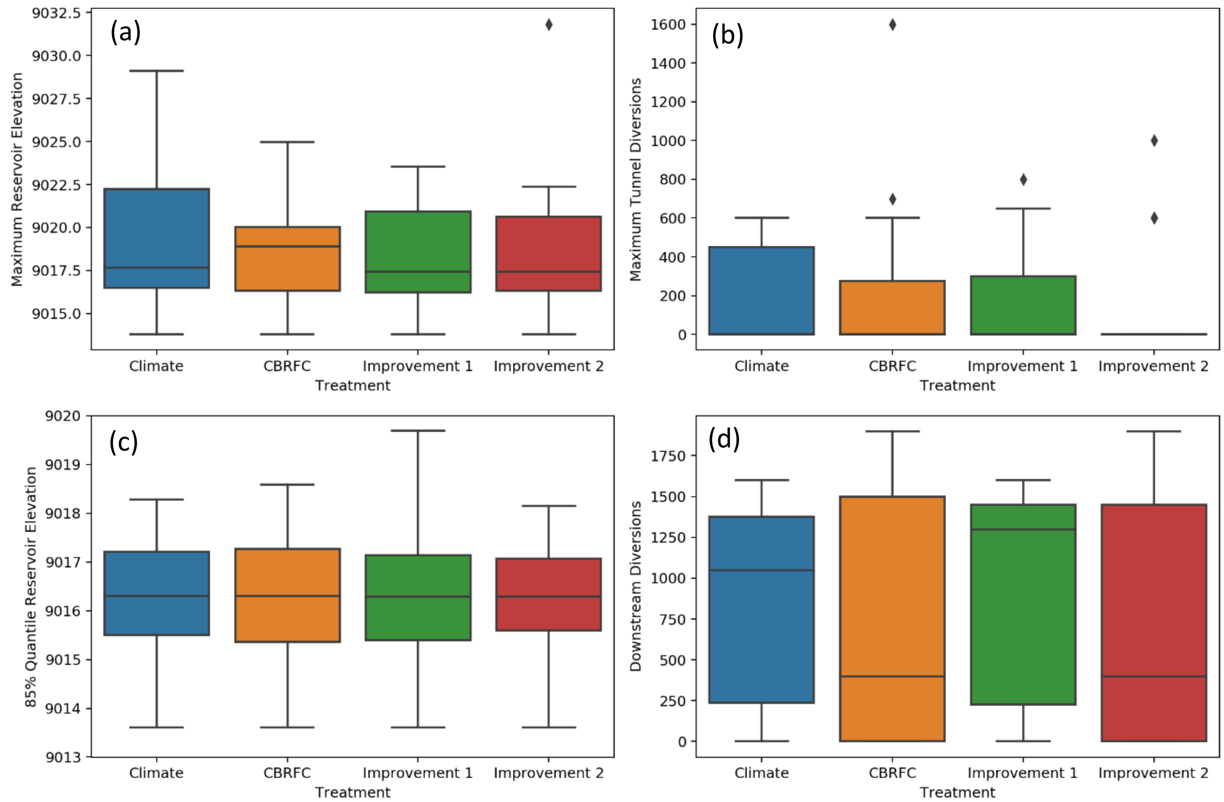

Figure 4-5 - Reservoir performance metrics for each forecast skill treatment group

The elicitation process using a gaming technique proved very successful in engaging DW operators with a system mimicking the information available to decision-makers, but the limited sample sizes made it challenging to differentiate clearly between small improvements in the result metrics. The greatest improvements in the decision-making process appear to be on the extremes when there is indication of a potential large event not provided in the *Climate* or lower skill forecast sets.

Improvements to this elicitation process may include means to expedite different scenarios to increase sample size; increase the number of knowledgeable operators playing the game who are capable of reviewing information and making operational decisions; and the addition of a 'perfect forecast' to understand the upper limit of operations against probabilistic information.

Finally, users were not aware of the different forecast qualities – users make decisions based on the forecast assuming each is the best available, thus when improvements are realized, it's simply because better information was given rather than their decisions were different. The gaming approach could be modified to provide the users some indication of forecast quality to control how their decisions are impacted. For example, would operators be less conservative under a high flow conditions pushing the storage higher if they knew the forecast was of higher quality? With that knowledge, we could then infer the value of not only improved forecasts creating better outcomes, but also improved user confidence affecting their operational strategy, further increasing the potential benefits from improved forecast skill.

5 VALUE OF FORECASTS USING STAKEHOLDER INTERVIEWS

The characteristics of the Dolores Project made it possible to examine how improved forecasts might impact reservoir management and operations by the DWCD, but also trace how water supply and forecast information impact the decision-making processes of agricultural and recreational users.

We conducted 23 semi-structured interviews with personnel from the DWCD, BOR, CBRFC, and MVIC, as well as with managers and technicians at the Ute Mountain Ute Farm and Ranch Enterprise, Dolores and Montezuma county extension agents, natural resource management agencies, recreational water users, and we conducted one focus group with four agricultural producers in the Full Service Area (Appendices 3 and 4). These interviews focused on if, and how, these water users were using streamflow forecasts or other water supply data, and how their decisions were impacted by water supply and DWCD's management decisions. To supplement these interviews, we conducted document analysis of nineteen years of DWCD board minutes (2001-2019) from March thru November. These documents provided insight into how allocation decisions for irrigation are made and communicated to users, and how those operational plans may evolve throughout the runoff season.

5.1 DOLORES PROJECT STAKEHOLDERS

5.1.1 Full-Service Irrigation Area

Irrigation has drastically changed the agricultural landscape in the area. The DWCD supplies irrigation water to 122 individual agricultural producers in the Full-Service Area (29,000 acres) in Dolores and Montezuma counties. Alfalfa is the primary cash crop grown on irrigated land, followed by corn, wheat, and beans. Most irrigators in the Full-Service Area can get three cuttings of alfalfa hay during the growing season.

5.1.2 Ute Mountain Ute Farm and Ranch Enterprise and Towaoc Municipal Water

The DWCD provides irrigation water to 7,700 acres of the Ute Mountain Ute Farm and Ranch Enterprise (FRE), and municipal water to the Town of Towaoc. In the mid-late 1800s, after being forced to cede their land to white settler encroachment, they settled in arid lands in southwest Colorado and Utah. They rejected the Dawes Act and land apportionment, and instead kept communal lands that were too arid for most farming, although some ranching was possible. Water is important culturally and ceremonially. For ritual purposes, water must be high quality and pure (e.g., spring water) in order to purify and rejuvenate ritual participants.

Prior to the Dolores Project, the Ute Mountain Ute tribe had unrealized legal rights to water since they did not have the infrastructure to deliver that water to the reservation. They accepted a smaller volume of junior water rights in the Dolores Project in exchange for foregoing their treaty rights. The build-out of the Dolores Project included the Towaoc Highline canal to provide agricultural and municipal water to the Town of Towaoc and surrounding areas.

The FRE is a tribally run commercial agriculture enterprise that primarily grows alfalfa, corn, and winter and spring wheat on 7700 acres of irrigated land. The FRE employs about 30-35 full time employees in addition to 5-7 contractors who bale the hay and an additional 5-7 employees at their corn mill facility. As the largest single recipient of water in the DWCD, the FRE receives approximately 24,000-acre feet of agricultural water, and often leases up to 4,000 AF of additional water from the DWCD or MVIC when it is available. Because FRE receives approximately 37” of water per acre for irrigation, and their irrigation water begins arriving almost a month earlier than in the FSA in early- to mid-April, the FRE can get five cuttings of alfalfa in the best years.

5.1.3 Recreational Users – Boating, River Access, and Fishing

Recreational users are highly dependent on water supply forecast information to understand if there will likely be managed releases or spills from the reservoir, and if so, what might be the recreational opportunities.

The Dolores River is ranked as one of the premier rafting experiences in the US. The main stem of the Dolores below McPhee Reservoir is one of the least developed river corridors in the western United States and has been considered for Wild and Scenic designation.

Prior to the completion of the McPhee dam, there was a strong recreation economy centered on rafting during the spring runoff season; however, after the completion of the project, rafting on the Dolores only occurs when there is runoff in excess of what the DWCD requires for allocated storage. Furthermore, multiple efforts to spur communication and cooperation between the recreational community, the agricultural community, DWCD, and environmentalist groups to increase releases to improve recreation opportunities and stream ecology have stalled [9].

There has been significant effort on the part of the boating community and DWCD to improve communications around the potential and timing for boatable spills. Based on conversations between DWCD, BOR, and the boating community, the DWCD now issues written summaries about the potential for managed releases[1]. Before the runoff season begins, the narratives from DWCD include probabilistic information about the likelihood of a spill. For example, “*it is highly unlikely that a release will occur*” in 2018 (DWCD, March 15, 2018) or “*The record snowfalls of early March have pushed forecasts up 50% driving the chances of a McPhee managed release, ‘spill’, over 50%.*” (DWCD, March 20, 2019).

When spills are likely, the DWCD convenes the Spill Committee that has representatives from the boating and agricultural communities, Colorado Parks and Wildlife (CPW), and environmental groups. They meet weekly to discuss the CBRFC forecasts and the potential timing and flow rates for any managed releases or spills. The DWCD has an understanding with the boaters that once release announcements are made on Thursday, they will not change them until after the weekend. DWCD also tries to meet the boaters’ preference of flow releases between 800-3000 cfs for approximately five days, particularly on weekends and holidays (e.g., Memorial Day weekend). These are not contractual agreements but are made in good faith between the boating community and the DWCD.

Like most communities, there is a diversity in levels of understanding and engagement with raw streamflow forecast information. Both private boaters and commercial outfitters we spoke with were sophisticated users of SNOTEL data and CBRFC forecasts who actively monitored snowpack and runoff conditions for the Dolores watershed as well as other major rivers in the area (e.g., the San Juan, Animas, and San Miguel).

[1] http://doloreswater.com/releases/

Figure 5-1 - Public fishing access on the Dolores River

5.2 Forecast Influenced Decision-Making - How DWCD Uses Forecasts

The reservoir operators at McPhee are heavily dependent on water supply forecast information based on a range of quantitative and qualitative sources. They use the official CBRFC probabilistic[2] volumetric forecasts that are issued at the beginning of each month and, beginning in 2000, the middle of the month during the April thru July runoff season as well. During the runoff season, the CBRFC provides forecasts for the volumes expected for each month. By the DWCD's request, CBRFC also provides a 15-day deterministic[3] ensemble forecast which is updated daily and includes recent weather events which would impact the rate of runoff. This information is particularly important for managed releases. During the runoff seasons, the reservoir operators communicate daily, or nearly every day, with the CBRFC forecasters who provide additional details about how the forecasts evolve and characterize the uncertainty in the forecasts.

DWCD also monitors the NRCS SNOTEL sites[4] that provide snowpack information and have their own low-elevation snow courses to help them gauge the accuracy of the CBRFC forecast. Additionally, they consult

[2] Probabilistic volumetric forecasts provide a range of possible runoff volumes (cumulative from April 1 - July 31) with the probability that they will be equaled or exceeded using historical meteorological sequences (in this case, 1981 to present) with hydrologic models of the current system states – this is the ESP methodology.

[3] Deterministic ensemble forecasts provide the traces for each hydrologic simulation.

[4] https://www.wcc.nrcs.usda.gov/snow/

NOAA CPC seasonal forecasts[5] and SNODAS[6], although they use these sources for situational awareness and do not incorporate them formally into the decision-making process.

McPhee operation plans are updated every 3-4 days at minimum during the runoff season and may be changed several times a day depending on real-time conditions, new forecast information, the amount of runoff, and whether there is an actively managed release from the reservoir into the river.

…VALIDATE SNOW CONDITIONS… A ROCK VISIBLE FROM THE OFFICE IS USED TO JUDGE THE SNOW DEPTH BASED ON HOW MUCH OF IT WAS VISIBLE.

In addition to official forecast information, operators, DWCD board members, and water users in the agricultural and recreation sectors are attuned to seasonal precipitation cycles, and many report ground-truthing SNOTEL snowpack information and CBRFC forecasts by driving or backcountry skiing into the mountains. Multiple people reported on using a rock visible on the mountain above the DWCD office to estimate the depth of snow. Both water managers and water users in the agricultural and recreational sectors explained that experiential understanding of the snow and water in the Dolores River Basin is an important strategy for optimal water management and water use.

The DWCD board and reservoir operators communicate water supply forecast information to irrigators and agricultural producers, utility managers, and to boaters and other land management agencies. The DWCD board meetings include briefings on water supply and discussions about whether there will be a full supply of water for the year, or whether there will be a shortage.

A full supply to meet DWCD's contractual obligations for agriculture, municipal, and ecological flows requires about 150,000 AF of runoff each year. It takes a total of 266,000 AF to fulfill these obligations and fill the reservoir, which has a full-storage volume of 381,051 AF. This happens approximately one third of the time (one in three years). In years with high snowpack and plenty of water forecasted, the DWCD and the reservoir operators may decide to communicate the irrigation allocations in April or May. In years where there is low snowpack, and less water is forecast by the CBRFC, the DWCD may caution that they expect a short supply, but will hold off on making an official allocation decision until June, since it is not unusual for large amounts of snow to accumulate in the mountains in May (aka Miracle May, such as in 2015).

For irrigators in the FSA, a full supply is 22 inches of water per acre for the irrigation season (April or May thru mid-October). Irrigation water is pumped from the Great Cut pumping plant, delivered through a series of laterals and canals, and arrives at metered boxes at the individual farm level. In many years, the DWCD board decides on an irrigation cap for each irrigator, and if there is enough water, the board may increase the cap and institute "conservation pricing" on additional inches of water per acre that can be purchased over and above the allotted amount.

[5] https://www.cpc.ncep.noaa.gov/
[6] https://nsidc.org/data/G02158

The DWCD reservoir operators prefer to use the P70[7] to make conservative allocation decisions earlier in the runoff season and then adjust to provide additional water over the course of the season when possible. The BOR uses the P50 for planning purposes, but the DWCD uses both the P50 and P70 because the CBRFC model is based on historical data using the ESP method and tends to skew a bit "wetter" than recent years. Experience has taught DWCD managers that, because of the importance of early season planting decisions for the agricultural sector, it is preferable to underestimate yearly streamflow and increase allocations than it is to overestimate and decrease allocations as the year progresses.

In years when there is more than sufficient water to meet irrigation allocations, there may also be a managed release (or spill) to the downstream channel. Releases are made anticipatorily of the forecasted runoff volume – errors in the forecast can create conditions where water is spilled early but then full storage is not achieved. Hence, releases are made conservatively before filling in order to nearly ensure the reservoir will reach full storage.

A Monitoring and Recommendation Committee provides input to help inform the release strategy and timing. If a raftable spill is expected (e.g., spills above 1000cfs for 5 days), there is an additional Spill Committee comprised of DWCD members, boaters, wildlife and public land managers, and other interested parties. The reservoir operators announce releases on their website, to local press, and regularly communicate to their contacts in the recreation sector. There has been considerable effort by the boating community, environmental advocates, and the DWCD personnel to collaborate and build trust.

DWCD usually "corrects" that based on their experience and uses the p-70 because the CBRFC is usually a little high; the p-70 is "safer" and more conservative.

Overall, managing McPhee Reservoir and the water supplies is a constant balance between fulfilling the contractual obligations made by the Dolores River Project for provide irrigation and municipal water supplies, but also to maintain sufficient water in the downstream channel to provide habitat for fish and maintain (or improve) the stream ecology, while also attempting to provide boatable flows for recreational users in years when there is enough water.

Forecasts for runoff are indispensable for informing these decisions, but errors by both forecasters and managers have created a culture of conservative operations by DWCD and the downstream stakeholders. These conservative decisions result in sub-optimal use of the available resources limiting the potential economic value. Increased forecast skill has the potential to increase agricultural yields, increase boater days, and better maintenance releases for ecological benefit.

[7] "p-70" refers the 70% exceedance probability.

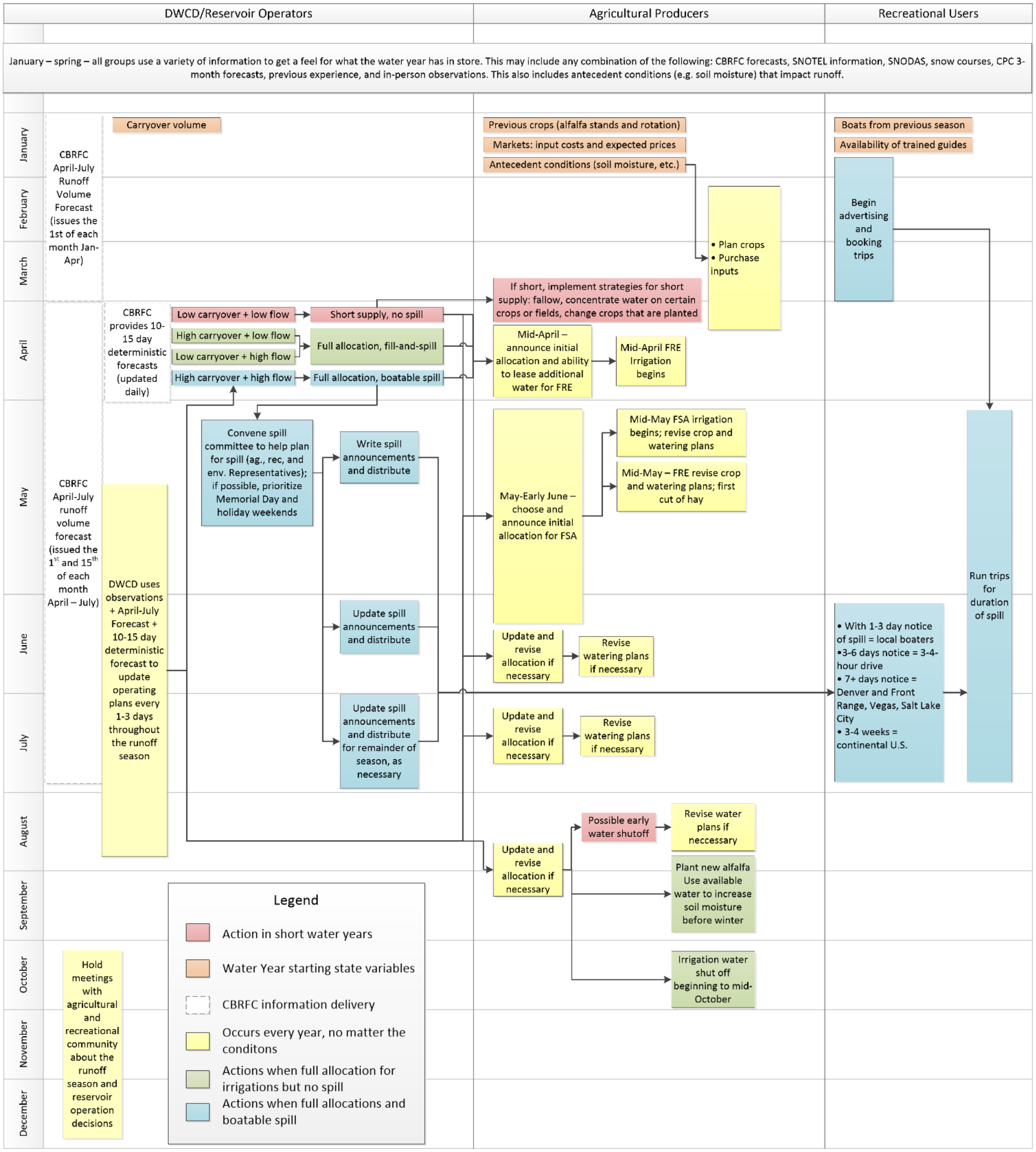

Figure 5-2 - Decision making workflow for DWCD

5.2.1 Agricultural Decision-making for the UMU FRE and FSA:

While the market prices for crops remains the primary driver of decisions for agricultural producers in the area, decisions are also dependent on the forecasted water deliveries. Decisions depend on the water supply allocated in any given year, but also on the antecedent conditions, such as soil moisture, that will impact how much water will be available and required for a specific crop mix. They also consider the amount of reservoir storage carryover when estimating what their water allocations for that year will be. If the reservoir filled the year before and there is a large amount of carryover, they may have a full supply even if run-off is projected to be very low (e.g., in early 2000s').

All of the producers with whom we spoke agreed that receiving additional water above the announcement *later* in the season was sometimes more frustrating than not receiving enough water relative to the announcement. While this may seem counter-intuitive, they explained that they make planting decisions based on the initial allocation announcements made by the DWCD, and that it was frustrating to end up with water at the end of the season that could have been used. For the FRE, the latest they could change planting decisions would be May 15, while the FSA producers reported it could be as late as the end of May or beginning of June.

5.2.2 Strategies for years with additional water (above the allocation made in April, May, or June)

The producers from the FSA reported that with a few extra inches in the fall, they would either not use it all, would water for their last cut of alfalfa (if they found out before they had stopped watering for too long, and if the extra amount was enough to produce another cut), or use it to increase the soil moisture heading into winter in order to create better planting conditions the following spring.

Producers in the FSA reported that a 75% supply of water or less was really the point at which they would need to start making difficult decisions about how best to use their water. This translates to 16.5” in the FSA, and a reduction of 6,000 AF for the FRE (from 24,000 to 18,000 AF total, or an average of 28” per acre).

5.2.3 Strategies for years with a short supply

Depending on the current cropping mix, irrigators have several strategies for years in which they expect to not receive enough water for full cropping.

Producers in the FSA reported that a 75% supply of water or less was really the point at which they would need to start making difficult decisions about how best to use their water.

One option is to concentrate water on certain crops and/or fields rather than spreading over all available lands. Individual irrigators can choose where, when, and how to put the water on their land. This means that if a farmer has 100 acres of irrigable land determined by the project, a full water allocation would be 22” for each of those 100 acres. However, the individual can choose to pool their allocation and concentrate 11” of allocated water on 50 acres of fields for the same irrigated depth. This flexibility helps farmers in regular years concentrate water on more productive fields or profitable crops, maximizing their constrained production.

Alternatively, irrigators may concentrate water on the first cut of alfalfa for all fields, and then only water the most productive fields. This allows the farmer to take advantage of any remaining moisture on the fields left from the winter. Regardless of allocation, the first cut of alfalfa yields the highest quality, and highest volume of hay that farmers would like to utilize. This may mean concentrating water on newer stands (since productivity decreases with the age of the stand). Further, if the allocation was enough to get two cuttings from their alfalfa fields, they may choose to water all fields thru the second cut and then stop. One farmer reported that he could get 2 cuttings of alfalfa with 16” of water, and 1 cutting with 10”. These types of decisions were common in 2013, a recent extremely dry year.

