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Valuing year-to-go hydrologic forecast improvements for a peaking hydropower system in the Sierra Nevada

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Abstract

We assessed the potential value of hydrologic forecasting improvements for a snow-dominated high-elevation hydropower system in the Sierra Nevada of California, using a hydropower optimization model. To mimic different forecasting skill levels for inflow time series, rest-of-year inflows from regression-based forecasts were blended in different proportions with representative inflows from a spatially distributed hydrologic model. The statistical approach mimics the simpler, historical forecasting approach that is still widely used. Revenue was calculated using historical electricity prices, with perfect price foresight assumed. With current infrastructure and operations, perfect hydrologic forecasts increased annual hydropower revenue by \$0.14 to \$1.6 million, with lower values in dry years and higher values in wet years, or about \$0.8 million (1.2%) on average, representing overall willingness-to-pay for perfect information. A second sensitivity analysis found a wider range of annual revenue gain or loss using different skill levels in snow measurement in the regression-based forecast, mimicking expected declines in skill as the climate warms and historical snow measurements no longer represent current conditions. The value of perfect forecasts was insensitive to storage capacity for small and large reservoirs, relative to average inflow, and modestly sensitive to storage capacity with medium (current) reservoir storage. The value of forecasts was highly sensitive to powerhouse capacity, particularly for the range of capacities in the northern Sierra Nevada. The approach can be extended to multireservoir, multipurpose systems to help guide investments in forecasting.

1. Introduction

Water management is confounded, at least technically, by uncertainty about current and future conditions of water supply and demand. Reducing supply-side uncertainty can help promote more transparent, economically efficient and equitable water management. Furthermore, it is a central motivation for hydrologic research generally [*Bales et al.*, 2006, *de Jong et al.*, 2009, *Liu and Gupta*, 2007, *Pappenberger and Beven*, 2006], including important advances in environmental sensing and computing infrastructure [*Hill et al.*, 2014, *Frew and Dozier*, 2012, *Kerkez et al.*, 2011] and improvements in hydrologic modeling [*de Jong et al.*, 2009]. However, while improvements in hydrologic prediction are ostensibly for better management of climate- and water-sensitive activities, better management is often assumed. This observation is not new. *Klemeš* [1977] observed

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that "we believe, or pretend to believe, that an increase of effort will automatically bring about a proportional improvement in the result; it has been in the name of the ensuing benefits that pressures have been, and are being, exerted for more data, more complex models, more advanced techniques, more powerful computers, etc." However, the law of diminishing returns applies to hydrologic information content and value [*Schramm*, 1974, *Klemeš*, 1977], such that forecasting improvements will not necessarily yield the same benefits as earlier improvements. The implication is not that next-generation measurement and modeling systems are valueless, but that improvements should be driven by their actual added value. This requires explicitly quantifying both costs and benefits of additional information, such as from better hydrologic models. However, whereas costs can be easily quantified [*Goninon et al.*, 1997], marginal benefits remain poorly quantified; this paper focuses on the latter.

Operational hydrologic forecasts generally use statistically based or relatively simple spatially explicit hydrologic models, with much inherent uncertainty. Statistical forecasts range in complexity from linear and univariate to nonlinear and multivariate, and are common in the western United States [*Perkins et al.*, 2009]. For example, the California Department of Water Resources (DWR) uses multivariate regression models to estimate year-to-go unimpaired runoff to support water allocation decisions [*Rosenberg et al.*, 2011]. While not as widely used, process-based hydrologic forecast models that use spatially explicit data have nonetheless been increasing in popularity in operational contexts, particularly for ensemble streamflow predictions [*Wood and Lettenmaier*, 2006]. For example, the U.S. National Weather Service River Forecasting Centers use the process-based Sacramento Soil Moisture Accounting Model (SAC-SMA; *Burnash* [1995]). Both approaches are imperfect, with uncertainties in initial conditions, anticipated future conditions, model structure, parameters, and observational data, as well as interpretation of model output. Reductions in uncertainty can benefit both types of forecast models.

Several studies of hydropower systems have assessed the improvements in generation and/or revenue from improvements in forecasting local hydrologic state variables, using stochastic dynamic programming [*Stedinger et al.*, 1984, *Barnard*, 1989, *Tejada-Guibert et al.*, 1995, *Kim and Palmer*, 1997]. Later hydropower studies turned to assessing the value of improvements in seasonal forecasting using climatic teleconnection variables such as sea surface temperatures, in addition to local phenomena, using simulation [*Hamlet et al.*, 2002, *Maurer and Lettenmaier*, 2004] and optimization [*Proveda et al.*, 2003, *Block*, 2011]. These studies indicate that potential benefits vary widely, depending on local characteristics of the system. For example, *Hamlet et al.* [2002] noted a potential hydropower revenue increase of 45% ($153 million per year) by including long-lead forecasts using El Niño/Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) information for operating the Columbia River system. In contrast, *Maurer and Lettenmaier* [2004] note relatively low potential hydropower revenue gain (1.7%) with perfect long-lead (12-month) forecasting of climate, soil and snow variables for the reservoirs of the Missouri River mainstem; the economic value of forecasting depended on reservoir capacity relative to inflow, with low value for both small and large reservoirs.

The present study addresses similar issues, but differs from previous studies in geographic setting and by using a more generic approach that considers incremental increases in year-to-go inflow forecast accuracy, without explicitly examining specific hydrometeorologic variables other than inflow, thus implicitly considering all forecasting variables in aggregate. *Klemeš* [1977] quantified the value V of better information as:

$$V(\Delta I) = L^{\star}(I) - L^{\star}(I + \Delta I) \tag{1}$$

where $L^{\star}$ is the loss from optimal operations given information quantity I and ΔI is a discrete amount of additional information. Here, a similar approach is used, with a more generic method to quantify additional information.

This paper aims to estimate the economic value of improved hydrologic information for hydropower systems in snow-dominated mountain basins, and understand how the value of hydrologic forecast skill varies with different infrastructure and management conditions. Two general hydrologic improvements are considered: increased accuracy of input into a statistical forecast model and general improvements in future inflow predictions.

2. Methods and Data

A numerical study was conducted using representative reservoir inflow forecasts in a hydropower optimization model to test the sensitivity of hydropower revenue to hydrologic forecast improvements and infrastructure capacity. The optimization model used deterministic inflows, composed of forecasted inflows from a SWE-dependent statistical inflow model, representative actual inflows from a physical hydrology model, or some combination of the two. Representative historical SWE and inflows were from the physical hydrology model so all hydrologic data were from an internally consistent data set; there is no accurate SWE data set in the study area. These models are described below.