Farmers may also let old alfalfa stands die and hold off planting new stands. In this area, alfalfa stands are rotated approximately every six years.

They could also alter the planting plan by replacing an older alfalfa stand with a crop that needs minimal irrigation (e.g., beans).

Finally, the farmers may determine the best option is to let the fields fallow. If the farmer is rotating out alfalfa and has prepared the field to plant, they may opt to delay planting and fallow the land.

However, there are still fixed costs for this option, including fees to DWCD for maintaining the operations and management (e.g., the FRE pays a base price of $83 per acre foot on the 24,000 allocation, whether or not the water is available for their use), and increased maintenance costs to farmers the following year for controlling weeds.

5.2.4 DWCD strategies for a short:

A “short” is a condition when forecasted yield is below the full allocated delivery, and downstream stakeholders may receive either reduced or no water based on seniority of water rights and the magnitude of the short.

Figure 5-3 - Dolores Project irrigated lands

DWCD will reduce allocations and alter the pricing mechanism (e.g., pricing = base price + unit price based on water used; they can adjust the base price down and the unit price up to encourage conservation, as one example). In some years where there is severe shortage and very low productivity, DWCD reduces the price overall to give the producers a break, although in short years when DWCD doesn't have sufficient water to sell, the short can become a financial hardship for them as well – they have significant O&M costs for infrastructure maintenance and staffing. This can become especially important with several short years in a row (e.g., early 2000s) that cause budget shortfalls for DWCD over consecutive years.

Another option is leasing excess municipal water to agricultural producers or leasing Class-A shares from MVIC (senior water rights holder) to the FSA users.

Activities also include meetings and communications with agricultural producers (including post-cards, in-person meetings, and phone calls) in order to negotiate with senior water rights holders (e.g., MVIC). This approach can avoid a call on water which triggers legal limits; they prefer to negotiate among themselves.

If the shortage is expected to be extreme, DWCD may pay for cloud seeding (e.g., Western Weather Consultants) to increase precipitation over the basin.

…VALIDATE SNOW CONDITIONS… A ROCK VISIBLE FROM THE OFFICE IS USED TO JUDGE THE SNOW DEPTH BASED ON HOW MUCH OF IT WAS VISIBLE.

5.3 How Dolores Stakeholders benefit from improved forecasts

We prepared an online scenarios game for the Dolores River and McPhee Reservoir operators; however, the participants preferred an in-person conversation to the scenario game, so we adjusted methods for data collection. Instead, we provided reservoir operators at McPhee with the improved RTI forecasts and the CBRFC reforecasts and interviewed them about the decisions they would make regarding allocations for irrigation and for managed releases/spills based on these two sets of information. We provided the numerical values (Table 5-1) and a graph of the ESP forecasts including the 10%, 30%, 50%, 70%, and 90% exceedance probabilities (see example year in Figure 5-5). We did not provide information about the carryover in the reservoir from the previous year in order to focus the decision solely on the forecasts.

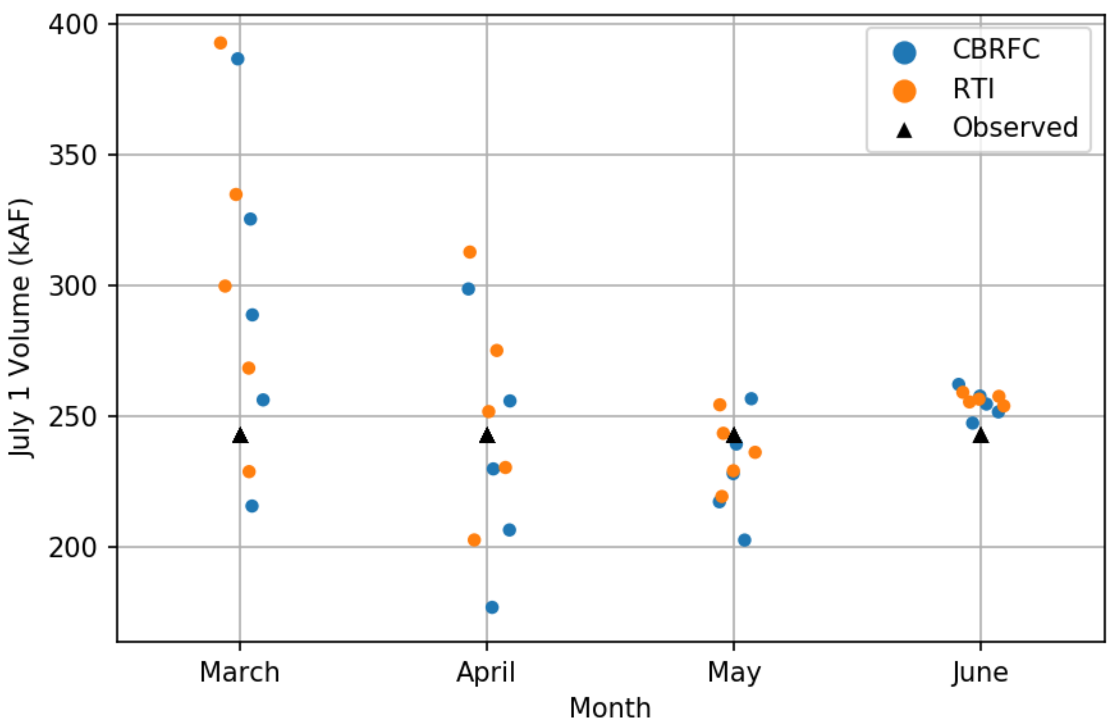

Figure 5-4 - Numerical values for the April thru July streamflow forecast and the observed July 1 runoff volume for the Dolores River, 2009

Due to the time-consuming nature of this method and personnel changes at DWCD, we were only able to discuss two years with one reservoir operator: 2008—a year with high snowpack and a managed spill lasting nearly 3 months; and 2009, with more average snowpack.

Table 5-1 - Numerical values for the April thru July streamflow forecast and the observed July 1 runoff for the Dolores River, 2009

Monthly stream-flow forecasts for 2009 (in kaf)				
Month	ESP	CBRFC reforecast	RTI forecast	July 1 observed flow
March	P10	386.8459	392.9477	
	P30	325.5058	334.9278	
	P50	288.8208	299.8447	
	P70	256.2701	268.4368	
	P90	215.6348	228.801	
April	P10	298.7435	312.8652	
	P30	255.8774	275.1927	
	P50	229.8494	251.7939	
	P70	206.469	230.3846	
	P90	176.8432	202.6437	
May	P10	256.7216	254.3915	
	P30	239.3783	243.478	
	P50	228.0579	236.1951	
	P70	217.2729	229.13	
	P90	202.5946	219.3003	
June	P10	262.1954	259.1765	
	P30	257.7311	257.6251	
	P50	254.6838	256.5561	
	P70	251.6725	255.4915	
	P90	247.3874	253.9621	
July 1 Observed				242.8025

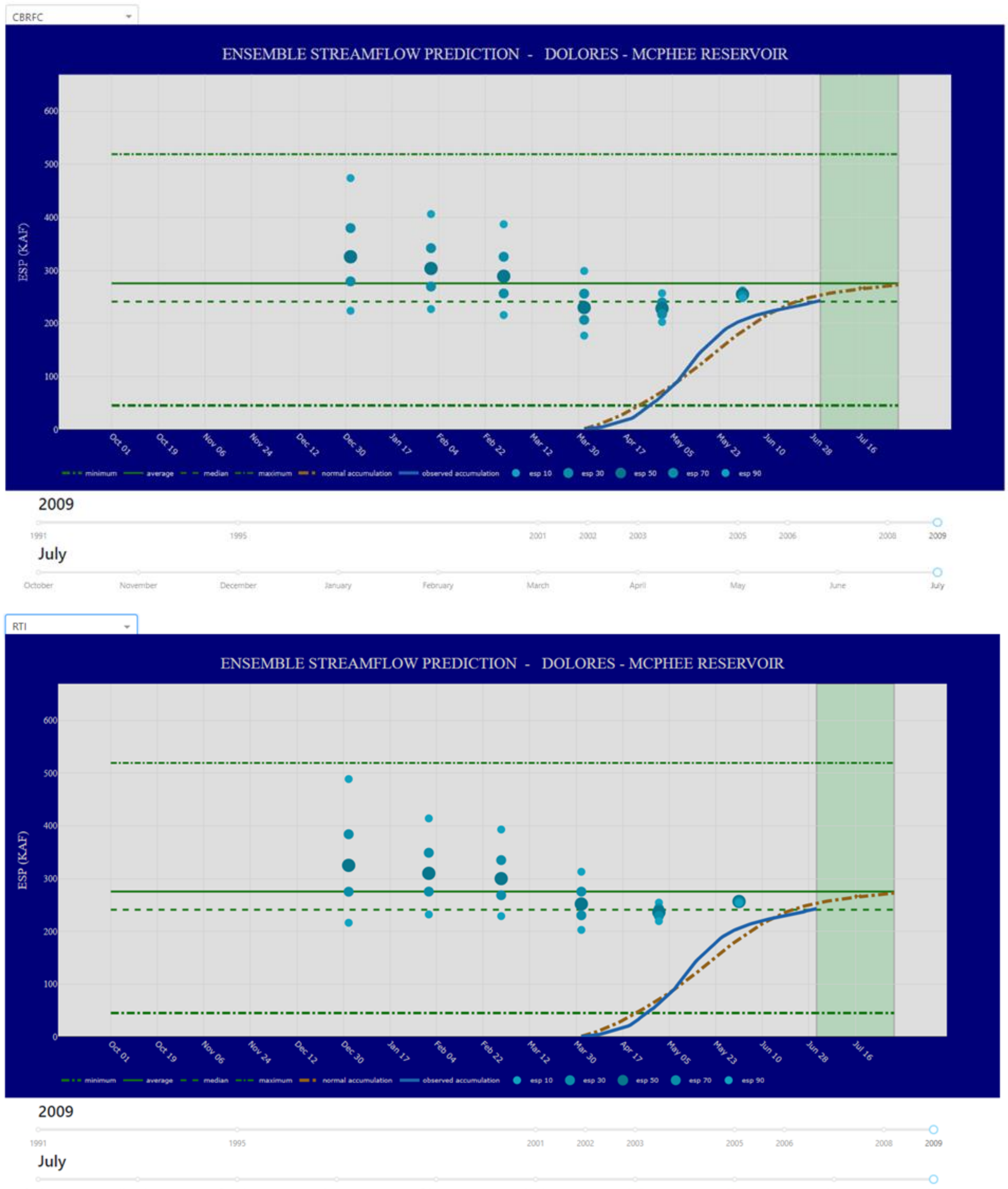

Figure 5-5 - The graphs of the CBRFC (top) and RTI (bottom) ESP forecasts showing the forecasts from January 1 to July 1 for April thru July runoff of the Dolores River

5.3.1 Elicited Impact of improved forecast in 2009

Would an improved RTI forecast for April-July runoff show enough difference to impact reservoir operating decisions for irrigation allocation and/or managed releases (i.e. boatable spills)? The year 2009 is a good test case, since the RTI forecasts on April 1 and May 1 were closer to the actual runoff than the CBRFC reforecasts. This is the period when DWCD is making decisions about how much irrigation water they will provide and the probability of having a managed release (Figure 5-4). We asked a key decision-maker at DWCD to make allocation and release decisions using the 1st of the month CBRFC reforecast and the RTI forecasts to assess how decisions may be impacted.

Based on the P50 and P70 volumes of the two forecast sets, the reservoir operator indicated that he would make different decisions regarding the probability of a full supply and a raftable spill based on the different RTI and CBRFC numbers. Considering the March 1 and April 1 forecasts, and not having information about the carryover in the reservoir, he indicated that with the CBRFC forecast, he would not feel comfortable guaranteeing a full supply for irrigation and would not expect a managed release. However, he indicated that he would communicate a full supply to the irrigators with the RTI forecast but would not expect a managed release; they would likely follow a fill-and-spill scenario.

This decision was based both on the absolute numbers and the amount of downward change between the March 1 and April 1 forecasts. He further indicated that ideally forecasts would be consistent between months, indicating a better, more reliable forecast. When DWCD sees large swings up or down, it makes them less feel less secure about decisions. It wasn't until the June 1 forecast that the numbers between the RTI and CBRFC forecasts were close enough to not make a difference in operational decisions.

FRE makes most of its planting decisions prior to May 15, however, and were unable to realize gains from the additional unexpected water supply

5.3.2 Elicited impact of missed forecast on the FRE and FSA, "Miracle May in 2015"

The official March 1 CBRFC forecast was for 230 kaf for the total April thru July runoff (p50) which would have provided a full supply of irrigation water; however, the official forecast on April 1 was revised down to 145 kaf, and fell to 110 kaf for the May 1 official forecast (Figure 5-6).

In April, the DWCD cautioned farmers in the FRE and FSA to expect a short supply, and communicated an estimated allocation of 10" of water per acre – much less than the full allocation of 22" – and the FRE allocation was shorted to 11,220 AF instead of the 24,000 AF full allocation. The FRE changed their planting plan accordingly and increased fallowed acres from 429 acres in mid-March, to 1389 acres in 18 fields at the beginning of April, to 2349 acres fallowed in 32 fields in mid-May. This included forgoing planned plantings of 9 fields of corn and allowing some winter wheat and older stands of alfalfa to die.

However, a "Miracle May" storm brought record-breaking snows that resulted in the reservoir having enough water to provide a full supply. The FRE makes most of its planting decisions prior to May 15, however, and so they were unable to realize gains from the additional unexpected water supply. At the end of the irrigation season, the FRE had used 21414 af of its allocated 24,000 af. The FSA also used a lower amount of water than what ended up being available due to early planning around an expected short supply based on the March, April, and May forecasts.

Data using RTI's forecasts are not available after 2012, so it is unclear to what extent a slight improvement in forecast quality may have aided agricultural decision making and the ability to take advantage of late-season changes to water supply forecasts.

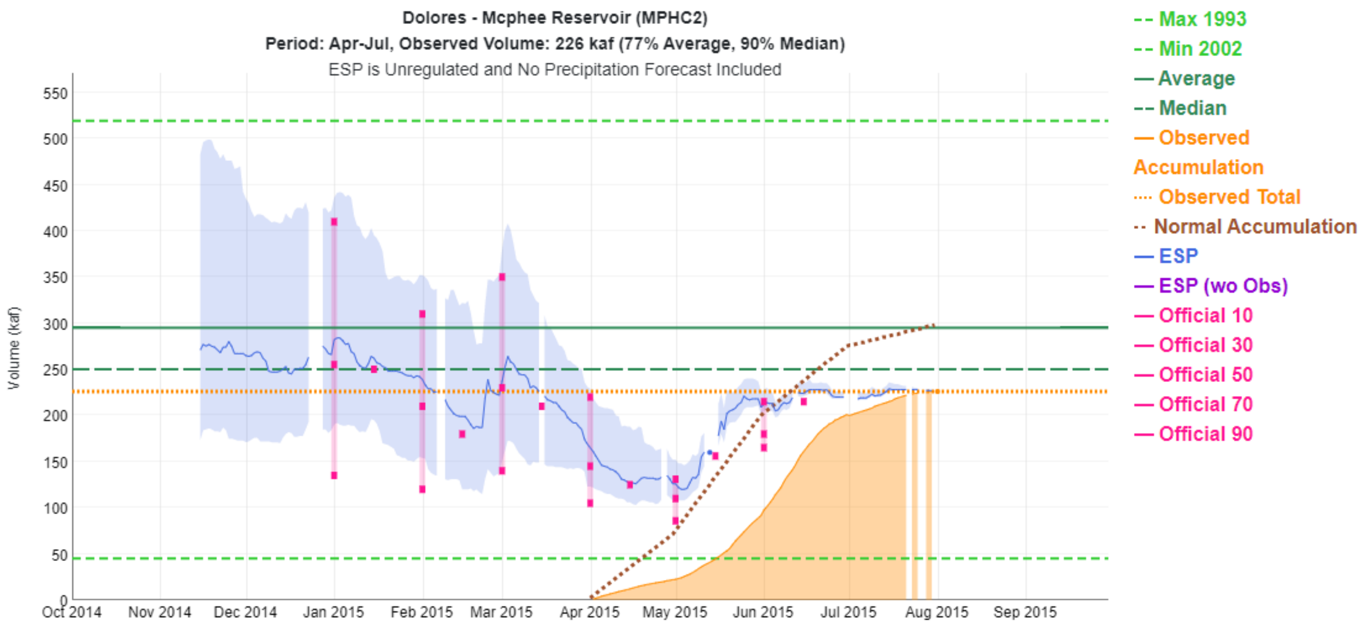

Figure 5-6 - Progression of water supply volume forecasts during "Miracle May" of 2015 (source: CBRFC)

5.3.3 Elicited Impact of Forecasts on Recreational Rafting

Based on conversations with rafting stakeholders, the timing of information about raftable spills is key for boaters. Boaters reported that increasing the lead time for notification of managed releases would increase the number of days and people who recreate on the Dolores River. With one to three days' notice of a managed release, it is mostly only local rafters from Dolores, Cortez, Durango, and the surrounding areas. With 3-6 days' notice of a release, boaters will come from 3-4 hours away, including from northern New Mexico, eastern Utah, and the western slope of Colorado and surrounding mountain towns. With a week or more notice of a release, boaters will come from as far away as the Denver and the front range of Colorado, Salt Lake City, and Las Vegas. With 3-4 weeks' notice or more, there will be boaters from across the country, including many commercial and private boaters.

Commercial outfitters have significant costs and risks associated with running trips on the Dolores. They begin booking spring and summer rafting trips as early as February and March, long before detailed information about specific dates for any managed release are available. However, they use their own expertise and experience of snowpack and runoff conditions to estimate the magnitude and timing of raftable flows on regional rivers. One outfitter reported that in 2019 that he began advertising potential trips on the Dolores to his clients in early March due to the high confidence in the forecasted spill. Rafting companies also need to ensure that they have enough trained guides with experience on the Dolores to safely run trips and move equipment between rivers – poor forecasts may result in significant investment losses for these smaller rafting companies.

Figure 5-7 - Snaggletooth Rapid, Dolores River, June 2019. (Photo credit: Brian Jokoby])

Rafting outfitters reported that it was considered very risky to run trips on the Dolores River because they can't rely on boatable flows with sufficient warning to plan, advertise, and mobilize. As a result, many outfitters stopped running trips on the Dolores River, and moved to the Animas, San Miguel, Arkansas, or other rivers with more reliable raftable flows. However, the Dolores remains a very attractive river to rafting enthusiasts due both to its unique beauty and the infrequency of the opportunity to experience it. To reduce risk, commercial outfitters report that they do not guarantee a particular river and reserve the right to move clients to another river with more favorable conditions.

In 2019, due to erratic streamflows and a cool, wet spring that impacted both the rate of runoff and agricultural demand, the releases on the Dolores started and stopped several times, making rafting difficult even though runoff was well-above average.

<u>Rafting the Dolores in 2019: Erratic Runoff and Streamflow</u>

The 2019 runoff season highlights the importance of both the April-July runoff forecasts and the 10-15 day weather forecasts on reservoir operations, particularly as it pertains to scheduling and managing releases.

In 2019, record-high snowpack in March-April meant that the DWCD and boaters knew there would be managed releases - the unknown was when spills would start and how long they would occur.

On March 20, 2019, the DWCD reported that record high snowfall in the mountains made the likelihood of a managed release lasting 2-4 weeks and starting in mid- to late May over 50% (DWCD March 20, 2019). On April 23, DWCD pushed the expected release start to late May or early June (DWCD, April 23, 2019). On May 3, they forecast the spill to begin on Memorial Day (DWCD, May 3, 2019). However, a cool, wet spring and a series of cold spring storm systems in May meant that peak runoff was almost a month late (peaking mid-June, well after the expected Memorial Day trips).

These meteorological conditions caused decreased irrigation demand from farmers who had to delay planting due to the cool, wet weather, resulting in erratic spills, starting and stopping several times in May and June, as the reservoir operators tried to balance inflows, outflows, and downstream demands. Starting and stopping of flows is challenging for rafters who prefer relatively steady or gradually varied conditions. Stoppage of flows can result in stranding of rafters downstream in remote locations with limited egress.

Reservoir operators are typically accustomed to three inflow peaks during the runoff season, with peak runoff around the end of May or beginning of June (Figure 5-9); however, in 2019, the runoff didn't peak until nearly three weeks later than usual and operators had to manage multiple peaks in runoff (Figure 5-8).

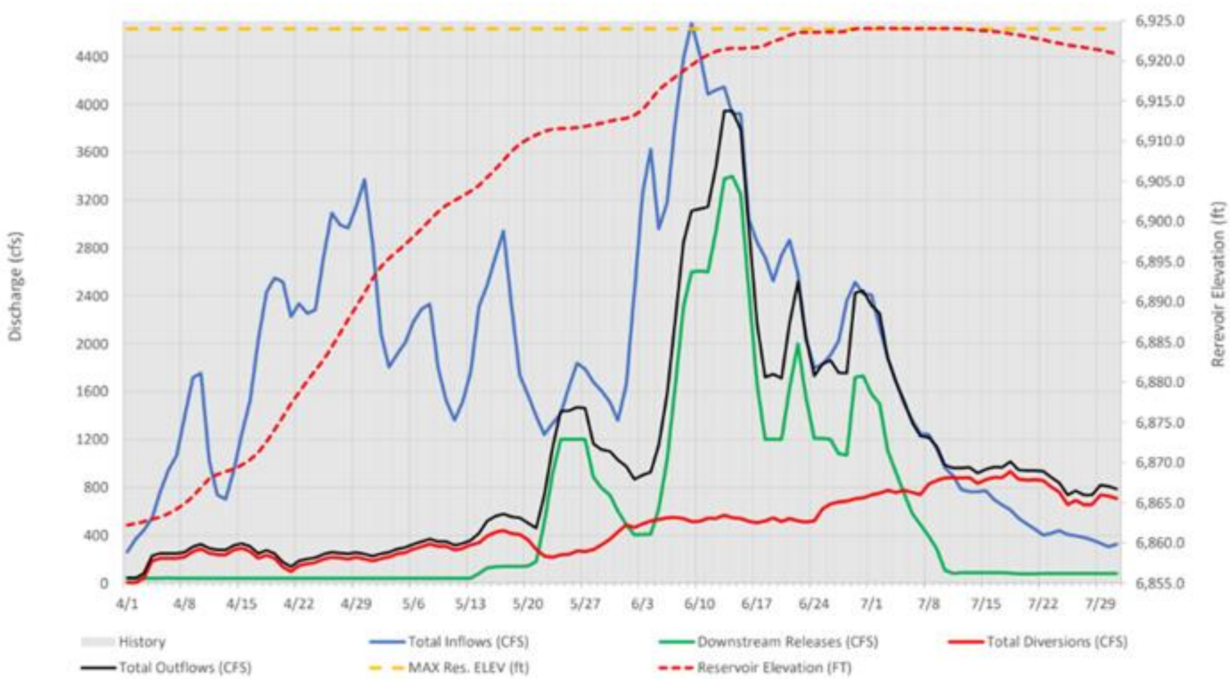

Figure 5-8 - McPhee reservoir operating plan, April 1-July 31, 2019. Courtesy of DWCD

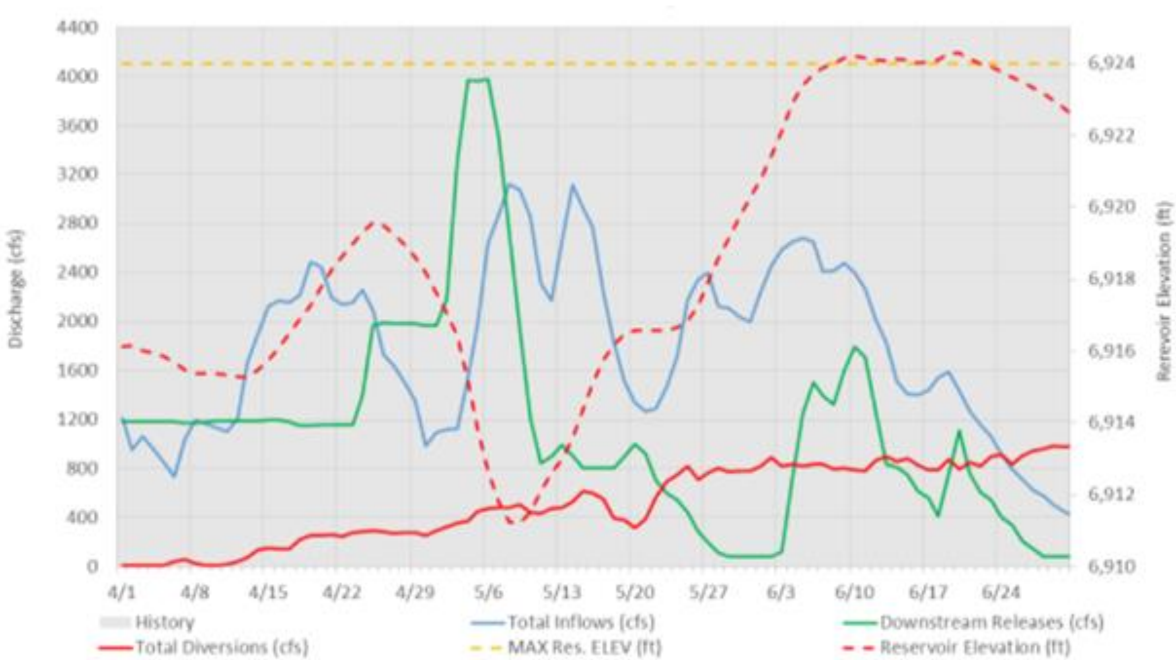

Figure 5-9 - McPhee reservoir operating plan, April 1-June 30, 2017. Courtesy of DWCD.

For boaters and rafting outfitters, erratic flows can be extremely difficult either impacting trips underway or can deter boating groups from even using the river entirely. During 2019, some scheduled trips on the Dolores had to be cancelled or moved to other rivers.

Even in a high water year with CBRFC April-July runoff forecasts of sufficient water to provide a full delivery supply, fill the reservoir to ensure carryover for the following year, and provide for boatable flows, there is still a large amount of uncertainty around the ultimate realized yield volume and timing. Increased skill in forecasts can help the DWCD reservoir operators maintain safe water levels, increase chances for steady releases at desirable boating flow rates, and improve the confidence from the recreational boating community to rely on the river for commercial trips or general use.

6 VALUE OF FORECAST QUALITY USING OPTIMIZATION METHODS

Optimization is used widely in the planning of reservoir operations and management [9] but is more limited in the real-time applications due to the complexity and computational burden. The advantage of optimization approaches, relative to rule-based methods, is that operation of the system becomes an emergent outcome of optimization rather than another required input (e.g. deterministic rule-based approach compared to optimization that drives decisions). Further, assuming the objective functions do not change, the optimization approach provides a consistent and objective method of prescribing operations in response to current conditions and forecasted streamflow.

In addition, some optimization methods can explicitly manage probabilistic forecasts in the form of streamflow forecast ensembles. When forecast quality improves, optimization methods can then provide a clear and consistent means of evaluating the effects of these improvements on optimal operating policy, and hence, a clear means of identifying the potential value from improved stream forecast quality.

A challenge with using optimization methods to make a single decision is the requirement to either have a single objective function, or to use multi-objective methods that apply weights and preferences to different objectives. Real world applications are extremely complex and include operational decisions that are driven by economic, social, and environmental factors, which may be challenging to fully represent within a numerical framework. As such, optimization methods may require gross simplifications of very complex human-driven decision-making processes.

This section discusses a study conducted by comparing variable forecast qualities based on historical ensemble members in a stepwise no-recourse optimization process. Historical ensemble members are modified to show improved forecasts, new optimization runs are completed, and the effects are evaluated to elicit the potential benefits of improved forecast quality.

6.1 SAMPLING STOCHASTIC DYNAMIC PROGRAMMING

There are several methods for utilizing ensemble streamflow forecasts in the decision-making process [10], but only a few explicitly use each ensemble member to inform the decision. One such method is called *Sampling Stochastic Dynamic Programming* (SSDP) [11]. Although very similar to the generalized deterministic approach of dynamic programming (DP) [12], it utilizes and optimizes over the expectation for each of the traces across the decision horizon, rather than through transition probabilities with methods like Stochastic Dynamic Programing (SDP) [13] [14].

The SSDP algorithm is computationally intensive and difficult to implement. To address these challenges through the creation of a ‘generalized’ algorithm for implementation of SSDP, RTI developed a programming system called RTI-ROSE, or RTI *Reservoir Optimization with Streamflow Ensembles* [15]. This application is intended to allow the rapid implementation of the SSDP algorithm to inform optimal decisions given a probabilistic streamflow ensemble.

Optimization is conducted over a single time horizon with multiple members indicating optimal decisions over the period, but over time, new forecasts are produced, and actual reservoir inflows and outflows are realized. Thus, to use this in an operational approach, perfect foresight is not available and optimization must occur in a stepwise manner – optimization is completed for the current timestep, decisions are made, realized inflow occurs positioning the reservoir at a new storage, and new forecasts are received which are again optimized over the horizon. This moving optimization window mimics how the process would be implemented in real-time systems and provides an indication of the 'best' decisions that can be made with probabilistic forecasts.

The truly optimal path is when the reservoir is optimized with perfect foresight. This condition can also be analyzed with SSDP but only using a single trace (the historical realized inflow), which simplifies to the deterministic DP method. This condition represents the maximum potential utility that can be realized by reservoir optimization for the given objectives.

When comparing the optimization of realized inflow against probabilistic inflow, we can then assess the potential benefits from better forecast quality – i.e., can better decisions be made with reduced uncertainty? Through optimization methods, subjective decisions and bias are removed, creating a platform for consistent results based on the inflow ensembles.

For purposes of this study, we focused on the McPhee Reservoir. The Dolores system is relatively straightforward, which eases the process of rule generation for optimization methods. There is a single reservoir with mostly unregulated inflows, and historical documentation on the project water balance is available from the USBR. In contrast, the Denver Water system includes multiple coordinated reservoirs, and its operations are based on longer-term climate projections, carry-over storage volumes, risk tolerance, forecasted supply demands, and many other factors, which make the system challenging to model in a manner representative of their actual target process. Although it is possible to model the DW system using an optimization approach, it would require several simplifications to maintain a tractable approach [16].

The objective function for McPhee Reservoir, as best elicited from DWCD staff and operators, includes the following main components:

1. Fill – a linear objective of filling the reservoir up to the maximum normal storage
2. Boat – a relationship relating higher flow releases to desirable boating conditions
3. Low Flow Penalty (Pen_1) – flows should not be greater than the minimum flow requirement for downstream environmental benefits
4. High Flow Penalty (Pen_2) – flows should not be greater than maximum allowable release to preserve safe non-flooding downstream conditions
5. High Storage Penalty (Pen_3) – storage should not be greater than maximum normal to maintain acceptable dam safety conditions

As such, the generalized objective function for this problem can be defined as:

$$\max\,(Obj) = \sum_{t=1}^{T} \omega_1^t \times Fill^t + \omega_2^t \times Boat^t - Pen_1^t - Pen_2^t - Pen_3^t$$

where ω_i are the objective function weights, and Pen are the respective penalty functions subtracted from the objective, for each timestep t. Through discussions with DWCD, it was determined that $\omega_1 \gg \omega_2$.

6.2 Synthetic Ensemble Generation

To test how optimal decisions vary given probabilistic information, we developed a set of controlled variations on historical ensemble members. For each simulation, the ensemble was adjusted using two parameters for *dispersion* and *bias*. Dispersion is the measure of scatter or variance between the ensemble members, whereas bias is the shift of members from the historically observed value. To maintain a tractable process for ensemble modification, simplified methods were employed to create a consistent approach to ensemble adjustment. In general, modifications were made with respect to the median of the ensemble members, and the historical reanalysis inflow (based on Reclamation records).

Dispersion Adjustment – the differences of ensemble members to the median can be reduced as a percentage.

100% - no modification, original dispersion from median of ensemble members

50% - traces are shifted by 50% of the difference from the median of ensemble members

0% - ensemble members would have no variance from the ensemble median

Bias Adjustment – using the median of the ensemble members, all members are adjusted as a percentage of the difference from median to the verified trace.

100% - no modification, original bias

50% - traces are shifted by 50% of this difference

0% - median of traces would equal the historical inflow

As seen in Figure 6-1, a gridded approach for a single ensemble forecast (April 1, 1997) shows the effects on adjusting bias and dispersion using this method, but adjustments are not shifted unrealistically to 0% on either Bias or Dispersion – this would be an extreme expectation from a forecast product. Instead, for each metric, a set of [50%, 75%, and 100%] was utilized, creating nine unique replicates of varying skill. In this case, bottom right of Figure 6-1 represents the original ensemble members at 100% for both Bias and Dispersion. Further, in each graph, the black-dashed line represents the actual observed reanalysis inflow for this streamflow forecast ensemble.

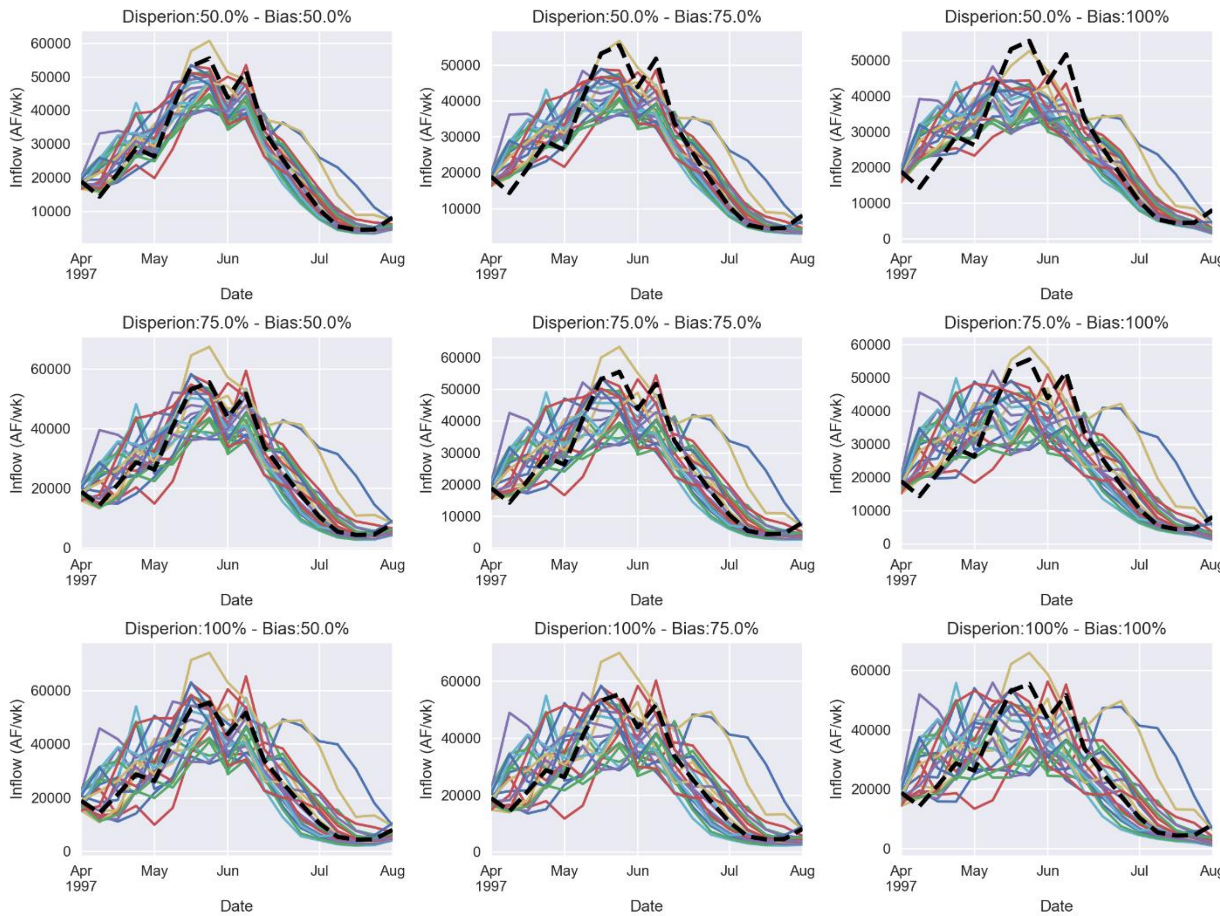

Figure 6-1 - Sample synthetic ESP modification of bias and dispersion, April 1, 1997, observed inflow (dashed-black line)

Using the SSDP algorithm, implemented through RTI-ROSE, stepwise optimizations are conducted forward in time. At each time step, new forecast ensembles are generated (using CBRFC reanalysis forecasts) and new reservoir decisions are made. Once a decision is made, the actual inflow, diversions, evaporation are realized with the given target storage, and a new storage level is achieved. At this time, a new forecast is received, and the process is repeated – in this manner, no-recourse decisions are made on a stepwise basis using probabilistic forecast information.

At the other extreme is a single-trace perfect forecast at the start of the runoff season. Under this condition, with the given objective functions, theoretically no better decisions may be made for positioning reservoir storage and making reservoir releases downstream.

6.3 Impacts and Benefits of Variable Forecast Quality

Benefits of improved forecasts, measured by utilizing ensembles of varying skill, is measured by direct responses of the system, including storage levels, storage timing, and reservoir releases. With improved forecasts, reservoir operators should theoretically be able to better manage storage and releases, thus improving water security and providing other potential economic benefits.

To test the optimization system and extract these performance metrics using the RTI-ROSE SSDP tool, a series of years were run independently [1991, 1997, 1999, 2003, 2006, 2007, 2008], where each year was initiated at the same storage levels as historically observed. A summary of available years is in Table 6-1, where each year has been categorized into Low, Average, or High runoff year based on total annual yield. A subset of years was selected from the period of record to assess a range of historical conditions with the same starting conditions, allowing the optimization method to be compared against historical performance of the reservoir.

Table 6-1 - Historical McPhee Reservoir Inflow Volumes; years categorized by 1/3 quantile groups [Low, Avg, High]

Date	Annual Yield (AF)	Hydrologic Regime	Date	Annual Yield (AF)	Hydrologic Regime
1984	293723.9076	High	**2002**	37359.47	Low
1985	308369.4509	High	**2003**	99411.7	Low
1986	309126.9547	High	**2004**	140120.2	Avg
1987	277421.7048	High	**2005**	252993.28	High
1988	132291.4632	Avg	**2006**	116827.12	Low
1989	132048.8529	Avg	**2007**	149953.23	Avg
1990	82333.25	Low	**2008**	222256.09	High
1991	144975.55	Avg	**2009**	149419.3153	Avg
1992	176693.33	Avg	**2010**	151340.635	Avg
1993	302309.9	High	**2011**	169277.9162	Avg
1994	147702.88	Avg	**2012**	83466.32788	Low
1995	283948.51	High	**2013**	78679.49428	Low
1996	105182.32	Low	**2014**	116799.5593	Low
1997	306998.97	High	**2015**	140803.7454	Avg
1998	193996.49	High	**2016**	155069.8198	Avg
1999	209426.1036	High	**2017**	225181.2527	High
2000	124786.58	Low	**2018**	38591.78232	Low
2001	128444.71	Low	**2019**	250052.2619	High

An example is shown in Figure 6-2 for the year 2007 using 1-week intervals for optimization (i.e., no-recourse decisions made weekly with new forecasts at each timestep). Each trace represents different forecast skill, in addition to the black dashed line which represents the perfect forecast and the gray dash-dot line which represents historical releases. For this year, we can see the top ensemble operations have the lowest dispersion regardless of bias levels.

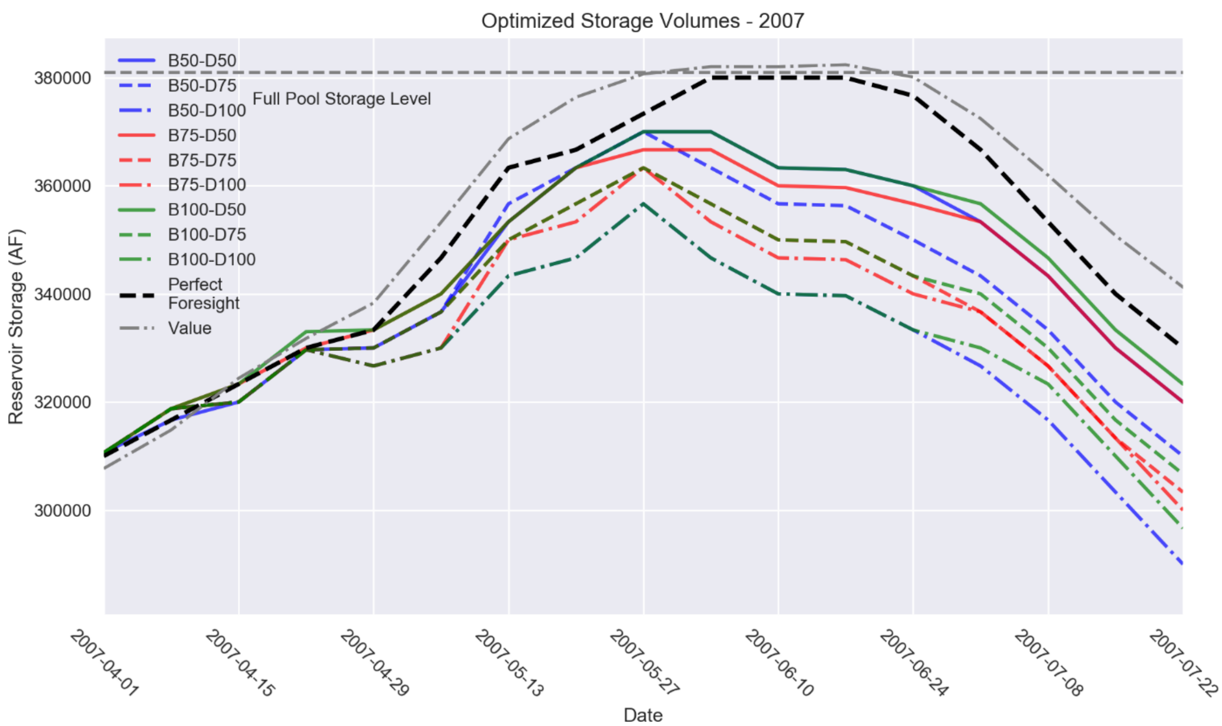

Figure 6-2 - One-step recursive optimization using probabilistic forecasts of varying quality – 2007

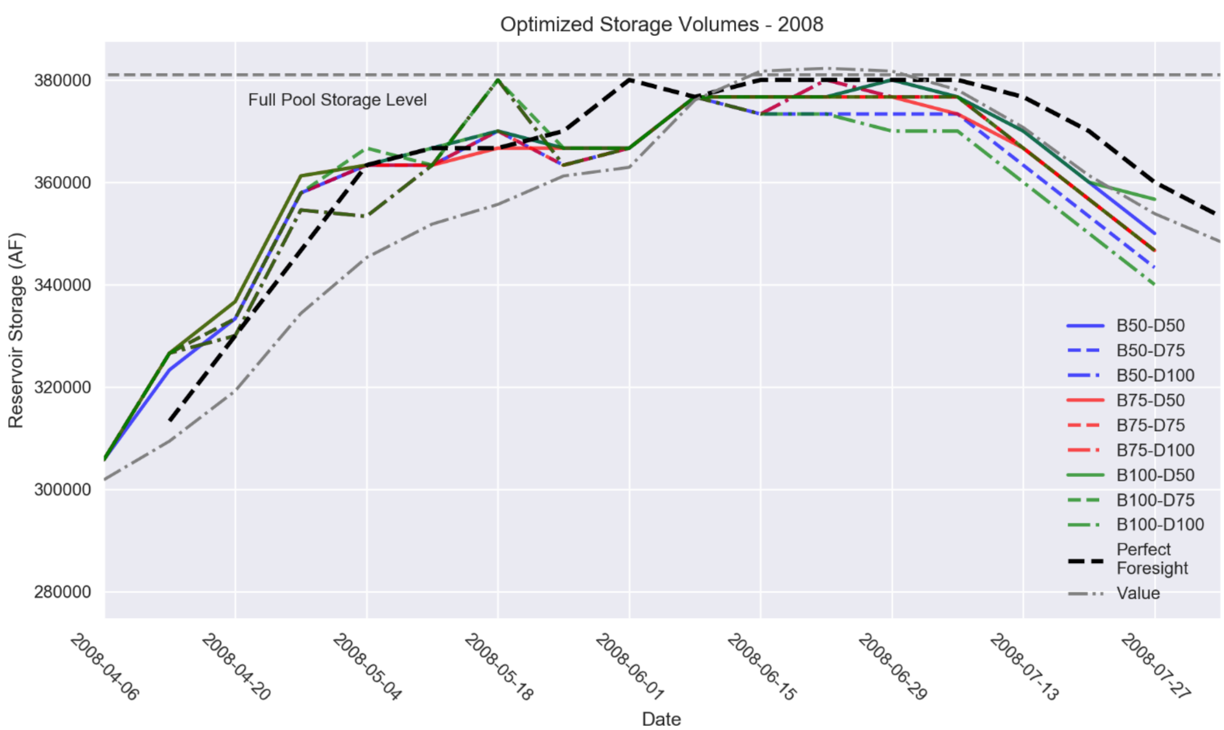

Figure 6-3 - One-step recursive optimization using probabilistic forecasts of varying quality - 2008

A similar assessment is shown in Figure 6-3 during a higher flow year. All the forecasts and ensemble members produce earlier peak storage levels, whereas historical releases resulted in full pool later in the season, when the optimal traces had already begun to decline. In this year, the perfect foresight maintains the most storage while maintaining the fixed demand requirements.