Four scenario sets, also described below, were considered (Table 1), consisting of variations in hydrologic forecasting capability or infrastructure attributes in a series of annually independent models spanning 58 water years (1952-2009). Each annual run was for 1 water year (October through September). First, systematic uncertainty in SWE was considered. Second, the economic value of general forecast accuracy under existing (base case) infrastructure configuration and operations was examined. Third, the benefit of perfect forecasts with different infrastructure capacities was assessed by varying both reservoir and powerhouse capacities. Finally, a more detailed variation in powerhouse capacity was examined for three reservoir sizes.

2.1. Study Site

For this study we used the multi-reservoir Yuba-Bear and Drum-Spaulding hydroelectric projects (YB/DS) in the upper Yuba River watershed in the northern Sierra Nevada, California (Figure 1), aggregated to a single composite reservoir. With a Mediterranean montane climate, inflow consists of highly variable rain-driven runoff in winter followed by snowmelt in late spring and summer.

Historically, precipitation in the YB/DS mostly occurred as snow above the system reservoirs [*Jacobs et al.*, 1995]. As in the rest of California and the western United States generally [*Perkins et al.*, 2009, *Rosenberg et al.*, 2011], snow is the major contributor to runoff, resulting in a strong causal correlation between snow accumulation and year-to-go inflow. This correlation is strongest from about March through May, when SWE is greatest, and weaker both earlier in the year, when future precipitation is unknown, and later in the year, when most snow has melted and flows are low (Figure 2).

Operations consist of hydropeaking with diversion-type high-head hydropower typical of the Sierra Nevada. Specifically, the YB/DS system diverts water for hydropower production and water supply in the adjacent Bear River watershed through four medium-sized reservoirs, with capacities ranging from 61.6 to 92.6 million m^3 (MCM) [*Nevada Irrigation District*, 2006, *PGE*, 2007] and storage capacity:annual inflow (S:I) ratios from 0.34 to 1.3. Operational objectives consist of spill minimization and revenue-maximizing timing of releases for hydropower, some water supply, and environmental releases [*Jacobs et al.*, 1995]. This study omits water supply objectives. The YB/DS reservoirs provide seasonal storage, with little inter-annual carryover, to shift energy production from winter and spring to summer, when energy prices are higher; we assumed no inter-annual carryover. When represented as a single reservoir, the system has minimum and maximum storage capacities of 62 and 324 million m^3, and a diversion capacity of 25.4 m^3/s. For simplicity, minimum storage was subtracted from storage capacity, for an operating storage capacity of 262 million m^3, or a S:I ratio of 0.51. Hydropower was similarly represented as a composite of ten hydropower plants, with a head of 957 m and an efficiency of 100% [see *Rheinheimer et al.*, 2013]. A constant instream flow requirement of 0.31 m^3/s (11.0 ft^3/s) was assumed, which is the aggregate of the historical IFRs below the three lowest reservoirs. Spill was assumed to be uncontrolled.

2.2. Hydropower Optimization Model

The hydropower operations decision model consisted of a single linear programming (LP) model [*Grygier and Stedinger*, 1985, *Yeh*, 1985, *Labadie*, 2004] with variable-length time steps, run anew at the beginning of each day with initial and boundary conditions updated as needed. For each new LP problem, hourly decisions with daily inflows were used for the first n days, with multiday time steps for decisions and inflows thereafter. Water allocation decisions were from the first day of each successive model run. The LP model was formulated in Python using Pyomo [*Hart et al.*, 2011] and solved with the GNU Linear Programming Kit (GLPK) [*Free Software Foundation*, 2014].

The operational objective is to maximize hydropower revenue, less penalties for unmet environmental flows, with management decisions for daily operations. The objective function includes hourly decisions during the initial n-day period and multiday decisions thereafter, represented as:

$$\max z = \sum_{d,h} \left(\pi_{d,h} - C_{d,h}\right) + \sum_{md} \left(\pi_{md} - C_{md}\right) , \tag{2}$$

where π and C are revenue and penalty (cost), respectively, for each hour during the initial days (d, h) and each subsequent multiday time step (md). Main decision variables consist of release through a main hydropower turbine, release through a low level (bypass) outlet into the river below, and storage, denoted as PH, LL, and S, respectively.

During the initial n-day period, hourly (h) revenue is calculated from hourly energy prices:

$$\pi_h = \sum_h P_h E_h , \tag{3}$$

where P_h is hourly energy price, assumed known with perfect foresight, and E_h is hourly energy. During each generic time step t (i.e., hourly or daily time step), energy E_t is calculated using:

$$E_t = \eta \cdot \gamma \cdot h \cdot PH_t , \tag{4}$$

where η is aggregate powerplant efficiency, γ is specific weight of water, h is head, and PH_t is turbine flow. Head is assumed constant, appropriate for the high-elevation hydropower plants considered here.

Revenue during the multiday time steps is approximated from piecewise-linear revenue curves that represent the total revenue generated by releasing a percentage of total release capacity [*Olivares and Lund*, 2012]. Each piece of the linearized revenue curve consisted of a fraction of total release capacity and a slope corresponding to the average price within that capacity range. This is represented as:

$$\pi_{md} = E_{md}^{cap} \cdot \sum_p m_{md,p} E_{md,p} , \tag{5}$$

where p represents each piece of the revenue curve, E_{md}^{cap} is the energy capacity during the multiday period, $m_{md,p}$ is the slope of the revenue curve piece, and $E_{md,p}$ is the energy produced by the fraction of flow corresponding to the piece.

Two costs (C) were included. First, penalties for not meeting environmental flows were imposed, with single, high-value linear penalties for each time step. However, environmental flows were sufficiently small that they were always met. Second, a small penalty was added for empty storage to prevent spill when the reservoir is not full.

Constraints include mass balances and infrastructure capacities. The mass balance constraint for each time step t, where $t \in \{d, md\}$, is:

$$S_t = S_{t-1} + I_t - (PH_t + LL_t + SP_t) \ , \tag{6}$$

where S_t and S_{t-1} are the storage at the end of the current and previous time steps, respectively, and I_t, LL_t, SP_t are, respectively, the inflow, low-level release, and spill during the current time step. Inflow was from the inflow model described below. Storage is constrained by maximum and minimum storage ($S^{min} \leq S_t \leq S^{max}$) and releases for hydropower are constrained by powerhouse turbine capacity ($PH_t \leq PH^{max}$). For each annual run, initial storage was assumed zero, and there was no final storage objective.