In general across all years assessed, perfect foresight allows for greater total peak storage increasing deliveries and minimizing the probability of water delivery shortages. Similarly, in most years, the perfect foresight performance is similar to the historical performance, which exceeds the SSDP optimization using the probabilistic streamflow ensemble forecasts. This indicates operators are either able to weight ensemble members, or utilize supplemental information beyond the forecast ensembles in support of their decision-making process.

Using each of the years, we then assess the output across different forecast skills for the core performance metrics. Storage metrics are related to the first component of the objective function, whereas preferred release profiles are related to the boating objective.

- Maximum reservoir storage (Table 6-2)

Mean June storage (

- Table 6-3)
- Mean June outflow (Table 6-4)

Table 6-2 - Annual Maximum Storage (AF) with Variable Forecast Skill

Year	Bias / Disp	50	75	100	Perfect Forecast	Hydrologic Regime
1991	50	333333.3	323092	299882.7	370000	Avg
	75	339758.7	323092	306758.7		
	100	339758.7	326425.4	306758.7		
1997	50	380000	380000	380000	380000	High
	75	380000	380000	380000		
	100	380000	380000	380000		
1999	50	380000	376666.7	380000	380000	High
	75	380000	380000	376666.7		
	100	380000	380000	376666.7		
2003	50	271000	266500	257500	237750	Low
	75	266500	266500	257500		
	100	283333.3	275500	257500		
2006	50	323333.3	316666.7	310000	326667	Low
	75	330000	320000	313333.3		
	100	323333.3	313333.3	306666.7		
2007	50	370000	370000	356666.7	380000	Avg
	75	366666.7	363333.3	363333.3		
	100	370000	363333.3	356666.7		
2008	50	380000	376666.7	380000	380000	High
	75	376666.7	376666.7	380000		
	100	380000	380000	380000		

Table 6-3 - Mean June Storage (AF) with Variable Forecast Skill

Year	Bias / Disp	50	75	100	Perfect Forecast	Hydrologic Regime
1991	**50**	325234.3	314519.4	290245.1	358000.0	Avg
	75	331852.7	314886.9	296953.6		
	100	332886.9	318220.3	296953.6		
1997	**50**	378666.7	374666.7	373333.3	376000.0	High
	75	378666.7	376000	373333.3		
	100	378666.7	374000	374000		
1999	**50**	370669	368169	368169	376666.6	High
	75	370669	369002.4	364835.7		
	100	370669	369002.4	364835.7		
2003	**50**	261717.5	257217.5	246048.7	229950.0	Low
	75	257217.5	257217.5	250548.7		
	100	274750.9	266217.5	248217.5		
2006	**50**	312620.3	302620.3	291064.9	320833.3	Low
	75	319287	305953.7	294377.4		
	100	312620.3	299287	287752.4		
2007	**50**	364082.6	356582.6	339916	378333.3	Avg
	75	360749.3	349916	346582.6		
	100	364082.6	349916	339916		
2008	**50**	375333.3	372666.7	374666.7	379333.3	High
	75	374666.7	374666.7	374666.7		
	100	375333.3	374666.7	372000		

During high flow years, the benefits from improved forecasts are marginalized with respect to probability of filling (e.g., 1997) –improved forecasts in high flow years do not increase the probability of full storage. This condition is the exception to the rule, though, as most years show significant improvements in storage (both annual maximum and June mean) with improved skill forecasts.

Table 6-3 highlights the mean storage for June – although reduced dispersion in the ensemble does help improve some of the operations, it is clear that reduced bias in the ensemble has the greatest effect on improved reservoir operations. This result is demonstrated consistently across all the test years and is independent of the hydrologic regime.

Table 6-4 shows the outflows, but it is more difficult to use lower or higher flows to infer the benefit from improved forecast skill. In years such as 1997, there is an increase of discharge with increased forecast skill, compared to 1999, where there is a reduction in mean discharge with increased skill – this opposite response is not intuitive. The objective function is highly weighted on storage benefits relative to release benefits, thus inferring the significance of this switching is challenging. Of note is the consistent gradient of differences between forecast skill sets, which is much more significant along the axis of bias compared to the axis of dispersion changes.

Table 6-4 - Mean June Outflow (AF/week) with Variable Forecast Skill

Year	Bias / Disp	50	75	100	Perfect Forecast	Hydrologic Regime
1991	**50**	6589.2	6048.1	6372	2218.7	Avg
	75	6541	5680.5	6413.9		
	100	5013.9	5680.5	6413.9		
1997	**50**	23651.2	19651.2	20317.9	34454.5	High
	75	23651.2	20317.9	20317.9		
	100	23651.2	22317.9	20984.5		
1999	**50**	10347.1	11180.5	12847.1	17510.5	High
	75	10347.1	10347.1	12013.8		
	100	10347.1	10347.1	12013.8		
2003	**50**	4807.6	4807.6	3007.6	2319.1	Low
	75	4807.6	4807.6	3007.6		
	100	4574.3	4807.6	3907.6		
2006	**50**	2091.3	2091.3	2841.3	2200.9	Low
	75	2091.3	2091.3	2862.1		
	100	2091.3	2070.4	2820.4		
2007	**50**	5852.1	6685.5	6685.5	3117.6	Avg
	75	5018.8	6685.5	5852.1		
	100	5018.8	5852.1	5852.1		
2008	**50**	13035.9	13702.5	13035.9	18567.8	High
	75	13702.5	13035.9	13035.9		
	100	13035.9	13035.9	14369.2		

6.4 DISCUSSION OF BENEFITS FROM IMPROVED FORECASTS

Through reductions in both bias and dispersion, the optimization model generally (but not always) shows improvements in the reservoir operations and decision-making process relative to the 'best' ensemble forecast. The term "Best", in the language of the optimization algorithm, is considered a weighted combination of both storage levels in addition to flow release rates. In some cases, storage may be moderated at lower levels indicating pre-full reservoir early spill releases – a demonstrated form of *forecast informed reservoir operations* (FIRO).

Even through testing a matrix of improved forecast scenarios, which increases the utility of operations, the skill of these scenarios do not match that of a perfect forecast (i.e. a theoretical B0-D0 single trace forecast), nor that of historical operations. In the perfect forecast case, the storage and release schedule is superior, with the highest potential utility. Interestingly, in many years the historical operations are near this 'optimal' perfect forecast profile, and well above any of the ensemble traces. This is not the result of iteratively developing rules to match historical operations, but rather signifies the influence of information beyond the ensemble streamflow forecast in guiding operational policy. This includes weather forecasts, interpretation of SNOTEL stations with DWCD snow surveys and visual observations, and the human element of understanding how the system may respond. This information is invaluable in determining reservoir positioning and release schedules and is not easily integrated into any optimization algorithm.

There is significant benefit in operations from improved forecast skill between the scenarios tested, but a more fundamental question should be asked around the realistic potential to reach even these levels of skill. Is it realistic to expect a 50% reduction in bias? Perfect forecast is clearly impossible, so any assessments of potential value from improved forecast should be centered in realistic regions of forecast skill improvement.

In principle, the RTI-ROSE optimization framework could also be used to assess the economic value of improved forecast information; however, doing so requires – at a minimum – specifying functions that translate reservoir storage levels and releases into economic values for all the main stakeholder beneficiaries. For example, total agricultural profits for irrigators could be expressed as a function of stored water, total benefits to rafters could be expressed as a function of downstream flows, and flood damages (negative benefits) to downstream residents could also be estimated as a function of flows. These values could be then be added together to estimate total benefits, which could then be compared for different forecast scenarios.

In practice, however, there are several challenges with implementing this approach (even setting aside the empirical challenges of estimating these stakeholder benefit functions). First, it assumes that dam operations are guided by an interest in maximizing the sum of economic benefits to all stakeholders. If operations are driven by other objectives, then an optimization model that maximizes the sum of benefits cannot be expected to simulate actual operational decisions. However, it may be interpreted as an approximation or as a benchmark for decisions. Moreover, the benefit functions by themselves may be useful for evaluating the economic implications and outcomes of other optimization or decision processes.

Second, this approach does not account for how forecasts may affect stakeholders' decisions and benefits with respect to water use. For example, farm profits may not only depend on the amount of water they receive, but also on their planting decisions that are based on water forecasts. Benefits to rafters may not depend only on downstream flows, but also on trip planning decisions that were previously made based on forecasts. In other words, a full assessment of the value of forecast information requires a modeling framework that also accounts for the optimization decisions made by these stakeholders.

Metrics of improvement defining the "Best" results are aligned to probability of filling the reservoir, fill level, and release profiles. There is additional value to other stakeholders not included in the optimization framework that could also redefine what is considered best – how would changes in bias or dispersion improve farming decisions? What is the economic value for the rafting community?

We need to consider benefits of improved forecasts conditioned on the stakeholder and end-user. Improved long-range forecasts are key for reservoir managers to plan allocations and delivery shortages during a drought impacting farmers production, but there is no benefit for dam safety engineers or recreational rafters during this condition. Conversely, rafters greatly benefit from improved forecast skill and lead-time during years in which there is excess flow, bringing potentially significant increases in revenue to local businesses. The benefits change based on the hydrologic regime. Some of these questions will be explored in the following Chapter 7.

The benefit from the use of an optimization tool may only be realized when a *decision* needs to be made; under drought conditions, demands through diversions are met as agreed to in compacts, but there are no decisions about when or how much to spill such as under full pool conditions. As such, this comparison of benefits from improved forecasts focuses on higher yield years when a spill may be expected.

In moving forward with improved forecasts, this assessment shows that

- the best improvements in operations are realized with reduced ensemble streamflow bias rather than dispersion in the ensemble set;
- the value of improved forecasts varies between hydrologic regimes;
- the determination of the 'value' is conditioned on the stakeholder group.

These factors make it challenging to effectively implement a single objective or weighted multi-objective optimization model into practical operations. If maximizing hydropower production was the only objective, then assessment of optimal operations and the increases in value would be relatively easy. For systems with multiple stakeholders, multiple objectives, and uncertainty in both inflows and demands, operations can be challenging requiring human knowledge and capacity to be infused in the decision-making process. In this case, even with probabilistic information, the human operations including variables beyond the ensemble members can outperform optimization methods. Significant increases in the value of improved forecasts can be realized by focusing on decreased bias, but also assimilating multiple data sources into the decision-making process.

7 ECONOMIC VALUE OF IMPROVED FORECAST SKILL

7.1 VALUE OF IMPROVED FORECASTS FOR DWCD PROJECT IRRIGATORS

As discussed in Chapter 5, each year project farmers must make early season planting and other planning decisions (i.e., during winter and spring months) before actual water supplies and final water allocations by the project are known with certainty. To address this uncertainty, they can mainly rely on water supply and allocation predictions from two sources. First, the DWCD makes monthly announcements regarding their *expected* water allocations (in inches per acre) for full-service project farmers. As previously described, these predictions are based on several data sources and reports, many of which are available on the CBRFC public website. Key among these data sources are the daily CBRFC April-July water supply forecasts for McPhee reservoir. Second, farmers can make direct use of the publicly available CBRFC forecasts and other data sources. Therefore, regardless of the direct information source used by farmers, the CBRFC water supply forecasts are a key underlying source of data.

Given the potentially important role of CBRFC streamflow and water supply forecasts in the project farmers' decisions, one way to assess their economic value is to conduct a "revealed preference" analysis. That is, we can analyze how farmers' observed decisions and alfalfa yields have varied with respect to changes in forecasts over multiple years, and we can then use this estimated relationship to infer the value provided by forecasts. This is the approach we describe in this section, with additional details about the methods, data, and results provided in Appendix A.

Our analysis relies on two main sources of data. First, we acquired 16 years (2002-2017) of crop report data for full-service farmers in the DWCD project. These data include farm-level and field-level information for over 100 farms and 28,000 project-allocated acres. They include reports of the number of acres allocated by the project for irrigation, the actual number of acres irrigated, and total annual output by crop-type. For the entire period 2002-2017, the data include information on the general type of commodity being produced (e.g., hay, beans, etc.), but more detailed data regarding the specific type of commodity (e.g. alfalfa hay) are only available from 2006 to 2017.

Second, we acquired data on actual and forecasted water inflows and storage levels for McPhee reservoir for the corresponding years. These data are summarized in Table 7-1. The first main indicator of actual water availability in each year is the volume of water stored in the reservoir at the beginning the year (i.e., carried over from the previous year). From 2002 to 2017, the volume varied from as little as 5 KAF at the beginning of 2003 to as much as 147 KAF in 2006, with an overall average of 86 KAF. The second main indicator is the total accumulated inflow to the reservoir from April 1 to July 31 each year. These inflow volumes ranged from a minimum of 45 KAF in 2002 to a maximum of 423 KAF in 2005, with an average of 218 KAF. Over a longer historical period extending back to 1981, the average observed annual inflow has been closer to 300 KAF.

For forecast data, we used CBRFC projections of total inflow volume to the reservoir from April to July. In particular, we selected the "50% exceedance probability" (P50) from the ensemble forecasts published on the first day of the months of January, February, March, and April. The last four columns of Table 7-1 report the forecast errors for each date and year. These errors are calculated as the difference between the forecast and the observed accumulated inflow volume for the year in question. Over the 2002-2017 period, there are both positive errors – i.e. over-predictions of inflows – and negative errors, but positive are more common. On average, the January, February, and March forecasts overpredicted actual inflows by 50 to 60 KAF, and the April forecast overpredicted by 21 KAF.

Table 7-1 - Summary Statistics for McPhee Reservoir Inflows and Inflow Forecasts 2002-2017

Year	Reservoir carryover (KAF)	Total April-July Inflow (KAF)	Reservoir Inflow Forecast (KAF)				Forecast Error (KAF)			
			1-Jan	1-Feb	1-Mar	1-Apr	1-Jan	1-Feb	1-Mar	1-Apr
2002	54	45	199	157	120	108	154	112	75	63
2003	5	146	240	191	206	201	94	44	60	55
2004	22	200	258	263	277	208	58	63	78	9
2005	55	423	262	337	358	364	-162	-86	-65	-59
2006	147	145	210	197	154	192	64	52	9	46
2007	119	205	292	252	246	205	88	47	41	0
2008	136	375	326	434	521	464	-49	60	146	89
2009	133	255	326	304	289	230	71	49	34	-25
2010	107	247	235	247	247	247	-12	0	0	0
2011	125	267	316	275	252	195	49	8	-15	-72
2012	142	111	248	249	243	174	137	138	132	63
2013	43	87	160	170	148	122	73	83	61	35
2014	22	173	316	287	281	268	143	114	108	95
2015	34	226	282	263	268	197	56	37	42	-29
2016	91	241	350	386	292	241	109	145	51	0
2017	143	346	269	444	473	411	-77	98	127	65
Average	86	218	268	278	273	239	50	60	55	21
Min	5	45	160	157	120	108	-162	-86	-65	-72
Max	147	423	350	444	521	464	154	145	146	95
% >0							75%	88%	81%	56%

To estimate the value of improved forecast information, we focus on mainly on alfalfa production by full-service farmers. Focusing on a single crop makes it easier to compare production levels across years (in tons), and alfalfa accounted for 62 percent of all crop acreage under production over the period 2006 to 2017. One limitation of focusing only on alfalfa is that data for this specific crop were not available for years before 2006. Therefore, we conducted a parallel analysis of all hay production from 2002 to 2017, with results reported in Appendix A.

Using these data, we began by analyzing whether there is evidence that water supply forecasts have an effect on irrigation decisions for alfalfa producers. Although the dataset provides limited detail about the specific amount and timing of irrigation during the growing season, it does provide estimates of the number of acres selected for irrigation each year. Therefore, using regression analysis, we examined whether differences in CBRFC water supply forecasts across multiple years have a statistically significant effect on the number of irrigated acres (as a percentage of the number of acres allocated by the project for irrigation). For the most part, we found that the inflow forecasts had positive and statistically significant effects on the percent of project-allocated acres that were irrigated each year.[8] The size of these effects varied across forecast dates, ranging from a 4.6 percentage point effect per 100 KAF increase for the January forecast to less than 1 percentage point for the March forecast. Although the earlier forecasts are generally less accurate, their larger effect on irrigated acreage may be due to planting and other planning decisions that must be made early in the year.

Given this evidence regarding the effects of forecasts on at least one key type of irrigation decision, we then analyzed whether there is evidence that water supply forecasts – and more specifically errors in these forecasts – affect the production levels and revenues achieved by alfalfa farmers. Our underlying hypothesis is that with perfect forecasts of water supplies (i.e., zero forecast error), farmers should in principle make optimal irrigation decisions that maximize production and revenue. Therefore, for any given level water supply and allocation that is *actually* realized in a year, any divergence from a perfect forecast --whether it be a positive (over-forecast) or negative (under-forecast) error-- is expected to have a negative effect on observed production levels (relative to production with a perfect forecast).

Again using regression analysis, we estimated a model of field-level annual alfalfa production as a function of (1) indicators of *actual* water supply levels to McPhee reservoir for the year, and (2) observed forecast errors for the period of record. As expected, we found that the actual water supply indicators – stored water carried over from the previous year and total observed April-July inflows to the reservoir – had positive and significant effects on production levels.

In addition, we found evidence that, controlling for these actual supply indicators, forecast errors – i.e., the absolute values of the difference between actual and forecasted inflows – had mostly negative and statistically significant negative effects on production. In particular, for the positive errors (i.e., over-forecasts), the size of the significant coefficient estimates suggests that each 10 KAF increase in the over-forecast decreases output by 3-4%. The size of the under-forecasts is also found to have negative and statistically significant effects on production for the regressions using the January and April forecasts.

These regressions are useful for analyzing the benefits of improved forecast information because, for any specified level of actual water supply indicators, they allow us to simulate what expected alfalfa production levels would be with smaller forecast errors. Moreover, with an estimate of the per-ton price of alfalfa, we can also estimate the effect of forecast errors on alfalfa revenues.

THE AVERAGE MARCH 1 FORECAST ERROR FOR APRIL-JULY INFLOWS HAS BEEN POSITIVE (OVER-FORECAST) AT 55 KAF

Over the 2006-2017 study period, annual alfalfa production in the study area has averaged 60,146 tons per year. Assuming a price of $225 per ton, for a typical year, this translates to roughly $13.5 million in revenue per year. As shown in Table 7-1, the average March 1 forecast error for April-July inflows has been positive (over-forecast) at 55 KAF. With the regression results, we can estimate the value of improved forecast information by estimating the expected increase in alfalfa revenue associated with a specific decrease in forecast error.

[8] One exception was the effect of the February 1 forecast, which was not significant.

For example:

1. The value of a perfect forecast relative a 55 KAF over-forecast, which would imply reducing the over-forecast from 55 KAF to zero, is expected to increase by annual alfalfa production by 24 percent (i.e. 14,400 tons), which translates to value equal to an increase in annual revenue of $3.2M
2. For an improved (but not perfect) forecast – e.g., reducing the 55 KAF over-forecast by 25 percent (13.75 KAF) – revenues are expected to increase by 5.5 percent, which translates to an annual value of $746,000.

Further details of this assessment may be found in Appendix A.

7.2 Inferring Economic Value for Boating Releases on the Lower Dolores River

In this section, we use economic benefit transfer methods [17] to infer the economic value of water releases from McPhee reservoir for whitewater boating on the Dolores river downstream from McPhee reservoir. To this end we estimate boater user-days from data contained in Bureau of Land Management (BLM) recreational site activity reports for the Dolores River Special Recreational Management Area (SRMA). With an estimate of boater user-days resulting from a rafting water release, we then transfer consumer surplus estimates for a whitewater boating day from a national recreational value database and relate releases, and economic values, to McPhee management and improved instream flow forecasts.

Whitewater Boating the Dolores River Below McPhee

The Dolores Water Conservancy District (DWCD) operates the Dolores Project with the McPhee dam and reservoir serving as the project's primary storage feature. The Dolores river provides project water for irrigation, municipal/industrial use, recreation, fish/wildlife, and hydroelectric power. While DWCD operators have a contractual obligation to provide water for irrigation and municipal/industrial uses, they also must manage flows to maintain wildlife downstream from McPhee Reservoir in the Dolores River.

In years when there is sufficient expected water storage, DWCD operators release water for whitewater rafting and kayaking. These rafting releases are closely followed by the whitewater boating community on account of the river's challenge and the area's spectacular beauty. Boaters have limited access and takeout points where most boaters or on multi-day trips, camping along their journey down the Dolores River. Bradfield boat launch is the first lower Dolores access point from which one can take a one-day trip to Mountain Sheep Point boat launch (19-mile trip) or continue on to Slick Rock, a 47-mile trip from Bradfield. The 47-mile Bradfield to Slick Rock stretch of the river winds through the Ponderosa Gorge with Class IV and Class V rapids during the peak of McPhee releases. Beyond Slick Rock, boaters float 50 miles to Bedrock, passing Gypsum Valley boat launch (14 miles from Slick Rock). Downstream from Bedrock, the Dolores crosses Paradox Valley with the next access out point along the Dolores at Gateway. The San Miguel river flows into the Dolores along this section of the river. With the inflow of the San Miguel, boating on the Dolores is less dependent on water released from McPhee. The BLM classifies the Dolores from McPhee to Bedrock as the Dolores River Special Recreational Management Area (SRMA). For this reason, we limit our analysis to whitewater boating in the Dolores SRMA.

Whitewater Boating Visitor Days Resulting from McPhee Releases

Ideally, we would like to know the number of boating days that result from a typical spill. Our project team obtained BLM reports that contained estimates of site visits and visitor days for six recreation sites that they manage in the Dolores SRMA. The six sites are Bradfield recreation site (boat launch), dispersed use in the Dolores SRMA, Gypsum Valley boat launch, Dolores River Overlook (picnic overlook above the canyon), Mountain Sheep Point recreation site, and Box Elder campground. We assume that dispersed use is non- boating use of the area and therefore not relevant. We also ignore the Dolores River Overlook since this is a picnic area high above the river. Box Elder campground data is not reported for most years and we did not consider it in the analysis. The remaining sites all provide boating access and allow some inference for boating days. The main boating access points in the Dolores SRMA are

Bradfield recreation (mile 0),

Mountain Sheep Point (mile 19),

Slick Rock boat launch (mile 47),

Gypsum Valley boat launch (mile 61), and

Bedrock boat launch (mile 97).

The BLM reports cover the first, second, and the fourth sites. Additionally, we obtained data from the Colorado River Outfitters Association (CROA)[9]. CROA provided boater user day counts by year for trips taken with commercial outfitters for 2001 to 2018. Though commercial trips should be covered in the BLM data, we use the CROA data as a cross check. The full panel of data from the two sources spans 2001 to 2018 and the BLM data additionally includes 2019.

According to McPhee managers, the typical rafting spill lasts 14 days that include two days ramp up and 2 days ramp down. Managers target minimum flows of at least 800 cfs. Using McPhee release data, we counted the number of days in each year when release flows exceeded 800 cfs and classify these days the number of whitewater "boatable" days in a year. Only eight of the nineteen years had boatable days: 2008 (73), 2017 (62), 2005 (41), 2019 (35), 2011 (20), 2009 (15), and 2016 (7).

The boater day counts provided by CROA make sense when contrasted with our boatable day counts. Across the years for which we have data, all the big CROA user day counts are found in our years with non-zero boatable days. CROA reported user days for these spill years ranged from 74 to 936. Five of the seven counts in these spill years exceeded 500. It would be ideal if we had counts for both commercial and private trips but unfortunately, we do not have this and so we infer the impact of spills on site visitor days in a year and then translate those site visitor days into boating user days. It is important to note that the BLM data is more of a rough guess at site visits and visitor days. There are quite a few entries in the reports that appear to be copied from year to year. Later years, post 2007, do not have this pattern and we rely on these later years in deducing boater user days.

Bradfield Recreation site is a logical first site to consider since it is the first boater access point on the lower Dolores. 2019, 2017, and 2016 all had spills. The average number of site visitor days at Bradfield in

[9] http://www.croa.org/wp-content/uploads/2019/05/2018-Commercial-Rafting-Use-Report-1988-2018.pdf

non-spill years post 2007 was 6778.8. The respective increase above this average in BLM visitor day estimates for 2019, 2017, and 2016 were 4447, 6156, and 3945. If we divide each of these increases by the number of spill days that year, we obtain estimates of visitor day increases from the spill per spill day to get 127, 99, and 563. Using the middle estimate from 2019, we would predict 1271 (127x10 days) more site visitor days (i.e., launches) at Bradfield per ten-day spill. Using 2016, the increase is significantly more at 5636 which does not seem reasonable given what see in the data and so we will use the 1271 visitor day increase for the analysis.

Next, we translate this estimated number of launches per 10-day spill into a total number of boating days per spill for those putting in at Bradfield. Boating from Bradfield to Mountain Sheep Point takes a day while boating from Bradfield to Slick Rock takes two to three days and boating from Bradfield to Bedrock takes four to six days. Assuming a third of Bradfield boaters exit Mountain Sheep Point (1 day), a third exit Slick Rock (3 days), and a third exit Bedrock (6 days) we estimate a total of 4,235 boater days for the 10-day spill. Shifting boaters away from the longer trips to shorter trips will obviously lower the estimated boater user days.

Using the same approach, we then estimate the number of boater days for those putting in at Gypsum. The average site visitor days at Gypsum in post 2007 non-spill years was 1167. For 2019, 2017, 2016, the increases in site visitor days were therefore respectively 776, 1758, 340. Scaling by days we get 22, 28, and 48. Gypsum is both an entry and exit point. To make inference about additional boater user days one has to assume the proportion of new visitor days that are entering. For example, using the middle 2017 number, 28, and assuming two thirds of the new users are entering and taking a two-day trip to Slick Rock results in 378 additional boater user days for a 10-day spill. Assuming everyone goes all the way to Bedrock for a 5-day trip we get 945 additional boater user days for a 10-day spill. For the purposes of our analysis, we assume half of those entering the water at Gypsum boat launch paddle to Slick Rock and half go all the way to Bedrock, resulting in 662 additional boater user days for a 10-day spill.

To estimate boater days from the Mountain Sheep Point, we must address an unusual feature in the data. Whereas from 2001 to 2012 the average of annual visitor day estimates is 15,757 with a range from 12,416 to 18,106, from 2013 to 2019 the average is 6108 with a range from 3546 to 9505. For this reason, we only consider the years 2013 to 2019. For these years the average of visitor days for non-spill years is 4258. For 2019, 2017, and 2016 increases above this average are respectively 3496, 4310, and 5147. Scaling by days we get 99.9, 69.5, and 735.2. Like Gypsum, Mountain Sheep Point is both an entry and exit point. Assuming two-thirds enter and go 2 days to Slick Rock using the middle 2019 number, 99.9, adds 1332 additional boater user days. Alternatively, assuming the same boaters go all the way to Bedrock in 5 days adds 3329 boater user days. Therefore, assuming half the boaters entering at Mountain Sheep Point take the 2-day trip and half take the 5-day trip we get an additional 2331 boater user days for a 10-day spill.

Table 7-2 - Estimated Number of Boater Days per 10-Day Spill

Launch Site	Boater Days
Bradfield	4,235
Gypsum	662
Mountain Sheep Point	2,331
TOTAL	7,228

Whitewater Boater Consumer Surplus for 10-Day Spill

When economists refer to the economic value as a whitewater boating day or trip, they are referring to consumer surplus for that day or trip. Consumer surplus is a user's total value for the trip less the cost of the trip. Consumer surplus is a monetary measure of the net benefit or net value for the trip or recreation day. There is a rich literature on the economic value of recreational activities including fishing, hunting, hiking, camping, bird watching, whale watching, and whitewater boating.

In 2016, the USDA Forest Service and the US Environmental Protection Agency funded an effort to create a recreational value database. Oregon State University Professor Randall Rosenberg [18] led this effort and the database is publicly available[10]. These agencies desired such a database so that values for user days could easily be incorporated into economic analyses. The database contains over 3000 user day value estimates for a wide range of activities. In particular, the database contains thirty-four per day value estimates for whitewater boating in the western US.

For benefits transfer, we seek values from studies that are the closest match to whitewater boating on the lower Dolores. In 1987, Bishop et. al published a study that estimated consumer surplus for whitewater boating in the Grand Canyon. The study was part of a large federally funded effort to consider changing flows in the Grand Canyon to improve river ecology and river recreation. Like the lower Dolores, floating the Colorado river through the Grand Canyon involves multi-day trips through scenic river canyon. The recreational database contains 12 boater user day value estimates from the study. The 12 estimates range from **$124 to $426** (2020 inflation adjusted). The wide range of estimates stems from the value for different flow levels. For our purposes we will use the minimum, $124, and the average of the 12 estimates, $278, and the maximum, $426, to create a plausible range of estimates of the value for a 10-day spill.

Total Inferred Boater User Days - 7228

Total Economic Value Using Minimum - $896,272

Total Economics Value Using Average - $2,009,384

Total Economic Value Using Maximum - $3,079,128

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[10] http://recvaluation.forestry.oregonstate.edu/

Our analysis suggests that the economic value generated by a 10-day spill falls in the range of $1M to $2M, giving us a rough idea of the potential benefits associated with a spill.

Inferring Economic Value for Improved Instream Flow Forecasts

DWCD operators' top priorities are to meet the project's contractual obligations to agricultural users, municipal/industrial users, and obligations to maintain lower Dolores river flows for fish populations and river ecology. It is only in years with anticipated yields greater than storage capacity that high flows for whitewater boating spills even potentially occur. The management problem is dynamic since reservoir storage facilitates carryover from one year to the next.

To illustrate one way that things can go wrong, in 2017 there were two whitewater boating spills, one in early May and another in early June. Boaters were happy. Unfortunately, the end of 2017 season flows were down and 2018 was a dry year leading to a short in 2018 early allotment announcement that kept deepening through the season. It was a tough year for producers who pointed to the previous year's spills, especially the spill in June, that could have been carried over into 2018. With perfect foresight, producers could have done considerably better in 2018.

The dynamic complexity of the problem naturally leads to a very conservative management approach to spills. Operators would like to wait as long as possible to make a decision about a spill as more precise forecast information comes in with the passage of time, while boaters would like plenty of advance notice in order to plan multi-week trips. While snow data assimilation methods are genuinely valuable in assessing the state of snowpack at any point in time, the forecast uncertainty that appears to matter the most for McPhee operators in relation to spills are seasonal weather forecasts, particularly those with long forecast windows. Ken Curtis, the DWCD manager, noted that while runoff accounts for around 80% of annual flows on average, weather variability over the season implies considerable volatility of realized flows for the remaining 20%. More precise long window weather forecasts would improve management in general but would likely have a major impact on whitewater boating spills.

Conservative management suggests that better weather forecasts could lead to more spills which provide an economic benefit of $1M to $2M for an additional 10-day spill. But this side of the benefits ledger is only realized in wet years. From the time the project was completed, spills occurred about 68% of the years. Thus, the probability that an improved forecast would matter regarding spill is modest. Additionally, we need to think about how the improvement translates into a change in the number of spill days. Even if the change were significant, the probability weighting suggests that expected benefits for a given year would be below $500,000.

There is another sider to the ledger that relates to the 2017 - 2018 example. A better long window weather forecast might have led to fewer spill days in 2017. The benefit there would be a greater carryover that would have led to increased 2018 agricultural production. Again, the expected value across years for this kind of benefit is modest but for the given year the benefit could be quite large.

8 CONCLUSIONS

Streamflow forecasts are essential for water managers planning reservoir operations and allocating limited storage volumes, for farmers scheduling their planting plan, and for recreational users planning boating trips, amongst other stakeholders. The question is not whether forecasts are of value, but instead what is their marginal value for improvements in forecast quality?

Through several different approaches, we elicited this information – first we applied a gaming approach where system operators at DW were provided with of varying skill levels, and we evaluated how this variation changed potential benefits. Second, we engaged with DWCD using a qualitative approach to assess how decisions are made, how decisions would change with different information, and how those changes would impact a range of stakeholders. Finally, we created an optimization system to evaluate quantitatively how decisions change using variable probabilistic forecast quality. With this information, we can move towards estimating the incremental improvements in economic value from improved forecast skill.

Through the stakeholder elicitation process, our team discovered a few differences between methods with opportunities to improve the effectiveness of each. Again, the gaming approach (Table 8-1) was used with DW, whereas a more qualitative approach was used with DWCD (Table 8-2).

Table 8-1 - Tradeoffs of the scenarios "gaming" approach

Pros	Cons
Provides comparable decisions made for same year with different forecast info (higher # of scenarios)	Time intensive for build out and for players
Test sensitivity and thresh-holds for change vis-a-vis decision-making	Monthly timesteps required to make the game tractable, but operators changing operations weekly / daily in reality
Test the sensitivity or thresholds for decision-making by artificially perturbing or creating the synthetic forecasts. Can ID what the change/improvement would have to be in order to effect a change or improve the decision-making outcome(s)	needs to be simplified to the point that it does not capture the vast majority of the complexity of the decision-making process
Focus on the artificial/synthetic scenarios with the 10% and 30% improvements	Does not include non-numeric information in the decision-making process

Table 8-2 - Tradeoffs for Qualitative approach

Pros	Cons
See value in improving confidence of decision even if it doesn't move the metrics from decisions	Time intensive (either by phone or in person)
Captures the nuances of how decisions are made, more accurate reflection of decision-making process and space	Difficult to test synthetic improvements through dialogue or hypothetical approach
Can ID value of the smaller improvements that will up confidence, but which might not be enough to change key performance metrics	

Improvements in forecasts may not be sufficient to improve decision-making and/or maximize management goals for several reasons:

- The science may not be able to provide forecasts that are improved enough to impact decisions. While a 2% improvement in uncertainty may be feasible and desirable from a scientific or engineering perspective, it is likely to be insufficient for a water manager to realize improvements in management decisions.
- Reservoir operators may prefer to manage conservatively, and this conservative bias may offset forecast improvements. This is especially true in areas such as the DWCD where the 30-year average runoff is greater than the 30-year mean forecast. Conservative management practices may also help reservoir managers keep their jobs by preventing situations in which water deliveries must be reduced over the course of the recreation or planting season.
- Legal mandates and contextual parameters can constrain decision-making flexibility and may outweigh any improvements in forecast information. For example, existing water rights laws, ongoing processes of re-negotiating the Colorado Compact and management of the Colorado River basin, or potential future conservation efforts related to the Endangered Species Act or National Conservation Areas may shift management priorities or targets and negate any additional benefits that could be realized from improved forecast information.

Even with an abundance of information collected around both the water resources management stakeholders and downstream end-users using the elicitation approaches, we were further challenged with creating a fully defined ‘value’, which is not always direct or quantitative. Value may come in the form of trust, may include social benefits for tribal rituals, or can be improved public safety on the rivers. Similarly, it was challenging to determine whether improved forecasts would affect the decision-making process.

Improvements in seasonal volumetric forecasts would have a greater impact on recreational users if there were also improvements in the 10-15-day weather forecasts. Improved understanding of both timing and volume of near-term runoff could *potentially* increase the number of years with boatable flows *if* this information allowed the DWCD to reduce the number of years that they followed a “fill and spill” strategy and could instead concentrate managed releases into a 5+ day managed release while still filling.

There is limited environmental benefit to improved forecasts because no additional water is allocated. Improvements in weather and volumetric forecasts might allow for better management of the Fish Pool, especially as it pertains to releasing water from the dam to improve stream habitat and/or to keep stream temperatures low to coincide with fish spawning and life cycles.

There are additional social benefits to improved forecast information, particularly as it pertains to establishing and maintaining trust between information providers and information users. One of the keys to producing useful information is trust between information providers and users – trust that the information provided is accurate and trust that important information will be communicated.

DWCD and DW trust the CBRFC to provide information both in the form of official forecast information as well as in more tailored briefs and phone call discussions with forecasters specializing in each particular region or watershed. Trust is vital to meeting contractual obligations for water delivery as well as to maintaining good relationships with water users in the agricultural and recreational communities and facilitating ongoing cooperation between these groups. Downstream end-users rely heavily on water managers for information on spills, and it has taken years to build up good working relationships between all levels of stakeholder groups.

More quantitative measures of the impact of improved forecasts can be estimated using optimization methods. The benefit of this approach is that marginal differences in forecast skill can be elicited precisely compared to subjective or qualitative approaches – responses of optimization systems use the information provided resulting in consistent and measurable output. This assessment utilized a Sampling SSDP approach, which can explicitly utilize all forecast ensemble members in the optimization process.

By using a controlled modification of ensemble streamflow forecast bias and dispersion, the direct effects on altered forecast decisions can be determined with the optimization model. The approach determined that improvements of bias were consistently more valuable than reductions in dispersion. Further, perfect foresight in the optimization model produced results consistently near historical performance, indicating that in actual operations, information beyond the ensemble streamflow members (e.g., remotely sensed products, snow stations, weather forecasts, etc.) are utilized. Mimicking the decision-making process in an optimization paradigm is extremely challenging with a range of stakeholders, objectives, and data utilized to inform the operators.

A quantified marginal benefit from improved forecasts with qualitative and quantitative interpretations of value make direct inference a challenge, but it is clear that higher skill forecasts do produce measurable gains in value for water managers and downstream end-users alike. Continued use of NASA remotely sensed products add value directly through the data assimilation process of forecasting models, or through improved weather forecasts, and indirectly through subjective integration by decision-makers. Without this information, poorer decisions would limit the potential value gained through proper management our limited water resources for social, environmental, and economic gain.

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APPENDICES

A. Agricultural Economic Assessment
B. VOI Streamflow Studies Tables
C. List of Interviews and Focus Groups
D. IRB-approved interview questions

Appendix A Agricultural Economics Assessment

A.1 Conceptual Model

To explain and model the behavior of DWCD farmers, we begin by assuming a simple water production (yield response) relationship for alfalfa:

$$y = f(w) \tag{1}$$

where

y = annual alfalfa yield per acre (in tons/acre/year)

w = annual water input per acre (in inches/acre/year)

Importantly, this relationship is assumed to be non-linear, such that the marginal product of water declines and either equals or approaches zero beyond some water input level.

As an example, we can assume the following functional form:

$$y = a - \left(\frac{b}{w}\right) \tag{2}$$

In this case, as shown in **Figure A.1**, the marginal product of water is continually declining (concave) and the parameter ***a*** represents the maximum yield per acre. For added simplicity, all water inputs are assumed to come from irrigation.

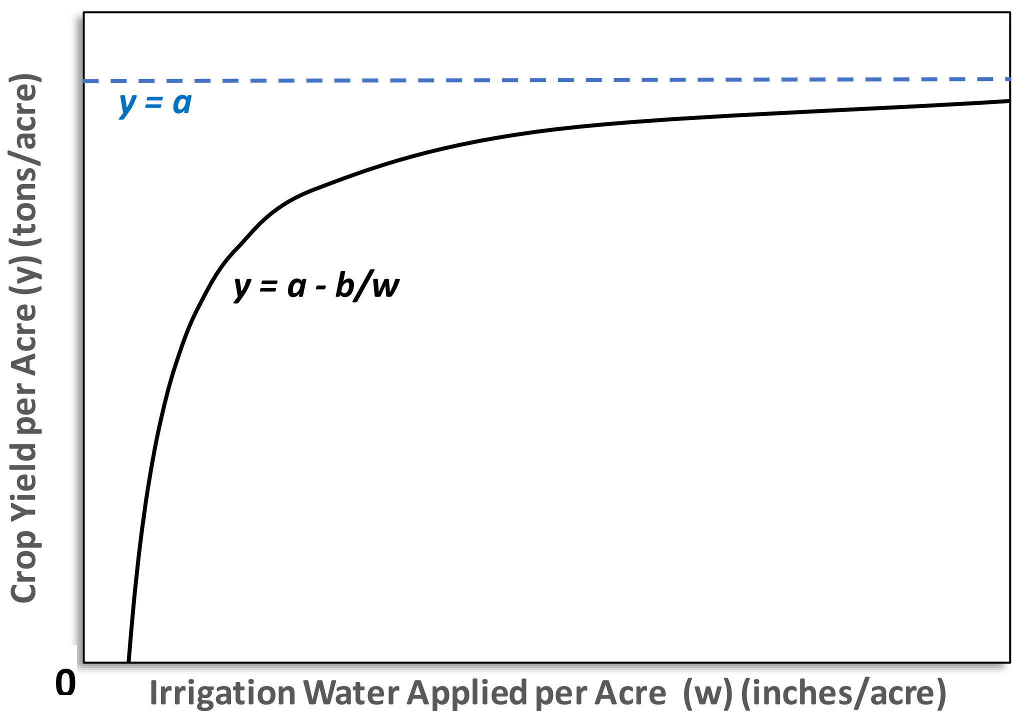

Figure A.1. Example yield-response function for alfalfa production

Each year (*t)*, DWCD project farmers receive a water allocation from the district. For each farmer *i*, this allocation (W_{it}) depends on (1) the number of acres allocated by the project to the farmer for irrigation and (2) the per-acre water allocation delivered to each farmer. This per-acre allocation depends on available water supplies for the year, which are primarily composed of water supplies carried over in the reservoir from the previous year and inflows during the year to the reservoir.

$$W_{it} = \overline{w}_t(C_t, S_t) * A_{it} \tag{3}$$

where

W_{it} = total water allocation for farmer *i* in year *t* (in acre-feet)

$\overline{w}_t$ = per-acre water allocation for all project farmers in year *t* (in inches/acre)

C_t = water stored in the reservoir at the beginning of the year (January) – i.e., carry-over from the previous year (thousands of acre-feet [KAF])

S_t = cumulative April-July stream inflows to McPhee Reservoir (thousands of acre-feet [KAF])

A_{it} = total number of project allocated acres held by farmer *i* in year *t*

The per-acre water allocation in each year, $\overline{w}_t$, is the same for each project acre. Although this allocation $\overline{w}_t$ is determined by the district each year, farmers do not necessarily apply this exact amount to each acre of their land. In some cases, they may only irrigate a fraction of their project acres, and in other cases they may distribute the water to more acres than are allocated by the project.

Therefore, a key early season decision for producers each year is how many acres to plant and irrigate. To model this decision, we begin by assuming that there is no uncertainty regarding water availability for irrigation at the time of the decision. In this case, the farmer is assumed to select the number of acres to irrigate (I_{it}) to maximize total production (Y_{it}), given their known water allocation (W_{it}) and the yield-response relationship *f(w)*.[11]

In other words, their objective function is:

$$\max_{I_{it}} Y_{it} = f\left({}^{W_{it}}/_{I_{it}}\right) * I_{it} \tag{4}$$

For illustration, if we assume the simple yield-response functional form in equation (2), then total alfalfa production for farm *i* can be expressed as:

$$Y_{it} = \left(a - b * \left({}^{I_{it}}/_{W_{it}}\right)\right) * I_{it} \tag{5}$$

A graphical representation of this production function is shown **Figure A.2**. Each curve shown in the graph corresponds with a different water allocation level (W), which is assumed to be exogenous to the farmer's production decision. For each water allocation *W*, alfalfa production *Y* initially increases with the number

[11] The fundamentals conclusions from the model do not change if we instead assume that the farmer's objective is to maximize revenues or profits, by including a known output price per unit and a simple cost structure.

of irrigated acres (I) and then decreases, such that maximum production is achieved at the turning point. For this functional form, alfalfa production is maximized when:

$$I_{it}^*(W_{it}) = \frac{aW_{it}}{2b} \tag{6}$$

In other words, I^*_{it} is the optimal number of acres to irrigate for farm i in year t, given their total water allocation for the year (W_{it}). With perfect information about this water allocation, we expect producers to select this number of acres.