Instream flow requirements (environmental flows) are modeled with a release constraint for each time step:

$$LL_t + IFR_t^{def} \geq IFR_t \ , \tag{7}$$

where IFR_t^{def} is the instream flow requirement deficit and IFR_t is the instream flow requirement.

2.3. Inflow Model

On any given initial day i, the daily and multiday inflow volumes used in the optimization (I_t in equation (6)) were aggregated from a year-to-go daily inflow time series consisting of a blend of actual and predicted inflows; improved prediction accuracy was represented by blending a greater proportion of actual inflows. Actual inflows were approximated by output from a physical hydrology model, while predicted inflows consisted of median inflows from the physical hydrology model scaled by year-to-go inflow regressed by SWE. The blending approach is described here, with the physical hydrology and regression models described below.

For initial day i, blended inflows for future day j were represented as:

$$I_{ij} = \alpha_{ij} \dot{I}_j + (1 - \alpha_{ij}) \hat{I}_{ij} \ , \tag{8}$$

where $\dot{I}_j$ is the actual inflow during day j, $\hat{I}_{ij}$ is the predicted inflow for day j, and α_{ij} is an inflow forecast blending factor for day j from initial day i. α_{ij} can vary by i and j to account for changing predictive capacity during different times of year. In this study, we assume α_{ij} only varies with future time step j. This reflects that historically accurate forecasts, such as low summer flows, are implicit in the forecast model rather than in α_{ij}. On any initial day i, the initial n-day period is with perfect hydrologic foresight, during which $\alpha_{ij} = 1$. This is followed by a m-day blending period between future days $j = n$ and $j = n + m$, during which α_{ij} decreases linearly from one to a final inflow forecast blending factor α_f . For days $j \geq n + m$, α_{ij} was held constant at α_f. This is expressed as:

$$\alpha_{ij} = \begin{cases} 1, & j \leq n \\ 1 - \frac{j-n}{m}\left(1 - \alpha_f\right), & n \leq j \leq n+m \ . \\ \alpha_f, & j \geq n+m \end{cases} \tag{9}$$

Year-to-go inflow hydrograph accuracy was represented in this study by changing α_f. The initial n-day period and m-day blending period were fixed at 7 days each. This approach, including the length of the blending period, is similar to that previously used by the California Nevada River Forecast Center (CNRFC) (A. Henkel, personal communication).

2.3.1 Physical Hydrologic Model

The Water Evaluation And Planning system (WEAP) [*Yates et al.*, 2005] was used to simulate daily runoff at several gaged locations within the Yuba River watershed, based on the weekly time step model described by *Young et al.* [2009]. Runoff for subwatersheds was aggregated to create a single inflow time series representing actual inflow ($\dot{I}_j$). Subwatersheds, defined by the gauged locations, were intersected with 250 m elevation bands, resulting in catchments, within which meteorological conditions and soil and vegetation characteristics were considered homogeneous. Vegetation was classified with GIS data from the U.S. Geological Survey (USGS) National Land Cover Dataset (NLCD) [*Homer et al.*, 2004]. Soil depth was classified using the USGS Soil Survey Geographic (SSURGO) Database [*NRC*, 2013]. Meteorological forcing was from two sources. Precipitation, temperature, and relative humidity were from the $1/16^\circ$ hydrometeorological data set described by *Livneh et al.* [2015] and wind was from DAYMET [*Thornton et al.*, 1997].

Calibration was automated with PEST [*Doherty*, 2015] using 13 physical parameters across three subwatershed groups, defined by geographic proximity. The reconstructed daily unimpaired flow data set developed for re-licensing the YBDS [*DTA Sacramento*, 2007] was used for model calibration and evaluation of daily discharge, with a calibration period of 1984–88, which included a range of water year types, and an evaluation period of 1989–99. Following *Moriasi et al.* [2007], the ratio of root mean square error to the standard deviation of observations (RSR), Nash-Sutcliffe efficiency (NSE) and percentage bias (PBIAS) were used to assess goodness-of-fit; these are defined and described by *Moriasi et al.* [2007]. Monthly inflow goodness-of-fit metrics for the period of the reconstructed data set (1975–2004) were "satisfactory," as defined by *Moriasi et al.* [2007], with RSR = 0.70, NSE = 0.51, and PBIAS = –24.9% (overestimation). The hydrology model generally over-estimated inflow through April and slightly under-estimated flows thereafter through July, indicating under-estimation of snow accumulation.

2.3.2 Statistical Inflow Estimation Model

Although multivariate regression models are often used in the region, typically with SWE, recent runoff, and air temperature as independent variables [*Rosenberg et al.*, 2011], a univariate regression with SWE was used in this study, as SWE accounts for most observed runoff variability in spring and summer. The regression model consisted of three steps. First, calculate historical median daily inflows ($\tilde{I}_d$). This is similar to the "median forecast" used by *Jacobs et al.* [1995]. $\tilde{I}_d$ does not depend on the date of forecast and is calculated just once using the representative historical inflows. Second, on each day of SWE measurement, estimate the regression coefficients between SWE and total year-to-go inflow using modeled hydrologic data spanning the period-of-record (WY 1952–2009), as follows:

$$I_{reg} = a \cdot SWE + b \; , \tag{10}$$

where I_{reg} is the regressed year-to-go total inflow and a and b are the regression coefficients. Example regressions are shown in Figure 2. Linearity was deemed adequate through July, when regression coefficient a remains high and year-to-go inflow becomes relatively low (less important for hydropower). Third, scale the median daily hydrograph using the SWE-runoff relationship with a scaling factor f:

$$\hat{I}_d = f \tilde{I}_d \tag{11}$$

where $\hat{I}_d$ is the scaled predicted daily inflow, converted as needed to multiday time steps for $\hat{I}_{ij}$ in equation (8). Scaling factor f is defined as:

$$f = \frac{I_{reg}}{\sum \tilde{I}_d} \,, \tag{12}$$

The statistical method was only applied from February through July, for reasons discussed above, on days when SWE is assumed measured. In between snow-measurement days, only the relevant remaining portion of the scaled daily hydrograph was used. Perfect hydrologic foresight (i.e., inflows from the physical hydrology model) was assumed for August-September forecasts, when runoff is relatively low and generally predictable. From October through January, when runoff is most unpredictable, median daily inflows were assumed. This regression method works well for this study, but in general becomes less valid as SWE decreases, such as with climate warming and anomalous low-SWE years.

The statistical regression model and source blending approach are demonstrated. Figure 2 shows the correlation between SWE and year-to-go inflow for specific days of the year. The correlation is strongest from April through June. Although the correlation becomes increasingly less linear through summer, a linear regression was used during all months, as the linear correlation remains strong through July, after which perfect hydrologic foresight was assumed.

Figure 3 shows how increasing α_{final} changes year-to-go prediction error for three representative days of the year, with error measured by NSE and mean absolute percent error (MAPE) [*Moriasi et al.*, 2007]:

$$NSE = 1 - \frac{\sum_{t=1}^{N} (F_t - A_t)^2}{\sum_{t=1}^{N} (A_t - A^{mean})^2} \,, \tag{13}$$

$$MAPE = \frac{1}{N} \sum_{t=1}^{N} \frac{|F_t - A_t|}{A_t} * 100\% \,, \tag{14}$$

where t is the time step, N is the total number of time steps, F_t is the forecasted inflow, A_t is the actual inflow, and A^{mean} is the mean actual inflow. These metrics can be calculated at any point in time over any arbitrary number of time steps; in this study, time step t is daily. Performance metrics do not necessarily improve through time, as reflected in the metric spreads (Figure 3), despite the correlation between SWE and year-to-go runoff increasing from February through June (Figure 2). This is because metrics are partly a function of the total number of time steps, which decreases through the year.

Mean year-to-go daily MAPE (MMAPE) was used as an error quantification metric for multiday time periods. Using this approach, any given value of α_f, which does not represent error *per se*, can be mapped to a representative, multiperiod error term. Figure 4 shows this with boxplots of mean annual MMAPE, i.e., mean of 365 year-to-go MAPE values across all years.

2.4. Electricity Prices

Hourly electricity prices were from the California Independent System Operator (CAISO) Open Access Same-time Information System (OASIS; oasis.caiso.com). As no representative data set of electricity prices exists, we used CAISO prices from the year 2006, when prices were relatively stable. Hourly electricity prices for 4 months in 2006 are shown in Figure 5. The profit-maximizing hydropower operator generates during large hourly spikes in electricity price from June through September, which result from peak energy demand for summer cooling and convex electricity supply curves [*Stoft*, 2002].

2.5. Numerical Study Design

The four scenario sets considered are as follows and as listed in Table 1.

2.5.1 Set 1: SWE Error

In this set, a systematic SWE error was introduced to equation 10:

$$I_{reg} = a \cdot (SWE_{actual} + \epsilon_{SWE}) + b \ , \tag{15}$$

where SWE_{actual} is the assumed true SWE from the physical hydrology model and ϵ_{SWE} is the systematic SWE error. SWE error was varied between $-/+$ 50% as approximate bounds on likely error, based on the authors' familiarity with the study area, and was held constant throughout each year. In this and the following set, we also included a reservoir one half the size of the existing reservoir. A larger reservoir was considered, but results were found to be insensitive to larger reservoir sizes; this point is further discussed below.

2.5.2 Set 2: Forecast Accuracy

The economic value of general forecast accuracy α_f under existing (base case) infrastructure configuration and operations was examined. SWE measurement frequency (f_{meas}) also was varied between monthly and daily.

2.5.3 Set 3: Infrastructure

Infrastructure, runoff, operating objectives, and institutional characteristics determine the discretionary power of a hydropower operator. The most important infrastructure characteristics for the reservoir in this study include storage capacity and powerhouse capacity, in relation to each other and to inflow characteristics. In this set, infrastructure capacity effects on the value of perfect hydrologic forecasts were assessed by systematically varying reservoir (S^{max}) and powerhouse (PH^{max}) capacities. Only base case (α_f=0) and perfect foresight (α_f=1) conditions were considered. SWE was assumed to be measured monthly in this and the remaining sets, as daily measurements did not substantially improve hydropower value.

The range of PH^{max} and S^{max} values selected was based on the approximate ranges of normalized capacities in the high elevation Sierra Nevada, expressed, respectively, as PH:I (annual powerhouse release capacity:annual inflow) and S:I (storage capacity:annual inflow). Calculating normalized capacities is not straightforward, however, as available (net) inflow depends on interbasin transfers, which cannot be computed directly. Based on a cursory analysis for a few reservoirs in the northern Sierra Nevada, normalized reservoir capacities were below about 1.5 and normalized powerhouse capacities were less than about 6, though these ranges are approximate.

2.5.4 Set 4: Powerhouse Capacity

In this set, the powerhouse capacity was varied with greater resolution and in a more targeted way than in set 3, for three reservoir sizes. Variation in storage capacity was not assessed further, since forecast value is relatively insensitive to normalized storage capacities typically encountered in the region.

3. Results

3.1. SWE Error

We first note the effect of systematic SWE error on assumed inflow, shown in Figure 6 for one dry year (1991) and one wet year (1996) for two dates (Feb 1 and Apr 1). Increasing or decreasing the error in SWE measurement yields a proportional increase or decrease in year-to-go runoff, as per equation 15.

Underestimation of SWE resulted in the greatest revenue loss, with maximum annual losses of about $4.0 million with -50% SWE measurement error with the existing reservoir (262 mcm), regardless of SWE measurement frequency (Figure 7). Some years had greater revenue with less accurate SWE measurement, owing to uncertainty in the regression between SWE and year-to-go runoff (Figure 2). On an annual basis for the existing reservoir size, a systematic SWE underestimation of -50% resulted in average annual revenue losses of about $0.7 million, out of an average of $66.3 million with no error. In contrast, overestimation resulted in no significant net difference. Averaged over multiple years, gains and losses from over-estimation of SWE tend to cancel out. On average, overestimation of SWE is at least as good as perfect estimation for the medium reservoir and almost as good for a smaller reservoir. In contrast, doubling the reservoir size had no significant effect on sensitivity to SWE compared to the existing capacity (data not shown). Underestimation of SWE results in greater revenue loss for the medium versus smaller reservoir. The benefit of SWE error reduction is greater when measurements are made daily, rather than monthly. These results did not vary significantly by water year type.