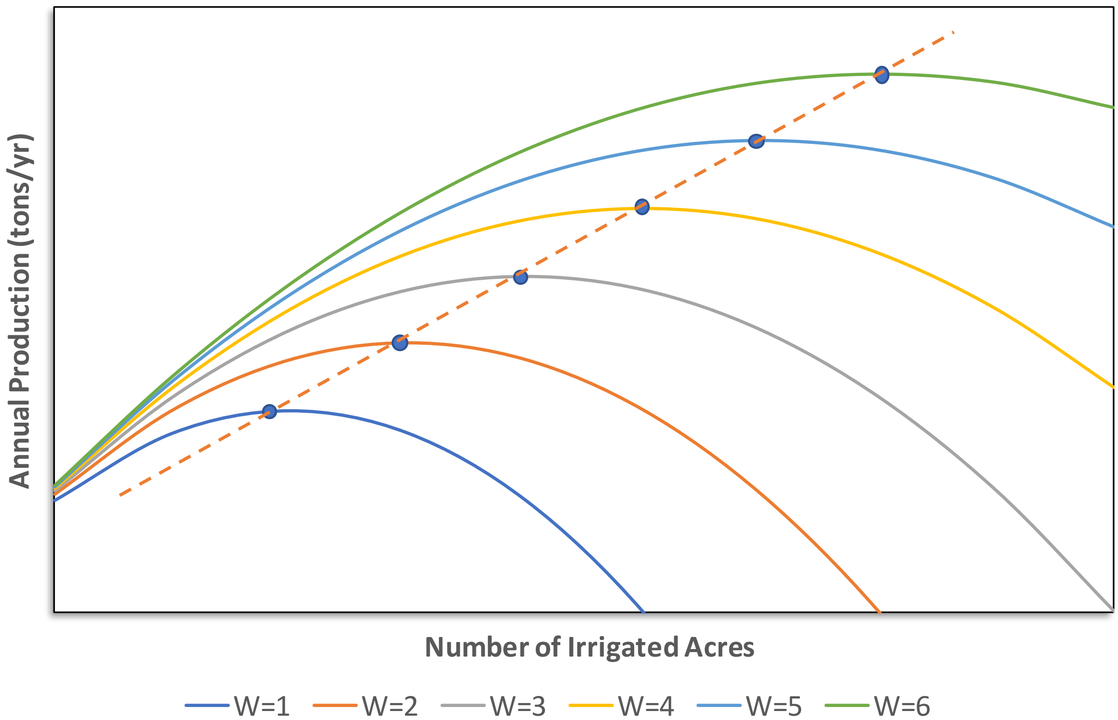

Figure A.2. Representation of alfalfa production in relation to water and land inputs

Similarly, the optimal level of production for farm i in year t can be expressed as the output that corresponds with I^*_{it} (given W_{it})

$$Y_{it}^*(W_{it}) = f\left(W_{it}/I_{it}^*\right) * I_{it}^* \tag{7}$$

For example, If we assume the simple yield-response functional form in equation (2), then optimal alfalfa production can be expressed as:

$$Y_{it}^*(W_{it}) = 0.5 * \left(a^2/2b\right) * W_{it} \tag{8}$$

As shown in Figure A.2, we expect that both the optimal level of irrigated acres (I^*) and the corresponding levels of production Y^* (i.e., the points along the dashed line) to increase with the level of total allocated water W. Moreover, for any given level of W, both increases and decreases in irrigated acres relative to I^* will result in lower levels of production than Y^*.

In practice, alfalfa producers must make decisions about the number of acres to irrigate and cultivate before their final annual water allocation is known. Instead, they must rely on expectations of water allocation $\tilde{w}_t$, which are based, at least in part, on (1) CBRFC streamflow forecasts $\tilde{S}_t$ for inflows to McPhee Reservoir and (2) observed water levels in the reservoir that have been carried over from the previous year. More formally, this can be expressed as follows:

$$\widetilde{W}_{it} = \widetilde{w}_t(\tilde{S}_t, C_t)/12 * A_{it} \tag{9}$$

where

$\widetilde{W}_{it}$ = predicted total water allocation for farmer *i* in year *t* (in acre-feet)

$\widetilde{w}_t(\tilde{S}_t, C_t)$= predicted per-acre water allocation for all project farmers in year *t* (in inches/acre), as function of the streamflow forecast

$\tilde{S}_t$ = CBRFC forecast of cumulative (April-July) stream inflows to McPhee Reservoir (thousands of acre-feet [KAF])

Therefore, when water allocation is not known with certainty, we assume that farmers will select the number of acres to irrigate by replacing W_{it} with $\widetilde{W}_{it}$ in equation (6). Assuming the example yield-response functional form, this means:

$$\tilde{I}^*_{it}(\widetilde{W}_{it}) = \frac{a\widetilde{W}_{it}}{2b} \tag{10}$$

In other words, with imperfect information about water allocation for the year, we expect producers to select this number of acres ($\tilde{I}^*_{it}$). Combining equations (3) and (10), we can express the percent of a farm's project acres that are irrigated as:

$$\frac{\tilde{I}^*_{it}}{A_{it}} = \frac{a * \widetilde{w}_t(F_t, C_t)/12}{2b} * 100 \tag{11}$$

With imperfect information, <u>actual</u> production levels depend on both the predicted water allocation (because this determines the selection of irrigated acreage) and actual water allocation.

$$\tilde{Y}^*_{it}(W_{it}, \widetilde{W}_{it}) = f\left({W_{it}}\Big/{\tilde{I}^*_{it}(\widetilde{W}_{it})}\right) * \tilde{I}^*_{it}(\widetilde{W}_{it}) \tag{12}$$

Importantly, this decision model implies that both over-predictions ($\widetilde{W}_{it} > W_{it}$) and under-predictions ($\widetilde{W}_{it} < W_{it}$) of water allocation will result in lower levels of alfalfa production, compared to a situation with perfect information (i.e., perfect forecasts). This result can be seen in Figure 2, where for any given level of actual water allocation (W), any change in the number of irrigated acres away from the optimal level (peak of the curve) will reduce production levels by moving down the curve to the left or right.

To examine how over- or under-predictions due to imperfect information affect actual production levels, we can decompose actual production with imperfect information as follows:

$$\tilde{Y}^*_{it}(W_{it}, \widetilde{W}_{it}) = Y^*_{it}(W_{it}) - \left[Y^*_{it}(W_{it}) - \tilde{Y}^*_{it}(W_{it}, \widetilde{W}_{it})\right] \tag{13}$$

The first component on the right-hand side of the equation is optimal production with perfect information. When combined with equation (3), this component is ultimately a function of carry-over storage

(C_t), actual inflow volumes (S_t), and the number of project acres (Ai_t). The second component is the difference in optimal production with and without perfect information. This component mainly depends on the difference between $\widetilde{W}_{it}$ and W_{it}, which itself depends primarily on the difference between forecasted inflows ($\tilde{S}_t$) and actual inflows to the reservoir (S_t). In other words, the second component depends on the size of the forecast error.

Using this framework, we can also estimate the value of improved forecast information to alfalfa producers. For simplicity, we will assume that the value alfalfa producer *i* receives from her productive activities (V_{it}) can be measured by the annual revenue she receives from selling her output

$$V_{it} = P_t * \tilde{Y}_{it}^{*}\left(W_{it}, \widetilde{W}_{it}\right) \tag{14}$$

where

P_t = price per unit of alfalfa produced (in $/ton)

In this case, the value of perfect forecast information ($VOPI_{it}$) can be expressed as the increase in value (revenue) received by going from an imperfect forecast (i.e., one with forecast error) to full knowledge of future inflows:

$$VOPI_{it}(S_t, \tilde{S}_t) = P_t * \left[Y_{it}^{*}(W_{it}[S_t]) - \tilde{Y}_{it}^{*}\left(W_{it}[S_t], \widetilde{W}_{it}\left[\tilde{S}_t\right]\right)\right] \tag{15}$$

Similarly, the value of improved forecast information ($VOFI_{it}$) can be expressed as the increase in value (revenue) received by going from one imperfect forecast ($\tilde{\tilde{S}}_t$) to a better, but still imperfect, forecast ($\tilde{S}_t$) -- i.e., one with smaller but non-zero forecast error:

$$VOFI_{it}(S_t, \tilde{S}_t, \check{\tilde{S}}_t) = P_t * \left[\tilde{Y}_{it}^{*}\left(W_{it}[S_t], \widetilde{W}_{it}\left[\tilde{S}_t\right]\right) - \tilde{Y}_{it}^{*}\left(W_{it}[S_t], \widetilde{W}_{it}\left[\tilde{\tilde{S}}_t\right]\right)\right] \tag{16}$$

Importantly, both value of information expressions shown above depend, not only on the forecast information, but also on the actual state of the world they are predicting (in this case, the actual inflow volume S_t).

A.2 Data

A.2.1 Farm Production and Irrigation Data

Data for this analysis were acquired from the DWCD, based on annual crop production reports, which are required by the Bureau of Reclamation for irrigators using project water. The DWCD provided anonymized reports for the period 2002 to 2017. These data are organized by owner and box (a subdivision of an owner's lot), and they include information on irrigation allotments and use, planting/grazing decisions, and a variety of metrics for production.

Over the 16-year period, the dataset contains water use data for 134 distinct owners (i.e., farm ID); however, on a yearly basis, an average of 92 distinct owners are represented in the data. An average of roughly 28,000 acres per year is allocated for irrigation to these farms by the project. Starting in 2006, the data contain more detailed information regarding the specific types of hay produced with project water. From 2006 to 2017, hay production accounted for an average of 79 percent all crop acreage under production, and alfalfa accounted for 62 percent.

Given this dominant use of DWCD water, our analysis focuses on hay and alfalfa production. We focus specifically on alfalfa for years when data are available (2006-2017); however, to take advantage of the four additional years of data (and to evaluate the robustness of our findings), we also broaden the analysis to include all hay production from 2002 to 2017. Because the number of irrigated acres in each year is reported at the box level, and because each box in each year is associated with a single crop, we first selected all the boxes in each year associated with hay production (N=4,406). For 2006-2017, we further narrowed this selection to focus on those associated with alfalfa production (N=2,332).

One of the limitations of the data in this form (at the box level) is that the number of acres allocated by the project to the farm (referred to as A_{it} in the conceptual model) – which is a key determinant the total water allocation to the farm (W_{it}) each year – is not reported at this level of disaggregation. Instead, the number of project-allocated acres is specified for *groups* of boxes within each farm, which we refer to as "box groups." Given this data limitation, we grouped and aggregated all selected data to the box group level. Therefore, in the empirical analysis, the subscript *i* refers to box groups, rather than entire farms or individual boxes.

Table A.1 summarizes the available data for box groups with hay production. The number of box groups varies by year, from a minimum of 91 in 2014 and 2015 to a maximum of 101 in 2007. Over the full period, 117 distinct farm IDs are represented in the data.[12] It is important to note that these data represent box groups where hay production occurred during the year, but not necessarily <u>only</u> hay production. Therefore, there is a difference between the total number of acres irrigated in these box groups (i.e., for all crops) and the number of acres used for hay production. Across all years, the average number of project-allocated acres per box group is 275.2 acres, average number of irrigated acres is 248.2 acres, and the average number of acres in hay production is 210.5 acres. It is also important to note that the data are not identified in a way that allows individual box groups to be tracked across years. As a result, the data cannot be treated or analyzed as a longitudinal panel of box groups. However, in each year, each box group is linked to a single farm ID, and these IDs can be tracked over time.

Table A.2 summarizes the data for box groups with alfalfa production. The number of box groups in this case varies from a minimum of 70 in 2015 to a maximum of 85 in 2007. Although 85 distinct farm IDs are represented in the data across all year, the number of farms with alfalfa production declines from 69 in 2006 to 54 in 2017. Across all years, the average number of project-allocated acres per box group is 315.2 acres, the average number of irrigated acres is 287.9 acres, and the average number of acres in alfalfa production is 203.6 acres.

[12] Six outliers, defined as box groups with a number of irrigated acres that is more than double the number of allocated acres, are removed from these data.

Table A.1. Summary Statistics for Box Groups with Hay Production (2002 – 2017)

Year	Variable	N	Mean	Std. Dev.	Min	Max
2002	All allocated acres	97	273.7	260.0	6.2	1,300.6
	All irrigated acres	97	217.1	216.7	6.2	852.5
	Hay production acres	97	201.5	201.6	6.2	809.0
	Hay produced (tons/yr)	97	389.5	396.3	1.8	1,751.0
2003	All allocated acres	100	266.3	243.4	2.6	997.7
	All irrigated acres	100	236.0	227.1	2.6	958.3
	Hay production acres	100	199.5	201.5	2.6	958.3
	Hay produced (tons/yr)	100	616.4	697.1	7.7	3,453.5
2004	All allocated acres	94	275.4	246.9	11.2	902.7
	All irrigated acres	94	249.0	228.2	0.0	910.0
	Hay production acres	93	197.4	187.3	7.0	831.3
	Hay produced (tons/yr)	94	731.2	806.2	0.0	4,123.3
2005	All allocated acres	98	269.4	251.8	11.2	1,317.5
	All irrigated acres	98	245.2	232.6	7.0	1,206.4
	Hay production acres	98	205.4	204.8	7.0	925.4
	Hay produced (tons/yr)	98	727.5	868.7	0.0	4,150.7
2006	All allocated acres	96	270.3	256.0	4.4	1,131.5
	All irrigated acres	96	251.3	243.1	5.0	1,127.0
	Hay production acres	96	228.8	221.2	3.0	907.0
	Hay produced (tons/yr)	96	877.1	961.4	1.2	4,549.0
2007	All allocated acres	101	266.1	237.3	5.5	891.0
	All irrigated acres	101	246.0	224.2	3.0	805.0
	Hay production acres	101	212.0	197.4	3.0	770.0
	Hay produced (tons/yr)	101	793.4	835.9	0.0	3,676.0
2008	All allocated acres	100	268.2	237.4	5.5	891.0
	All irrigated acres	100	247.9	224.5	3.0	805.0
	Hay production acres	100	213.6	197.7	3.0	770.0
	Hay produced (tons/yr)	100	799.9	837.0	0.0	3,676.0
2009	All allocated acres	99	261.1	251.3	5.5	1,131.5
	All irrigated acres	99	245.3	239.6	5.0	1,080.0
	Hay production acres	99	209.6	207.5	3.0	932.0
	Hay produced (tons/yr)	99	842.5	948.0	7.4	4,320.0
2010	All allocated acres	98	269.1	243.7	5.5	920.9
	All irrigated acres	98	254.8	234.0	5.0	932.0
	Hay production acres	98	212.2	192.8	3.0	867.0
	Hay produced (tons/yr)	98	850.6	884.5	12.0	4,530.6
2011	All allocated acres	94	278.7	263.7	5.5	1,035.8
	All irrigated acres	94	263.1	245.4	5.5	1,000.0
	Hay production acres	94	215.0	210.6	3.0	891.0
	Hay produced (tons/yr)	94	844.2	961.6	0.0	4,659.8
2012	All allocated acres	97	274.2	259.5	5.5	937.6
	All irrigated acres	97	253.6	246.4	1.5	1,012.0
	Hay production acres	96	226.4	221.2	1.5	932.0
	Hay produced (tons/yr)	96	862.1	1049.7	0.0	5,287.4

Year	Variable	N	Mean	Std. Dev.	Min	Max
2013	All allocated acres	93	286.9	257.1	6.2	946.1
	All irrigated acres	93	222.6	219.0	0.0	941.7
	Hay production acres	92	193.8	196.2	6.2	871.7
	Hay produced (tons/yr)	93	263.6	295.9	0.0	1,537.9
2014	All allocated acres	91	294.3	258.0	6.2	946.1
	All irrigated acres	91	272.1	246.2	6.2	1,061.0
	Hay production acres	91	228.0	220.5	6.2	928.7
	Hay produced (tons/yr)	91	665.7	780.3	1.3	3,890.1
2015	All allocated acres	91	277.9	249.5	6.2	1,087.1
	All irrigated acres	91	246.0	224.1	6.2	1,060.0
	Hay production acres	91	204.6	192.3	6.2	853.0
	Hay produced (tons/yr)	91	776.3	930.7	0.0	4,247.5
2016	All allocated acres	96	286.8	268.2	6.2	1,384.9
	All irrigated acres	96	255.7	239.6	6.2	1,260.0
	Hay production acres	96	206.5	211.0	6.2	1,260.0
	Hay produced (tons/yr)	95	834.7	1081.5	0.0	6,507.8
2017	All allocated acres	93	289.2	265.3	6.2	1,384.9
	All irrigated acres	93	268.4	247.7	6.2	1,245.0
	Hay production acres	93	214.5	212.7	6.2	1,245.0
	Hay produced (tons/yr)	92	772.3	940.8	0.0	5,937.2

Table A.2. Summary Statistics for Box Groups with Alfalfa Production (2006-2017)

Year	Variable	N	Mean	Std. Dev.	Min	Max
2006	All allocated acres	84	297.4	262.0	11.2	1,131.5
	All irrigated acres	84	278.1	248.0	7.0	1,127.0
	Alfalfa production acres	84	209.5	193.7	7.0	832.0
	Alfalfa produced (tons/yr)	84	844.0	920.5	22.5	4,286.5
2007	All allocated acres	85	298.9	243.0	5.5	891.0
	All irrigated acres	85	277.3	229.3	3.0	805.0
	Alfalfa production acres	85	214.2	182.5	3.0	770.0
	Alfalfa produced (tons/yr)	85	826.9	804.4	0.0	3,676.0
2008	All allocated acres	84	301.8	242.8	5.5	891.0
	All irrigated acres	84	280.0	229.3	3.0	805.0
	Alfalfa production acres	84	216.1	182.7	3.0	770.0
	Alfalfa produced (tons/yr)	84	835.1	805.1	0.0	3,676.0
2009	All allocated acres	79	303.8	261.8	5.5	1,131.5
	All irrigated acres	79	286.5	249.0	5.0	1,080.0
	Alfalfa production acres	79	206.9	187.8	5.0	932.0
	Alfalfa produced (tons/yr)	79	862.0	898.8	7.4	4,320.0
2010	All allocated acres	83	302.3	248.7	5.5	920.9
	All irrigated acres	83	287.6	238.2	5.0	932.0
	Alfalfa production acres	83	193.2	176.5	5.0	867.0
	Alfalfa produced (tons/yr)	83	807.7	843.8	14.4	4,530.6

Year	Variable	N	Mean	Std. Dev.	Min	Max
2011	All allocated acres	75	327.7	273.2	5.5	1,035.8
	All irrigated acres	75	308.8	253.8	5.5	1,000.0
	Alfalfa production acres	75	207.5	197.2	5.5	773.0
	Alfalfa produced (tons/yr)	75	842.0	928.8	0.0	4,363.8
2012	All allocated acres	77	322.6	268.2	5.5	937.6
	All irrigated acres	77	299.4	254.9	5.5	1,012.0
	Alfalfa production acres	77	207.3	208.9	5.5	886.9
	Alfalfa produced (tons/yr)	77	805.2	960.9	0.0	5,287.4
2013	All allocated acres	79	319.9	262.5	6.2	946.1
	All irrigated acres	79	248.9	226.5	6.2	941.7
	Alfalfa production acres	79	181.9	190.8	6.2	871.7
	Alfalfa produced (tons/yr)	79	230.7	258.7	0.0	1,275.6
2014	All allocated acres	76	329.3	264.6	6.2	946.1
	All irrigated acres	76	301.8	255.2	6.2	1,061.0
	Alfalfa production acres	76	197.8	216.1	6.2	928.7
	Alfalfa produced (tons/yr)	76	600.2	781.5	1.3	3,890.1
2015	All allocated acres	70	324.0	255.0	6.2	1,087.1
	All irrigated acres	70	286.8	233.5	6.2	1,060.0
	Alfalfa production acres	70	195.7	193.2	6.2	853.0
	Alfalfa produced (tons/yr)	70	780.5	935.6	3.0	4,247.5
2016	All allocated acres	74	333.3	279.9	6.2	1,384.9
	All irrigated acres	74	297.2	251.8	6.2	1,260.0
	Alfalfa production acres	74	198.9	207.4	6.2	1,190.0
	Alfalfa produced (tons/yr)	74	845.9	1039.0	0.0	6,303.0
2017	All allocated acres	75	329.2	272.3	6.2	1,384.9
	All irrigated acres	75	307.5	253.6	6.2	1,245.0
	Alfalfa production acres	75	212.2	208.5	6.2	1,175.0
	Alfalfa produced (tons/yr)	75	817.7	957.3	0.0	5,791.6

A.2.2 Hydrologic Data

To analyze irrigation and production decisions for project farmers, we acquired two main types of hydrologic data for McPhee Reservoir. First, we acquired historical data from the DWCD on actual reservoir storage levels for the period of interest. Second, we acquired historical water supply forecast and observed inflow data from the CBRFC. These data are summarized in **Table A.3.**

The first main indicator of actual water availability in each year is the volume of water stored in the reservoir at the beginning the year (i.e., carried over from the previous year). From 2002 to 2017, the volume varied from as little as 5 KAF at the beginning of 2003 to as much as 147 KAF in 2006, with an overall average of 86 KAF. The second main indicator is the total accumulated inflow to the reservoir from January 1 to August 1 each year. These inflow volumes ranged from a minimum of 45 KAF in 2002 to a maximum of 423 KAF in 2005, with an average of 218 KAF. Over a longer historical period extending back to 1981, the average observed annual inflow has been closer to 300 KAF.

For predicted water availability in each year, we use CBRC forecasts as the main indicators. For each year, we selected four forecasts of the total inflow volume to the reservoir from April to July. The four selected forecasts are those published on the first day of the months of January, February, March, and April. More specifically, we used the “50% exceedance probability” (P50) forecasts from each date. As shown in Table A.3, the average forecasts for the 16-year study period are similar across the four forecast dates, but they vary considerable from year to year.

The last four columns of Table A.3 report the forecast errors for each date and year. These errors are calculated as the difference between the forecast and the observed accumulated inflow volume for the year in question. Over the study period, there are both positive errors – i.e. over-predictions of inflows – and negative errors, but positive are more common. On average, the January, February, and March forecasts overpredicted actual inflows by 50 to 60 KAF, and the April forecast overpredicted by 21 KAF.