3.2. Forecast Accuracy

A perfect streamflow forecast provided an average annual increase in revenue of $0.8 million, or about 1.2% of $66.3 million average revenue, for both daily and monthly SWE measurements (Figure 8). Revenue increases were generally higher in wetter versus drier years, as indicated by the quintiles in Figure 8, ranging from $0.14 million per year (2nd quintile) to $1.6 million per year (4th quintile). A reservoir with half the existing capacity resulted in a higher gain from perfect forecasting in the first three quintiles and lower values in the wetter two quintiles, for a similar average gain. Doubling the reservoir capacity had no significant effect on the benefit (data not shown).

3.3. Infrastructure Characteristics

The value of perfect forecasts depends on both storage and hydropower plant capacity (Figure 9). Sensitivity to storage capacity is affected primarily by spill (Figure 9b). A small normalized storage capacity (S:I<0.3) sees no change in hydropower generation or spill, as the optimal strategy is to always generate at capacity, unless electricity prices are less than zero, so forecasts have no additional value for small hydropower reservoirs. For medium normalized storage capacities (0.3–0.8), the value of perfect forecasts depends on both relative storage and powerhouse capacity. In this range, operational decisions affect both spill, representing lost energy, and release timing. For high normalized storage capacity (>0.8), forecasting value is sensitive to powerhouse capacity, but less sensitive to storage capacity. The influence of powerhouse capacity is greater for PH:I=3, with a large increase in revenue with a perfect forecast at about PH:I=1.9.

Figure 10 shows the effect of powerhouse capacity in greater detail. These figures show peak revenue, averaged across all years, at PH:I of 2.25, 1.75 and 1.75 for the smaller, existing, and larger reservoir sizes, respectively. The differentiation by water year quintile in Figure 10 is consistent overall with incremental changes in perfect foresight (Figure 8). Finally, we note that the sensitivity of forecast value to powerhouse capacity is not smooth, as linearization of nonlinear behavior in LP models generally results in nonsmooth responses.

4. Discussion

In this study, improved SWE measurements showed some benefit, though sensitivity to SWE error was masked by error in the year-to-go inflow regression model. On any given date, using the statistical regression (Figure 2) results in either under- or overestimation of year-to-go total inflow, even with no SWE error, reducing overall value to SWE estimates. This error is also reflected in Figure 3, in which SWE is assumed known, and which shows significant inflow forecast error when α_f=0, i.e., just using the relationship in Figure 2. This indicates that the value of reducing SWE error is somewhat limited across all years, and suggests that benefits from better data also may require a better runoff model.

In contrast, perfect forecast skill showed a maximum expected value of just under one million dollars per year (1.2%) assuming historical price levels and good snow measurements. Given that multivariate and nonlinear regression models may be somewhat better than the linear model used here, this value represents an approximate upper bound on the economic gain from perfect foresight, and, therefore, on the annual expenditures that the hydropower utility should be willing to pay for additional hydrologic information. This value may grow with increasing value of hydropeaking as renewables expand in electricity generation.

In many if not most years, this low relative value is to be expected, and would be predicted by *Klemeš* [1977], who noted that "contrary to the prevailing opinion, a reservoir can be operated quite reasonably even on the basis of very limited hydrologic information." Though *Klemeš* [1977] was describing the sensitivity of an operating policy to the hydrologic record length, the notion applies equally to the revenue-maximizing hydropower reservoir with seasonal storage considered here, with variable, price-driven operations.

The decreasing expected marginal value of additional information seen in Figure 8 also has implications for investments in water resources information systems. Since perfect information is unattainable, the actual economic value of and willingness-to-pay for additional information, as derived from the intersection of the mean curve in Figure 8 and an information supply curve, is less than the value of perfect information. To develop supply curves requires a detailed accounting of the marginal costs of better forecasting, which was not done in this study. The concavity of the curves in Figure 8 also show that investments in forecast systems become increasingly less valuable as forecasts improve, as *Klemeš* [1977] suggested.

The insensitivity of forecasting value to reservoir size with larger reservoirs is due to little to no spill with larger reservoirs. The value remains sensitive to powerhouse capacity, however, as the operator must still optimize timing of hydropower generation.

Improving the physical hydrology model would not substantially alter the findings of this study. The performance of the physical hydrology model, used to represent actual flows, also affects assessed economic value of forecasting. Greater accuracy would likely show greater SWE, as the model over-predicted winter runoff (i.e., under-predicted SWE). This would result in stronger spring SWE-runoff linearity in the statistical model and, therefore, a more accurate statistical model. A more accurate statistical model would, in turn, result in decreased benefits from forecast improvements. However, as this study shows, most value is already accounted for with even imperfect forecast models, so a decrease in forecasting value with more accurate actual flows would be relatively small.

The estimated benefits of hydrologic information from this study is limited to the case of the single hydropower operator. There is an economic difference between value of information for a single water-using firm and that for an entire industry (e.g., the energy industry or the information-using public generally), particularly in terms of how operational decisions affect prices. Single firms are typically price takers, whereas industry decisions can affect market prices. Here, the short-term bidding strategy of the single hydropower operator is assumed to not affect prices, the approach typically used in bidding strategy studies [*Deb*, 2000, *Díaz et al.*, 2011].

Benefits from improved forecasts would also be higher if some benefits accrue to other management objectives. Hydrologic information in the public domain is a non-rivalrous, non-excludable good, serving multiple firms and purposes simultaneously, including water management, forest management, drought planning, scientific and other purposes [*Hanemann*, 2006]. All traditional water management priorities are present in the Yuba River watershed, but only hydropower generation in the upper Yuba River was considered here. The quantities reported for single-purpose studies such as this provide lower-bound estimates of the economic value of better hydrologic information to society generally. Although the approach used here is appropriate for multiuser cases, the economic interpretation here is insufficient in a broader measurement and forecast information context.

Expanding the numerical study to include different infrastructure characteristics (storage and powerhouse capacities) illustrates how the magnitude and relative value of better hydrologic forecasts is system-specific, although some generalizations can be made. For small and large reservoirs relative to net annual inflow, powerhouse capacity is the most important factor affecting the value of hydrologic forecasts. For the northern Sierra Nevada, most powerhouses are within a capacity range in which the value of better hydrologic information is highly variable, but where there is potentially significant value if the cost of next-generation forecasting systems are low.

This work can be extended in several ways for greater applicability to other systems. First, the general approach here should be extended to examine the importance of specific hydrologic parameters, including initial conditions (SWE, soil moisture, etc.) and future conditions (precipitation, temperature, etc.). These variables could be considered in either statistical or spatially explicit hydrologic models. Second, the approach can be extended in complexity to larger systems as well as other management objectives. Third, climate change and resulting hydrologic nonstationary and uncertainty should be examined, as optimal operations depend on assumptions about inflow hydrology. Finally, variations in the value of water should be considered, as the value of forecasts directly depends on the value of water. In the kind of hydropower system considered here, this would entail different electricity prices, as with different energy supply portfolios.

5. Conclusion

Although more information is generally better, there are limits to the value of hydrologic forecasting investments under historical hydrologic and electricity demand conditions. The average potential additional value of perfect forecasts was found to be about \$0.8 million per year out of \$66.3 million mean annual revenue, or about 1.2%. However, within these limits, there are likely opportunities for further investments, depending on the cost of additional information. From a classical microeconomic perspective, the decision to invest in better hydrologic forecasting infrastructure and methods should be based on actual (not relative) costs and benefits.

A range of contextual factors affects the benefits (and costs) of improved hydrologic knowledge, including the sensitivity of the forecast model and its accuracy to measured state variables, infrastructure capacity, and operational constraints. In this study, regression model accuracy was relatively insensitive to SWE, resulting in little overall improvement in operations with decreased SWE uncertainty. For hydropower systems such as those in the Sierra Nevada, forecasting value is more sensitive to powerhouse capacity than to reservoir storage.

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Table 1: *Scenario Set Definitions*

Parameter	Units	Set 1 SWE Error	Set 2 Forecast Error	Set 3 Storage & PH Capacity	Set 4 PH Capacity
ϵ_{SWE}	no units	-0.5 to 0.5	0.0	0.0	0.0
α_f	no units	0.0	0.0 to 1.0	[0.0, 1.0]	[0.0, 1.0]
f_{meas}	(time step)	[month, day]	[month, day]	month	month
PH^{max}	(m^3 s^{-1})	25.5	25.5	0 to 175	0 to 100
S^{max}	(million m^3)	[131, 262]	[131, 262]	0 to 600	[131, 262, 524]
IFR_t	[m^3 s^{-1}]	0.31	0.31	0.31	0.31

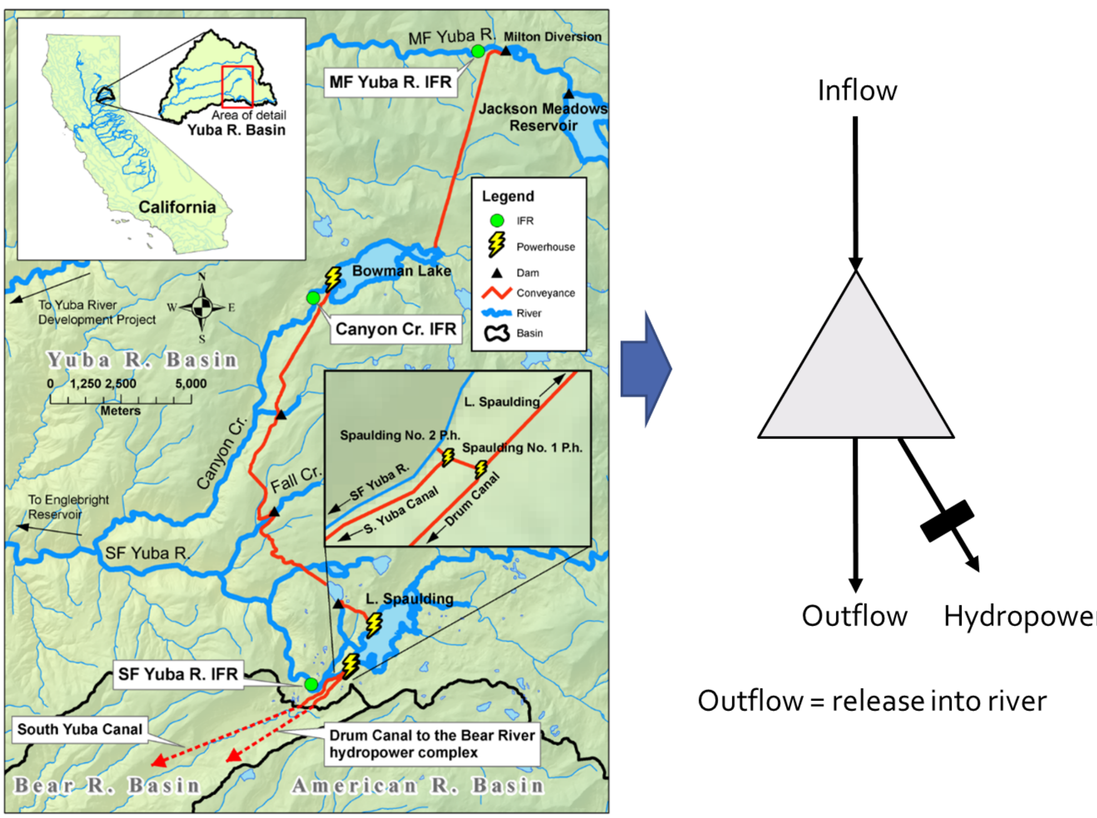

Figure 1: *The location of the Yuba-Bear/Drum-Spaulding hydropower complex and its representation as a single reservoir.*

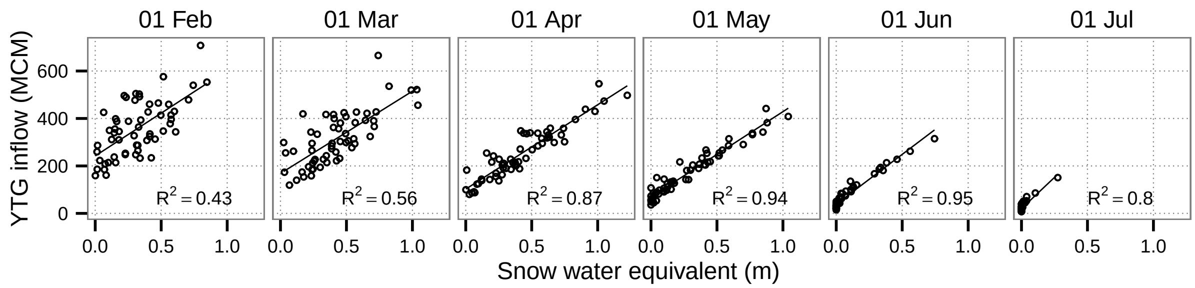

Figure 2: *Regression between snow water equivalent (SWE) and year-to-go (YTG) inflow on specific days of the year based on modeled historical SWE and inflow data.*