Table A.3. Summary Statistics for McPhee Reservoir Inflows and Inflow Forecasts 2002-2017

Year	Reservoir carryover (KAF)	Total April-July Inflow (KAF)	Reservoir Inflow Forecast (KAF)				Forecast Error (KAF)			
			1-Jan	1-Feb	1-Mar	1-Apr	1-Jan	1-Feb	1-Mar	1-Apr
2002	54	45	199	157	120	108	154	112	75	63
2003	5	146	240	191	206	201	94	44	60	55
2004	22	200	258	263	277	208	58	63	78	9
2005	55	423	262	337	358	364	-162	-86	-65	-59
2006	147	145	210	197	154	192	64	52	9	46
2007	119	205	292	252	246	205	88	47	41	0
2008	136	375	326	434	521	464	-49	60	146	89
2009	133	255	326	304	289	230	71	49	34	-25
2010	107	247	235	247	247	247	-12	0	0	0
2011	125	267	316	275	252	195	49	8	-15	-72
2012	142	111	248	249	243	174	137	138	132	63
2013	43	87	160	170	148	122	73	83	61	35
2014	22	173	316	287	281	268	143	114	108	95
2015	34	226	282	263	268	197	56	37	42	-29
2016	91	241	350	386	292	241	109	145	51	0
2017	143	346	269	444	473	411	-77	98	127	65
Average	86	218	268	278	273	239	50	60	55	21
Min	5	45	160	157	120	108	-162	-86	-65	-72
Max	147	423	350	444	521	464	154	145	146	95
% >0							75%	88%	81%	56%

A.3 Model Results

Based on the previously described conceptual model, the first step in our analysis is to examine whether and to what extent there is evidence that inflow forecasts affect irrigation decisions. Specifically, for each box group in our dataset, we calculate the ratio of the number of acres irrigated to the number of project allocated acres. It is important to note that, because of the way the data are reported, the box groups analyzed include irrigation for other crops besides hay and alfalfa, but hay and alfalfa account for a majority of the acreage in these selected groups. Based on equation (11), we then regress this ratio on both observed and predicted measures of water availability.

Table A.4 reports ordinary least squares (OLS) regression results for the sample of box groups with hay production (2002-2017). The dependent variable, which is irrigated acres expressed as a percentage of allocated acres, ranges from 0 to 200 percent, with a mean value of 90.5 percent. Values greater than 100 percent are possible for box groups in farms that have more land than is allocated for irrigation by the project. A separate regression was run for each of the four monthly forecasts due to high correlation between them.

Table A.4. OLS Regression Models for Percent of Allocated Acres that are Irrigated (Farm Blocks with Hay Production, 2002-2017)

Variable	January 1 Forecast		February 1 Forecast		March 1 Forecast		April 1 Forecast	
	coeff		coeff		coeff		coeff	
Intercept	71.568	***	81.444	***	82.898	***	83.238	***
	(25.83)		(41.14)		(51.35)		(52.97)	
Reservoir carry-over	0.029	***	0.029	***	0.033	***	0.034	***
	(2.51)		(2.49)		(2.91)		(3.03)	
Reservoir inflow forecast	0.061	***	0.024	***	0.017	***	0.018	***
	(6.06)		(3.64)		(4.43)		(4.37)	
R-squared	0.0348		0.0204		0.0194		0.0187	
N observations	1,538		1,538		1,538		1,538	
N farms	117		117		117		117	

t-statistics in parentheses, based on robust standard errors, clustered by farm ID
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Although the overall explanatory power of the regressions is low, with R-squares 0f 0.04 and less, we do find that statistically significant effects for the two explanatory variables included. In each regression, both the carry-over storage from the previous year and the forecast inflow for the current year have positive and significant effects on the percentage of land irrigated. The coefficients on the carryover variable suggest that each 100 KAF increase in carry-over from the previous year increases the percent of allocated acres that are irrigated by between 2.9 and 3.4 percentage points. As for the effects of the inflow forecasts, the regression using the January forecast has the highest coefficient. It implies that a 100 KAF increase in the forecast increases the percent irrigated by an expected 6.1 percentage points, compared to between 1.7 and 2.4 percentage points for the other three forecasts.

Table A.5 reports OLS regression results for the smaller sample of box groups that specifically include alfalfa production. As previously discussed, this narrower focus also reduces the timeframe of the analysis to the period 2006 to 2017. The results are similar regarding the sign and statistical significance of the variables, but with a few differences. The effect of reservoir carryover is larger in this subsample, such that a 100 KAF increase would augment the percent of allocated acres that are irrigated by between 6 and 7 percentage points. The estimated effects of inflow forecasts are more varied across regressions, ranging from a 4.6 percentage point effect per 100 KAF increase for the January forecast to less than 1 percentage point for the March forecast. The regression using the February forecast does not find a statistically significant effect for the forecast variable.

Table A.5. OLS Regression Models for Percent of Allocated Acres that are Irrigated (Farm Blocks with Alfalfa Production, 2006-2017)

Variable	January 1 Forecast		February 1 Forecast		March 1 Forecast		April 1 Forecast	
	coeff		coeff		coeff		coeff	
Intercept	72.336	***	81.298	***	82.656	***	82.642	***
	(22.53)		(34.29)		(42.08)		(41.85)	
Reservoir carry-over	0.067	***	0.064	***	0.065	***	0.064	***
	(4.77)		(4.12)		(4.37)		(4.27)	
Reservoir inflow forecast	0.046	***	0.014		0.009	*	0.011	***
	(4.27)		(1.62)		(1.91)		(2.07)	
R-squared	0.0459		0.0318		0.0306		0.0310	
N observations	941		941		941		941	
N farms	84		84		84		84	

t-statistics in parentheses, based on robust standard errors, clustered by farm ID
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In general, these findings support the expected relationship between actual and predicted water supplies and the size of the area selected for irrigation. Given this finding, the next step is to examine whether and to what extent measures of water availability, based on both observed and forecast reservoir conditions, have an effect on hay and alfalfa production levels. In particular, we estimate regressions that are based on equation (13) in the conceptual model.

Table A.6 reports OLS regression results for the box groups with hay production. As in the previous analyses, we run separate regressions for each of the four monthly forecasts. The dependent variable in each case is the natural log of total hay production (in tons) by the box group in that year, and the first explanatory variable is the natural log of the number of project-allocated acres for the box group. The logarithmic transformation of these variables is used to address the rightward skewness of their distributions. The number of project-allocated acres is included in the regression because it is one of the main determinants of the box group's total water allocation (equation [3]) and an indicator of the size of the farm unit. The coefficient (i.e., elasticity) estimates for this variable, are consistently positive and statistically significant, and indicate economies of scale – i.e., a 1 percent increase in project allocated acres is expected to increase output by 1.2 percent. The next two explanatory variables are measures of actual water availability, which are also key determinants of the box group's total water allocation.

Table A.6. OLS Regression Models for Log (Annual Hay Production [tons/yr]) by Farm Block (2002-2017)

Variable	January 1 Forecast		February 1 Forecast		March 1 Forecast		April 1 Forecast	
	coeff		coeff		coeff		coeff	
Intercept	-1.417	***	-0.835	**	-1.029	***	-1.107	***
	(-3.74)		(-2.45)		(-3.04)		(-3.1)	
Log(Allocated acres)	1.237	***	1.241	***	1.239	***	1.238	***
	(20.53)		(20.79)		(20.72)		(20.73)	
Reservoir carry-over	0.0026	***	0.0033	***	0.0028	***	0.0031	***
	(3.44)		(4.44)		(3.61)		(4.24)	
Total reservoir inflow April-July	0.0024	***	0.0006		0.0015	**	0.0009	*
	(2.75)		(1.01)		(2.56)		(1.87)	
Size of inflow over-forecast	0.001		-0.004	***	-0.003	***	-0.001	
	(0.73)		(-3.86)		(-4.9)		(-1.08)	
Size of inflow under-forecast	-0.003	*	-0.001		-0.004		0.001	
	(-1.94)		(-0.6)		(-1.28)		(0.67)	
R-squared	0.4512		0.4544		0.4533		0.4504	
N observations	1,541		1,541		1,541		1,541	
N farms	116		116		116		116	

t-statistics in parentheses, based on robust standard errors, clustered by farm ID
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Both carryover storage from the previous year and total observed inflow to the reservoir during the year have positive and mostly significant effects. The coefficients for the carryover volume suggest that each 10 KAF increase is expected to increase production by about 3 percent. The coefficients for actual inflows are more varied across regressions. This variation is most likely due to variation in the level of statistical correlation between the actual inflow variable and the forecast error variables, which are generally highest in January and lowest in March. In the regression including the March forecasts, each 10 KAF increase in actual inflow is estimated to increase production by about 1.5 percent.

The last two variables are measures of forecast error. They take the forecast error values reported in the last four columns of Table A.3 and separate the “over-forecasts” (positive values in the table) from the “under-forecasts.” The over-forecast value is equal to forecast error if the forecast error is positive, and it is otherwise equal to zero. The under-forecast value is equal to the *absolute value* of the forecast error if the forecast error is negative, and it is otherwise equal to zero. In other words, both measures have positive or zero value, and both are expected to have a negative effect on total yield.

We find that the size of the over-forecasts in February and March have negative and statistically significant effects on hay production. The April over-forecast also has a negative effect, but it is not significant, and the January over-fast is positive but not significant. For the under-forecasts, we only find that the January under-forecast has a statistically significant (but only at a 0.1 percent level) and negative effect. The effects are negative but not significant for the February and March forecasts and positive but not significant for the April forecast.

Therefore, the results provide evidence that, controlling for farm size and actual water supplies, over-forecasts (which were more common than under-forecasts during the study period) have had a negative effect on total hay production. The size of the coefficients for the February and April over-forecasts suggest that each 10 KAF increase in the over-forecast decreases output by 3-4%. The evidence regarding under-forecasts is less conclusive. The coefficient for the January forecast suggests that a 10 KAF increase in the size of the under-forecast reduces output by about 3 percent; however, this robustness of this finding is not supported by similar estimates from the regressions using the other monthly forecasts.

Table A.7 reports results for a similar regression analysis using data from the box groups with alfalfa production, which again is restricted to the years with available data (2006-2017). The overall findings regarding the effect of the number of project-allocated acres is similar to the hay production model, with statistically significant elasticity estimates of 1.2 in each regression. The effect of carry-over is also consistently positive and significant, but with larger estimated coefficients, suggesting that each 10 KAF increase in carry-over volume increases alfalfa production by about 6-7 percent. The effect of actual reservoir inflows is also consistently positive and significant; however, as in the hay production model, the magnitude of the estimated coefficient varies across models. Again, the lowest correlation between actual inflows and forecast errors in the March regression, which indicates that each 10 KAF increase in actual inflow volume increase output by 2 percent.

Table A.7. OLS Regression Models for Log (Annual Alfalfa Production [tons/yr]) by Farm Block (2006-2017)

Variable	January 1 Forecast		February 1 Forecast		March 1 Forecast		April 1 Forecast	
	coeff		Coeff		coeff		coeff	
Intercept	-2.123	***	-1.301	***	-1.446	***	-1.452	***
	(-4.09)		(-2.7)		(-3.12)		(-3.13)	
Log(Allocated acres)	1.204	***	1.203	***	1.204	***	1.200	***
	(14.11)		(14.1)		(14.13)		(14.05)	
Reservoir carry-over	0.007	***	0.006	***	0.006	***	0.006	***
	(7.13)		(6.59)		(6.75)		(6.47)	
Total reservoir inflow April-July	0.004	***	0.001	*	0.002	***	0.001	**
	(4.02)		(1.71)		(3.33)		(2.2)	
Size of inflow over-forecast	0.000		-0.003	***	-0.004	***	-0.003	***
	(0.3)		(-2.85)		(-5.24)		(-2.92)	
Size of inflow under-forecast	-0.013	***	0.000		-0.025	**	0.000	
	(-5.4)				(-2.12)		(0.01)	
R-squared	0.4827		0.4779		0.4835		0.478	
N observations	945		945		945		945	
N farms	84		84		84		84	

t-statistics in parentheses, based on robust standard errors, clustered by farm ID
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In these regressions, the size of over-forecasts for inflows has a consistently negative and significant estimated effect on alfalfa production, except for the regression using the January forecast (no effect). As in the hay production model, the size of the significant coefficient estimates suggests that each 10 KAF increase in the over-forecast decreases output by 3-4%. The under-forecasts are found to have negative and statistically significant effects on production for the regressions using the January and April forecasts. However, the magnitudes of these coefficients are very high.

These results provide further evidence that forecasts errors have an overall negative effect on production, in this case specifically on alfalfa production. This evidence is generally more consistent and robust for over-forecasts, but the results for the under-forecasts suggest similar effects.

Given these estimates, we can also estimate the effect of forecast errors on alfalfa revenues, and we can estimate the value of information associated with perfect and improved forecasts. To do this, we used data from the USDA National Agricultural Statistics Service (USDA NASS) [13] to obtain an average estimate of $225 per ton Colorado alfalfa hay prices in recent years.

Over the 2006-2017 study period, annual alfalfa production in the study area has averaged 60,146 tons per year. As shown in Table A.3, the average March 1 forecast error for April-July inflows has been positive (over-forecast) at 55 KAF. Based on the regression results in Table A.7, reducing an over-forecast of 55 KAF to zero (i.e., to a perfect forecast) is expected to increase by annual alfalfa production by 24 percent (i.e. 14,400 tons). Assuming a price of $225, for a typical year, this translates to a VOPI equal to an increase in revenue of $3.2 million. Based on the regression results, we can also estimate the value of improved (but not necessarily perfect) forecast information. For example, reducing an over-forecast of 55 KAF by 25% (13.75 KAF) is expected to increase revenues by 5.5 percent, which translated to a value of $746,000.

[13] https://downloads.usda.library.cornell.edu/usda-esmis/files/c821gj76b/9019sk86q/fn107g042/agpr0220.pdf

Appendix B VOI Streamflow Studies Tables

Background on the Value of Information from Streamflow Forecasts: Conceptual Model and Review of the Literature

To address the fundamental research question of this project – what are the socioeconomic impacts of decisions based on improved streamflow forecasts? – it is useful to begin by defining a conceptual framework for valuing forecasts. The framework can then be used as a framework for reviewing and summarizing the current state of knowledge regarding the magnitude and determinants of these values.

In short, the value offered by streamflow forecasts is derived from the information they provide to decision makers. This information has the potential to improve the choices they make. Therefore, to assess the economic value of streamflow forecasts, we rely on a value of information (VOI) approach. The basic principles of this approach date back several decades (Howard, 1966); however, it has evolved and been increasingly used in environmental, health, and earth science applications (Adams et al., 2013; Laxminarayan and Macauley, 2014). The VOI approach focuses on decision making under uncertainty –i.e., when future conditions that will affect the outcome of a decision are out of the control of the decision maker and not known with certainty. It examines how information changes the choices made by decision makers, and how the outcomes of these choices depend on both the choices made and the conditions that end up occurring.

In the VOI framework, the level of well-being achieved by a decision maker is typically represented by a utility function, such as the following.

$$U = U(D,S)$$

This function says that the well-being/utility (*U*) realized by a decision maker depends on (1) the state of the world that occurs (*S*) after a decision is made and (2) the actions (*D*) taken by the decision maker before the state of the world is known. Depending on the context, U can be expressed in monetary terms (i.e., dollar benefits) or in other units that are relevant indicators of the decision makers well-being.

For example, the decision context could involve an individual whose choice *D* is whether to book a non-refundable rafting trip on a river. The state of the world *S* that is unknown at the time of the decision is the streamflow on the day of the trip. The level of utility realized depends on both the choice made and the streamflow conditions that occur on the day of trip.

Because *S* is not known with certainty at the time of the decision, the decision maker is assumed to be guided by an *expected* utility function such as the following.

$$EU = E(D, F)$$

This function represents the level of utility that the decision maker expects to achieve based on (1) *information* about the future state of the world (*F*) at the time of the decision and (2) the action taken before the state of the world is known (*D*).

In the example of the river rafter, the information *F* could be a streamflow forecast for the day of the trip. The expected level of utility depends on the combination of the choice made and the forecast.

The decision maker is therefore assumed to choose the action *D* that maximizes *EU*, given the information available. In other words, their **objective function** is to maximize EU, given the information available (and other relevant constraints on their behavior). This a priori optimal decision (*D**) can be represented by a **decision function**, such as:

$$D^* = D(F)$$

In the example of the river rafter, the decision function could be used to predict, for any streamflow forecast, what the rafter's choice would be.

This same decision function can then also be used to determine the action that *would be* optimal if the state of the world were known (D**). In other words, knowing S after the fact, the ex post optimal decision can be represented as:

$$D^{**} = D(F{=}S)$$

Given these components, the value of new or improved information can be assessed by analyzing the change in the utility level attained with the information. One simple example is the ex post value of perfect information (VOPI). That is, how much better off would the decision maker be if she had known S with certainty (i.e., with a perfect forecast of F=S) , compared to a situation where information was not perfect (F≠S).

$$VOPI\ (F, S) = U(\ D[S], S) - U(\ D[F], S) = U(D^{**},S) - U(D^{*},S)$$

Importantly though, ex post VOPI can only be evaluated after the fact, when S is known with certainty; therefore, it depends on the realization of S. In addition, it only has a positive value if the decision would have been different with less than perfect information. In the example of the river rafter, if the ex post optimal decision (D**) would have been to book the trip, but the decision with an imperfect forecast was to not book, the VOPI is the benefit that would have been received from a rafting trip with good streamflow conditions. If the opposite is true, and the rafter books a non-refundable trip that cannot happen because of poor streamflow conditions, then VOPI is the cost of booking the trip, which could have been avoided.

The same basic approach can be used to specify the ex post value of improved (but not perfect) information. In this case, one compares one type of imperfect information (*F1*) with better information that is still not perfect (*F2*)

$$VOII\ (F1, F2) = U(\ D[F2], S) - U(\ D[F1], S)$$

Although useful as a starting point for valuing information, VOPI and VOII measures have inherent limitations. First, they only provide values for a single combination the actual state of the world (S) and the predicted value with imperfect information (F). In practice, to achieve a more comprehensive understanding of a prediction/forecast model, one must estimate VOPI and VOII for a large number of relevant combinations of S and F.

Second, it is often more important and relevant to assess the value of information from an ex ante perspective – i.e., to measure *expected* value of information (EVOI). In other words, what is the maximum amount decision makers would be willing to pay for the information (given uncertainty about the future state *S* of interest)? In this case, the simple VOPI and VOII functions need to be expanded to address the range of potential states of the world and their associated probabilities, as well as the probabilities of different information, conditional on each of those states. As a result, the computational requirements for full scale ex ante VOI analyses can become substantial.

Given this conceptual framework and to establish a baseline for our study, we conducted a detailed search of the published literature for studies that have applied a VOI approach to estimate values for streamflow forecasts. Based on this search we identified ten main studies of interest, all published over the period 1995 to 2018. The study area, methods, and key findings of each study is summarized in a standardized format in Table B.1. Six of the studies were conducted in the U.S. (five in West Coast states and one in the Missouri River Basin), two in Canada (Quebec), and two in Europe (Norway and Spain). Snowpack is a significant contributor to streamflows in all the areas analyzed.

The ten selected studies examine a variety of different decision contexts and objectives; however, all but one study focus on reservoir operation decisions, especially with respect to maximizing hydropower generation or revenues (six studies). Other objectives include managing flows and reservoir levels for recreation, agriculture, water supply, and environmental flows. The key decision (control) variable for all the reservoir operation studies is the quantity of water released; however, the time frame for these decisions varies substantially across studies from very short term (hourly or daily) to monthly or seasonal releases. The other study (Matte et al., 2017) focuses on short-term (daily) emergency management decisions in the context of flood mitigation. In addition to reservoir operation decisions, one of the studies (Lines et al., 2018) also focuses on water allocation announcement decisions by reservoir operators and on farmers' planting decisions based on these announcements.

The types of streamflow forecasts analyzed, compared, and valued in these studies also vary depending on the decision context. They vary in terms of forecast period (from a few days to several months), forecast frequency (daily to seasonal), and update frequency. They also vary from simple deterministic forecasts (including "perfect" forecasts based on actual data as an upper-bound point of reference) to more complex stochastic and ensemble forecasts. With the exception of the two studies conducted in Quebec, which focus on short-term forecasts, all the studies examine the benefits of incorporating snow-pack information to improve streamflow forecasts.

Applying the VOI approach requires each study to specify a decision model that can be used to predict the value of the decision variable (e.g., reservoir release) based on different types of available information (e.g., streamflow forecasts). Eight of the studies reviewed here used optimization models to represent decision makers' behaviors, ranging from a simple discrete choice framework under a limited number scenarios (Lines et al., 2018) to more complex dynamic and/or stochastic programming approaches incorporating thousands of scenarios. As an alternative to optimization, two of the studies relied on existing reservoir operating rules for the systems being studied to represent the decision process.

In a VOI context, optimization models are attractive because they inherently maximize the benefits of available information (assuming that the objective function being optimized accurately represent the benefits of those affected by the decision). However, these models may overstate the *actual* value provided by information, when *actual* decision processes are simpler or more constrained.

In other cases, even if the optimization or operating rules used in the VOI analysis accurately represent the decision process that is actually used, it may be difficult to translate the results into units that reflect the values of beneficiaries. For example, Anghileri et al (2016) assume that the reservoir operator's objective at Oroville Dam in California is to select the daily releases that result in the smallest combined annual water supply deficits (in square terms) with respect to pre-defined targets for irrigation, municipal water supply, and environmental flows. Although they find that incorporating forecasts into the optimization process can reduce annual supply deficits (squared), it is difficult to translate these reductions into monetary value terms for the downstream beneficiaries.

Estimating VOI requires comparing the outcomes of decisions made under different forecast conditions but the same actual conditions. Six of the studies used historical records of streamflows to represent actual conditions for their simulation runs, and the others used hydrologic models to develop simulated time series of streamflows. Depending on the application, the actual flow estimates ranges from less than one year to several decades of data.

In addition to assessing VOI associated with different types of forecasts, several of the studies analyzed the sensitivity of VOI estimates with respect to other model inputs or assumptions. The most common factors included in these sensitivity analyses relate to reservoir storage capacity or the ratio of this storage to stream inflow. Other commonly analyzed factors are selected determinants or drivers of the demand for or value of reservoir releases such as electricity prices, hydropower generation capacity, or other water demand parameters. Two of the studies (Lines et al., 2018; Matte et al., 2017) also examine the sensitivity of VOI with respect to measures of risk aversion among decision makers.