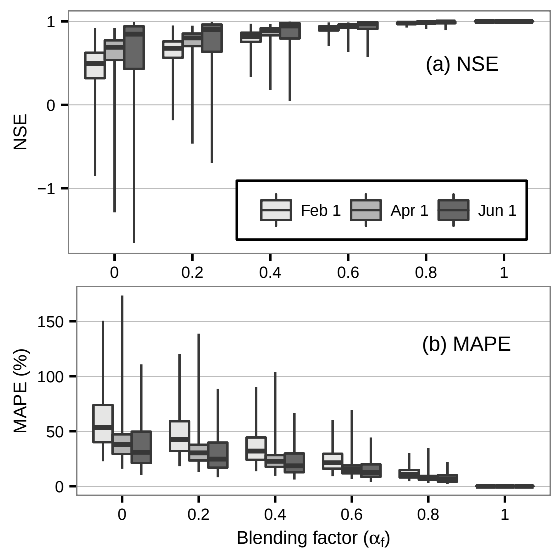

Figure 3: *Inflow forecast metrics by blending factor (α_f, equation (9)) for 3 days of the year. Metrics include a) Nash-Sutcliffe efficiency (NSE), b) mean absolute percent error (MAPE). $\alpha_f = 0$ represents statistical regression and $\alpha_f = 1$ represents perfect foresight. Whiskers span value ranges.*

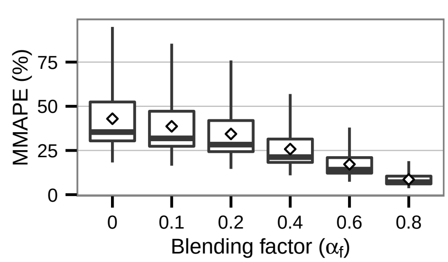

Figure 4: *Inflow forecast mean daily mean absolute percent error (MMAPE) by blending factor (α_f). Diamonds show the aggregated MMAPE. $\alpha_f = 0$ represents statistical regression and $\alpha_f = 1$ represents perfect foresight. Whiskers span value ranges.*

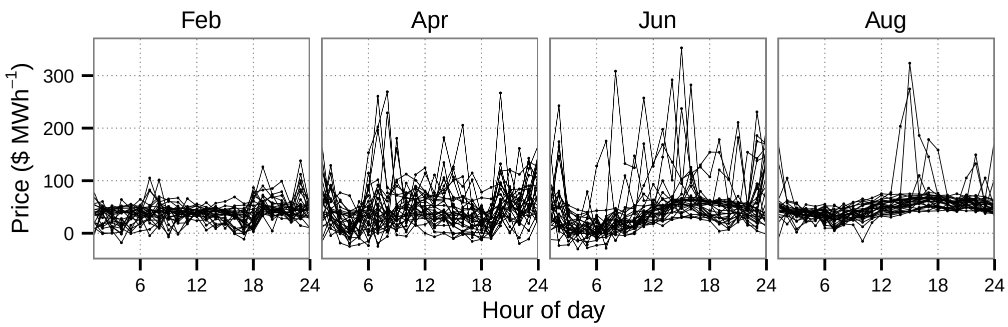

Figure 5: *Hourly California Independent System Operator (CAISO) northern region hourly electricity prices by month for 2006.*

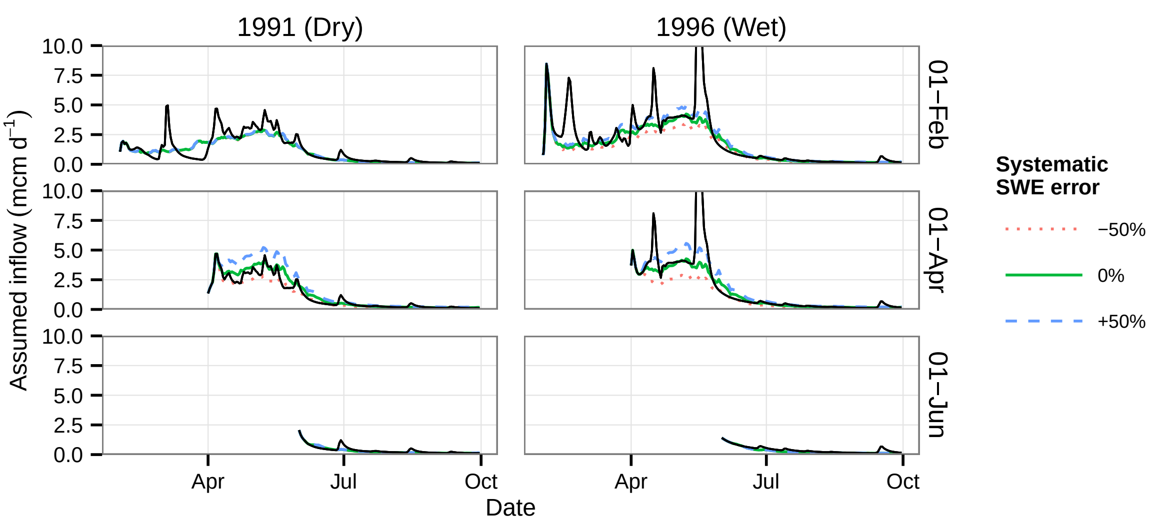

Figure 6: *Effect of systematic snow water equivalent (SWE) error on regressed median inflow hydrograph (I_{reg}) for 2 years, with actual inflow hydrograph from hydrology model (black lines) superimposed. First 7 days are assumed with perfect forecast.*

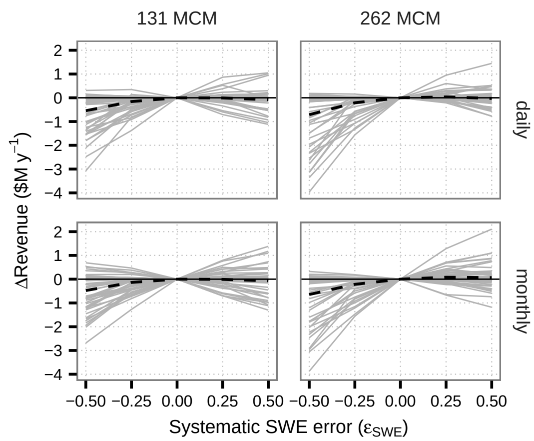

Figure 7: *Mean annual hydropower revenue with systematic snow water equivalent (SWE) error (ϵ_{SWE}) compared to no SWE error ($\epsilon_{SWE} = 0.0$) for all years. Each line is 1 year out of the 58 year record. Dashed line shows mean.*

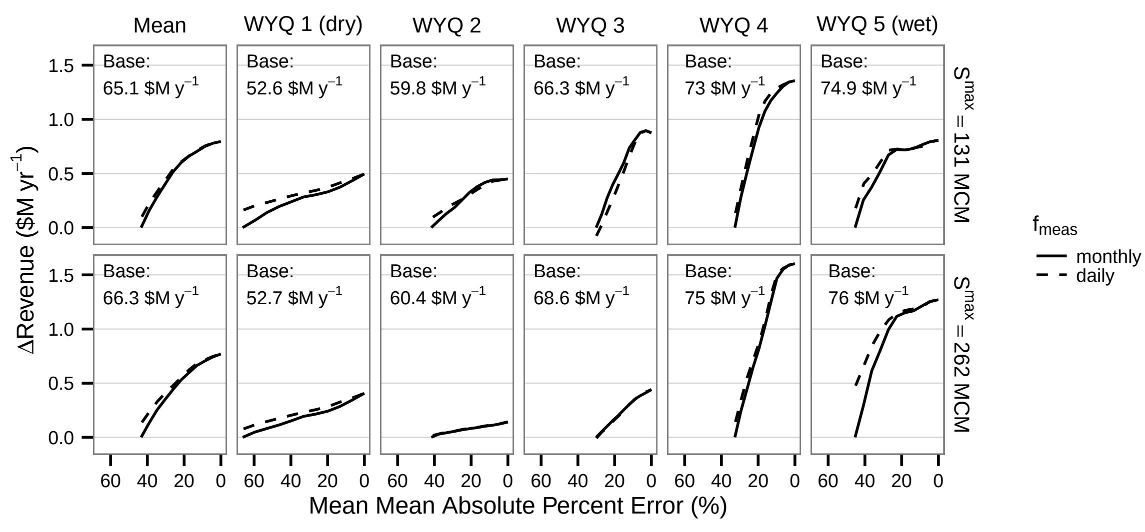

Figure 8: *Magnitude change in hydropower revenue (ΔRevenue) with reductions in mean mean absolute percent error (forecast improvements) by water year quintile (WYQ) and hydrologic measurement frequency (f_{meas}) for two reservoir sizes.*

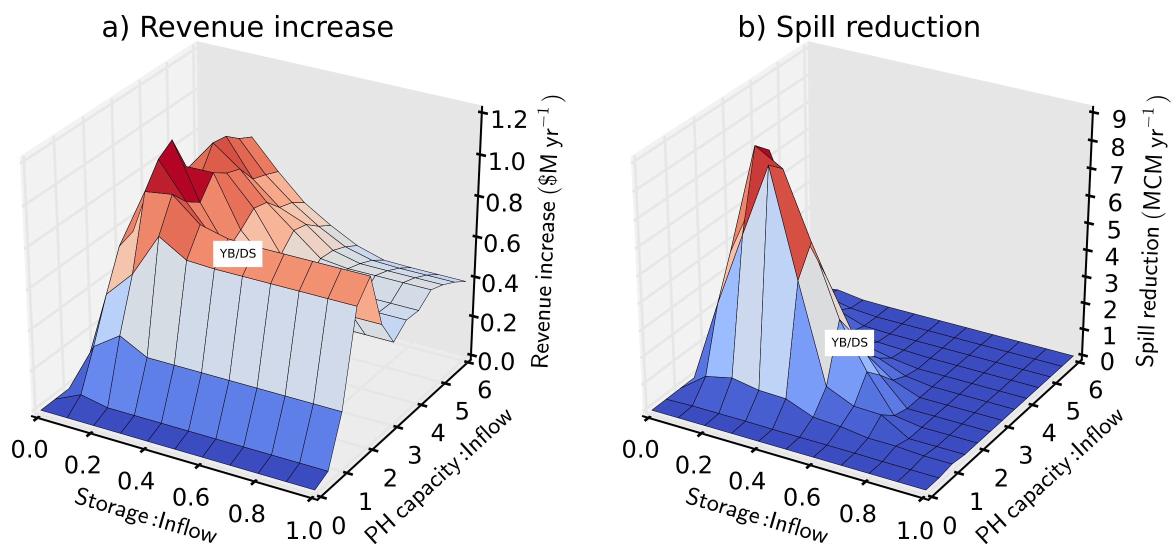

Figure 9: *Surface plots of a) revenue increase (forecast value) and b) spill reduction with perfect hydrologic foresight compared to statistical forecasts by different reservoir and powerhouse (PH) capacities normalized by mean annual inflow. Colors scale to the z-axis. "YB/DS" indicates the Yuba-Bear/Drum-Spaulding system.*

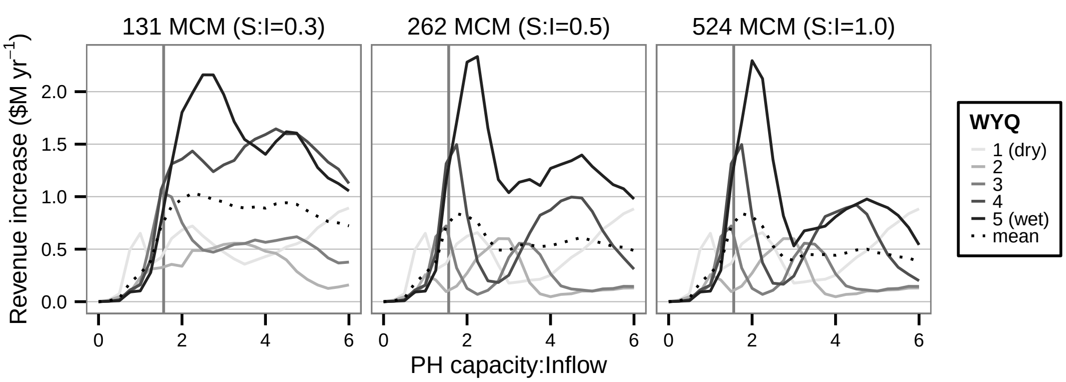

Figure 10: *Mean annual magnitude increase in hydropower revenue with perfect hydrologic forecast by powerhouse capacity:inflow and water year quintile for three normalized storage capacities (S:I). Vertical lines indicate the Yuba-Bear/Drum-Spaulding system.*