Generally speaking, the studies find that the information contained in streamflow forecasts can provide meaningful value to decision makers and that improved forecasts (e.g., by incorporating snowpack information) increase this value. However, the magnitude of these benefits varies significantly across studies For example, for the Yuba River multi-reservoir system they study, Rheinheimer et al. (2016) estimate that the upper-bound benefits associated with a perfect hydrologic forecast would be an increase in annual hydropower revenue of 1.2 percent on average. For the for the main-stem reservoirs in the Missouri River system analyzed, Maurer et al., (2004) estimate that total increases in hydropower generation benefits would be less than 2% even with perfect forecasts. For the Skagit River System, Kim et al., (1997) estimate that incorporating seasonal flow forecasts for the snowmelt season increases annual value of hydropower generation by an average of 5%. In contrast, Odegard et al. (2017) find that including snow measurement in streamflow forecasts for a could increase annual hydropower production at a Norwegian plant by as much as 10 percent. For the Columbia River system, Hamlet et al, (2002) estimate that incorporating climate forecasts into long-lead streamflow forecasts could increase annual net income from nonfarm hydropower by over 20 percent.

As previously mentioned, several studies also analyze the sensitivity of VOI estimates for reservoir operations with respect to differences in the size (volume) of the reservoir or the ratio of size to annual inflow. The general finding is that VOI decreases with respect to both metrics (i.e. streamflow forecasts are more valuable when the flow being forecast represents a larger portion of reservoir volume). Maurer et al. (2004) summarize findings from six studies, including their own, which shows a distinct downward relationship between the percent increase in hydropower revenues with perfect forecast information and the ration of system volume to annual inflow. They attribute the relatively low value from their own study (<2%) to be in large part a function of the system's large size relative to inflow volume.

Two studies also examine the relationship between streamflow forecast VOI and the risk aversion of those who use or benefit from the information. Matte et al. (2016) for example find that the value of forecast systems in the context of flood mitigation is very sensitive to the level of risk aversion among emergency management decision makers. For example, risk-averse end-users in their study tend to put relatively more weight (negative) on high flood consequence scenarios (independent of probability); therefore, improved forecast reliability in the upper tail of the distribution is particularly valuable for them. In contrast, in the Lines et al. (2018) study, it is the less risk-averse beneficiaries (farmers) who benefit the most from additional forecast information.

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Table B.1 – Summary of Value of Information Literature Review

Citation	**Kim, Y.O. and Palmer, R.N., 1997. Value of seasonal flow forecasts in Bayesian stochastic programming. Journal of Water Resources Planning and Management, 123(6), pp.327-335.**
Context	Skagit, WA power system supplying Seattle. The hydropower dams on Skagit River (785MW in total). Snowmelt dominated in Spring
Decisionmaker's Objective	Maximize value of energy generation over planning period (year)
Control variable(s) for decisionmaker	Monthly releases from each reservoir for hydropower production
Decisionmaker's solution model	Nonlinear dynamic programming models incorporating different types of flow forecast information and uncertainty (deterministic, stochastic, bayesian stochastic)
Forecast description	Long term. Monthly inflow forecasts based on historical record (1928-1988), estimated serial month-to-month correlation, and snowmelt runoff model - monthly energy prices are deterministic based on historical averages
Forecast alternatives	(1) deterministic inflow forecast (average historical flow for each month) (2) stochastic monthly inflow forecast without persistence (average and variance of historical flow for each month) (3) stochastic monthly inflow forecast with persistence (adding serial correlation) (4) stochastic monthly inflow forecast augmented with seasonal snow-based inflow forecast (used in Bayesian optimization model)
Actual streamflow method	Observed inflows 1928-1988
Sensitivity analyses	- value with perfect information (actual inflows) NOT modeled - vary size of main reservoir - vary energy demand requirement - vary energy price
Key Findings	- stochastic models outperform deterministic - seasonal flow forecast adds additional value; incorporating seasonal flow forecasts for the snow-melt season increases annual value of generation by an average of 5% - adding reservoir capacity adds value to stochastic model but not seasonal flow forecast

Citation	**Ødegård, H.L., Eidsvik, J. and Fleten, S.E., 2019. Value of information analysis of snow measurements for the scheduling of hydropower production. *Energy Systems*, *10*(1), pp.1-19.**
Context	Norway, single hydropower reservoir/facility, at most 15% snow contribution (size not specified)
Decisionmaker's Objective	Maximize expected annual income from hydropower (limit time that reservoir level is above or below specified limits); carryover to next year not addressed
Control variable(s) for decisionmaker	Weekly water release from reservoir for hydropower, select from discrete levels (J = 2 or 4)
Decisionmaker's solution model	Dynamic optimization model using Least Squares Monte Carlo
Forecast description	Long term (year); probability of weekly reservoir inflow for year; no adjustment during year - Based on observed 10-yr mean of inflow for each week - Electricity price varies over time but is known/deterministic
Forecast alternatives	Include snow measurement (scalar value) to improve probability forecasts; scalar value takes on discrete values with equal probability
Actual streamflow method	Simulated inflows based on observed 10-yr means and variance for each week (50,000 scenarios generated)
Sensitivity analyses	- Vary precision of snow information - Vary discrete release levels - Vary reservoir size relative to inflow
Key Findings	- More snow information increases VOI, with an estimated increase in annual hydropower production at the plant by as mcuh as 10%. - More discrete production levels increases VOI - Smaller reservoir relative to inflow increases VOI
Citation	**Linés, C., Iglesias, A., Garrote, L., Sotés, V. and Werner, M., 2018. Do users benefit from additional information in support of operational drought management decisions in the Ebro basin?. Hydrology and Earth System Sciences, 22(11), pp.5901-5917.**
Context	Spain, Ebro basin, three reservoir system predominantly supplying agriculture (98,000 ha)
Decisionmaker's Objective	Reservoir operators: announce water curtailment and adjust allocation appropriately if shortage is predicted Farmers: maximize profits from crop production;
Control variable(s) for decisionmaker	Reservoir operators: drought declaration and volume of water to supply/curtail to farmers in emergency situation every 2 weeks March-October Farmers: area and types of crops, number of plantings monthly November to March

Decisionmaker's solution model	Reservoir operators: choose curtailment if estimated water supply is less than predicted demand by farmers Farmers: From a set of discrete crop planting options, choose the one with highest expected profit (given water forecast)
Forecast description	Dichotomous forecast of the system's surface water availability for the season (good vs. bad)
Forecast alternatives	1) only reservoir levels used to predict water availability 2) reservoir levels AND satellite-based snow pack data used for prediction
Actual streamflow method	Observed monthly reservoir levels 2001 to 2014
Sensitivity analyses	
Key Findings	Value of information varies across farmer types with different decision options Less risk averse farmers benefit from information that may allow them to plant crops with high re-turn
Citation	**Anghileri, D., Voisin, N., Castelletti, A., Pianosi, F., Nijssen, B. and Lettenmaier, D.P., 2016. Value of long-term streamflow forecasts to reservoir operations for water supply in snow-dominated river catchments. Water Resources Research, 52(6), pp.4209-4225.**
Context	California, Oroville reservoir (10K km2 drainage, 5 billion m3 annual inflow); interannual reservoir in snow-dominated river basin
Decisionmaker's Objective	Minimize water supply/release deficit (squared) with respect to daily water demands for irrigation, municipal supply, environmental flows, while observing flood control constraint. Hydropower not in-cluded.
Control variable(s) for decisionmaker	Daily water release from reservoir
Decisionmaker's solution model	Deterministic dynamic optimization using single trace (average of ensemble members) - Minimize squared deficit of daily release relative to total daily demand (exogenous)over 1 year hori-zon Demand is based on observed past diversions; squared term penalizes large daily deficits – spreads them out - Flood control is included as a constraint (rule curve) – upper bound on reservoir storage
Forecast description	Long term: daily inflows for one year, single trace (deterministic), updated weekly - Future based on average of 49-member 365 day climate ESP approach with VIC hydrology model - “Nowcast” actual and current conditions using observed meteorology and VIC model - Mass balance reservoir model with evaporation

Forecast alternatives	(1) perfect forecast (2) worse forecast: “climatology” (1960-2010 daily average simulated inflow) (3) hybrid with perfect for remaining water year (seasonal) and climatology thereafter (inter-annual)
Actual streamflow method	Simulated with VIC hydrology model using observed meteorology for each year from 1960 to 2010. In each year, the remaining 49 years of meteorology are used as the ensemble for the ESP
Sensitivity analyses	- Vary water demand - Vary capacity-inflow ratio
Key Findings	- ESP performs better (minimizes deficits) in drier years - ESP has limited value in this case because forecast skill is seasonal (spring) whereas objectives are annual water supply with longer lead time needs - ESP would be most valuable with high demand and lower capacity, which would make management more seasonal (than inter-annual)
Citation	**Rheinheimer, D.E., Bales, R.C., Oroza, C.A., Lund, J.R. and Viers, J.H., 2016. Valuing year-to-go hydrologic forecast improvements for a peaking hydropower system in the Sierra Nevada. Water Resources Research, 52(5), pp.3815-3828.**
Context	California, Yuba River, multi-reservoir system aggregated to composite single reservoir (262 million m3 capacity). Snow-dominated in spring. Little interannual carry-over
Decisionmaker's Objective	Maximize annual hydropower revenues less penalties for unmet environmental flows.
Control variable(s) for decisionmaker	Hourly then daily water release from reservoir
Decisionmaker's solution model	Linear programming model
Forecast description	Long term “year-to-go” daily; updated daily based on hydrology model. Actual modeled inflow blended with “predicted inflow” based on median inflows. - Electricity prices deterministic
Forecast alternatives	(1) perfect forecast (no blending) (2) actual values blended with snow water equivalent (SWE) data enhanced prediction
Actual streamflow method	Simulated with hydrology model using 1952-2009
Sensitivity analyses	- Systematic error added to SWE model - Changing blending factor - Vary storage capacity to inflow ratio - Vary powerhouse release capacity to inflow ratio - Vary powerhouse capacity
Key Findings	- Perfect hydrologic forecasts increase annual hydropwer revenues by an average of 1.2% - Insensitivity of forecast value to reservoir size due to little spill in larger reservoirs

Citation	**Maurer, E.P. and Lettenmaier, D.P., 2004. Potential effects of long-lead hydrologic predictability on Missouri River main-stem reservoirs. Journal of Climate, 17(1), pp.174-186.**
Context	Missouri River 3 mainstem (sequential) dams (Fort Peck, Garrison, Oahe)
Decisionmaker's Objective	Maximize hydropower revenues (flood control, navigation, water supply, recreation, environmental flows were set as constraints)
Control variable(s) for decisionmaker	Monthly time-step releases for hydropower from 3 reservoirs
Decisionmaker's solution model	Operating rules based on adaptations of system's master water control manual
Forecast description	Long term (12-month) monthly stream flow
Forecast alternatives	- "Perfect forecast" generated using observed system monthly inflow sequences 1968-1997 - Alternative forecasts generated by stochastically adding error to observed values
Actual streamflow method	Observed system monthly inflow sequences 1968-1997
Sensitivity analyses	- Hypothetical reduction in system storage - Varying perfect knowledge of climate, soil mosture, and snow pack
Key Findings	- Small benefits in percentage terms -- for the main-stem reservoirs, total increases in hydropower generation benefits are less than 2% even with perfect forecasts. - Increase in benefits with smaller capacity system
Citation	**Hamlet, A.F., Huppert, D. and Lettenmaier, D.P., 2002. Economic value of long-lead streamflow forecasts for Columbia River hydropower. Journal of Water Resources Planning and Management, 128(2), pp.91-101.**
Context	Columbia River Basin (OR/WA); snow-dominated; relatively low reservoir storage system; seasonal peak flows out of phase with peak energy demand
Decisionmaker's Objective	Maximize hydropower revenues at major storage and RoR dams in Canada and US while managing for flood control and other uses
Control variable(s) for decisionmaker	Monthly reservoir releases for hydropower
Decisionmaker's solution model	Reservoir rule curves
Forecast description	Long term (12-month) monthly stream flow ensemble forecasts with snow pack info and VIC hydrol-ogy model, updated monthly - Electricity prices: average monthly spot market prices projected by Bonneville Power Admin
Forecast alternatives	- Increasing (by 6 months) forecast lead time by adding information from long-lead climate forecast - Perfect forecast of climate category
Actual streamflow method	Monthly time step ColSim reservoir simulations driven by naturalized streamflows from 1931 to 1988
Sensitivity analyses	Revised rule curves for reservoir operation

Key Findings	Considerable improvement in reservoir operations for hydropower generation
Citation	**Matte, S., Boucher, M.A., Boucher, V. and Fortier Filion, T.C., 2017. Moving beyond the cost–loss ratio: economic assessment of streamflow forecasts for a risk-averse decision maker. Hydrology and Earth System Sciences, 21(6), pp.2967-2986.**
Context	Canada, Quebec, Montmorency River, small flood-prone watershed
Decisionmaker's Objective	Maximize expected utility for flood emergency managers, where utility is a function of flood damage and flood damage can be mitigated by emergency management spending
Control variable(s) for decisionmaker	Emergency management spending which reduces the damages associated with floods of different sizes
Decisionmaker's solution model	Optimization model maximizing utility
Forecast description	Short term. 1 to 5-day horizon, updated every 3 hours
Forecast alternatives	Variations in forecast uncertainty captured by: 1. “Dressed” deterministic forecasts, using past error statistics 2. Meteorological ensemble forecasts passed on to the HYDROTEL distributed hydrologic model 3. Ensemble forecast with random noise applied to precipitation and temperature inputs.
Actual streamflow method	Observed stream-flow for 2011-2014 study period
Sensitivity analyses	- Vary risk aversion coefficient in utility function - Vary damage multiplier
Key Findings	- Value of forecasting system strongly depends on decision maker’s risk aversion - Forecast quality in traditional sense does not necessarily translate to higher value when risk aversion is included
Citation	**Tejada-Guibert, J.A., Johnson, S.A. and Stedinger, J.R., 1995. The value of hydrologic information in stochastic dynamic programming models of a multireservoir system. Water resources research, 31(10), pp.2571-2579.**
Context	California Shasta-Trinity System 2 reservoirs and 5 power plants; snow-dominated in Spring
Decisionmaker's Objective	Maximize the value of energy produced, with penalites for shorfalls on water supply
Control variable(s) for decisionmaker	Monthly releases for hydropower
Decisionmaker's solution model	Nonlinear stochastic dynamic programming SDP models incorporating different types of flow forecast information and uncertainty (deterministic, stochastic,...)
Forecast description	Long term: Monthly inflow forecasts based on historical record (1895-1977), Markov chain model of streamflow persistence, and snowmelt runoff model; updated monthly - monthly energy prices are deterministic based on historical averages

Forecast alternatives	(1) deterministic inflow forecast (average historical flow for each month) (2) stochastic monthly inflow forecast without persistence (average and variance of historical flow for each month) (3) stochastic monthly inflow forecast with persistence (adding serial correlation) (4) stochastic monthly inflow forecast augmented with seasonal snow-based inflow forecast
Actual streamflow method	Monthly inflow historical record (1895-1977)
Sensitivity analyses	- Vary targets and penalties
Key Findings	- Largest benefits of including additional hydrologic state information for objective with large penalties on shortages
Citation	**Boucher, M.A., Tremblay, D., Delorme, L., Perreault, L. and Anctil, F., 2012. Hydro-economic assessment of hydrological forecasting systems. Journal of Hydrology, 416, pp.133-144.**
Context	Canada Quebec Gatineau Basin, 2 reservoirs and 3 hydropower plants
Decisionmaker's Objective	Maximize hydraulic generation of the valley
Control variable(s) for decisionmaker	Daily releases to turbine flow and spill from Baskatong reservoir
Decisionmaker's solution model	SOHO linear stochastic programming model
Forecast description	Short-term: Deterministic and ensemble 10-day forecast with daily time-step
Forecast alternatives	- Low resolution ensemble - Post-processed ensemble to address under-dispersion
Actual streamflow method	September 1 to December 17, 2003
Sensitivity analyses	
Key Findings	- Both deterministic and ensemble forecasts result in higher total electricity production and lower number of inundation days over the simulation period

Appendix C List of Interviews and Focus Groups

Interview/Focus Group	Sector	Organization
Interview	Reservoir Operators	DWCD
Interview	Reservoir Operators	DWCD - reservoir operations
Interview	Reservoir Operators	DWCD - reservoir operations
Interview	Reservoir Operators	Reclamation
Interview	DWCD	DWCD staff
Interview	DWCD	DWCD board member
Interview	Agriculture	Ute Mountain Farm and Ranch
Interview	Agriculture	Ute Mountain Farm and Ranch
Interview	Agriculture	Ute Mountain Farm and Ranch
Interview	Agriculture	Ute Mountain Farm and Ranch
Focus Group	Agriculture	Agricultural producer -- FSA
Focus Group	Agriculture	Agricultural producer -- FSA
Focus Group	Agriculture	Agricultural producer -- FSA
Focus Group	Agriculture	Agricultural producer -- FSA
Interview	Agriculture	Montezuma County Extension
Interview	Agriculture	CSU Ag Extension, SW CO Research Center
Interview	Agriculture	CSU Ag Extension, SW CO Research Center
Interview	Agriculture	Dolores County Extension
Interview	Agriculture	Montezuma Valley Irrigation Company
Interview	Recreation	Dolores River Boating Advocates
Interview	Recreation	Commercial outfitter
Interview	Recreation	Commercial outfitter
Interview	Recreation	USFS
Interview	Recreation	BLM
Interview	recreation	BLM
Interview	Ecological	CPW Durango Office
Interview	Colorado Water Law	Western Resource Advocates

Appendix D IRB-approved interview questions

Interview Questions for DW and DWCD areas:

1. What decisions do you use streamflow forecast information for? How do you use it? When?
2. What forecast information do you use when making these decisions?
3. What elements of the forecast do you pay most attention to/matter the most in this process? (e.g., uncertainty, lead time, frequency)? What elements of the forecast would be most helpful to improve?

Prompt: Would this be the same during a very wet year, like the current year, or in very dry years, like 2017-2018?

4. What other factors impact your decisions? (e.g., how important is the forecast in the suite of information that you consult?)
5. What years were the forecasts very helpful? In what years were the forecasts least helpful?

Prompt: Ask about specific years (e.g., 2017-18 drought; current wet year)

Prompt: What makes a forecast bad? What makes it good?

6. How does your decision-making process and use of forecast information change based on the conditions (e.g., a dry year, a wet year, successive dry years, etc.)?

Prompts: Think about the year that we were just talking about. Did you change when or how often you look at forecast information? Did you seek additional information to supplement the forecast? Did you change your management practices based on the forecast information?

7. Think about [choose a year that they have been discussing]. Knowing what you know now about the water conditions for that year, what would you have done?

Prompt: Please look at these scenarios (scenario game). What would you do with this forecast information?

Prompt: If I could give you a crystal ball and give you a perfect forecast for that year, and tell you exactly what was going to happen with the water, what would you have done?

Additional Questions for Reservoir Operators and Water Managers in DW and DWCD:

1. Do you communicate forecast information to other groups? If so, whom do you communicate with? How do you pass along this information (e.g., email, press release, etc.)?
2. Are there spatial/location-specific forecasts for which increased precision is more important?

Additional Questions for Ag Extension Agents in DWCD:

1. Do you communicate any forecast information to the ag community? If so, whom do you communicate with? How do you pass along this information (e.g., email, press release, etc.)?
2. In your experience, how does the agricultural community respond to water reduction/availability? In other words, what do they do in particularly dry years? What about in very wet years?

Additional Questions for Recreation Outfitters (e.g., Rafting Companies and Angling Guides) in DWCD:

1. Do you communicate any forecast information to other groups? If so, whom do you communicate with? How do you pass along this information (e.g., email, press release, etc.)?
2. Where do go when there isn't enough water?

TO CONCLUDE: Do you have any questions, or is there anything else that you would like to add that I didn't ask you about?

Focus Group Questions / Discussion Prompts:

1. Do you use streamflow or water availability forecast information to inform decisions? How do you use it? When?

Prompt for Ag Community: Do streamflow forecasts or water availability forecasts impact your decision on what to plant, how much to plant, or when/where to graze?

Prompt for M&I: Do streamflow forecasts or water availability forecasts impact your decision on how to manage water useage?

Prompt for Recreation: How does release information from McPhee Reservoir impact the number of days you can raft, or where and when you can fish?

2. What streamflow forecast or water availability forecast information do you use when making these decisions? Where do you get that information?
3. *IF THEY USE FORECAST INFORMATION:* What elements of the forecast do you pay most attention to/matter the most in this process? (e.g., uncertainty, lead time, frequency)? What elements of the forecast would be most helpful to improve?

IF THEY USE SOME OTHER WATER AVAILABILITY FORECAST INFORMATION: What elements of the water availability forecast do you pay most attention to/matter the most in this process? (e.g., uncertainty, lead time, frequency)? What elements of the forecast would be most helpful to improve?

Prompt (same for both): Would this be the same during a very wet year, like the current year, or in very dry years, like 2017-2018?

4. What other factors impact your decisions? (e.g., how important is the forecast in the suite of information that you consult?)
5. What years were the forecasts very helpful? In what years were the forecasts least helpful?

Prompt: Ask about specific years (e.g., 2017-18 drought; current wet year)

OR Prompt: What makes a forecast bad? What makes it good?

OR Prompt: Think of a year that the forecast let you down. How? Was it the timing, the amount, etc?

6. How does your decision-making process and use of streamflow or water availability forecast information change based on the conditions (e.g., a dry year, a wet year, successive dry years, etc.)?

Prompts: Think about the year that we were just talking about. Did you change when or how often you look at forecast information? Did you seek additional information to supplement the forecast?

Prompt for Ag Community: Did you change your planting or grazing practices based on the forecast information?

Prompt for M&I: Did you change your water management practices based on the forecast information?

Prompt for Recreation: Did you decide to change locations or increase/decrease the number of days for rafting/fishing based on that forecast information?

7. Think about [choose a year that they have been discussing]. Knowing what you know now about the water conditions for that year, what would you have done?

Prompt: If I could give you a crystal ball and give you a perfect forecast for that year, and tell you exactly what was going to happen with the water, what would you have done?

TO CONCLUDE: Do you have any questions, or is there anything else that you would like to add that I didn't ask you about?