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Assessment of Folsom Lake Response to Historical and Potential Future Climate Scenarios

by

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Abstract

An integrated forecast-decision system for Folsom Lake (California) is developed and used to assess the sensitivity of reservoir performance to various forecast-management schemes under historical and future climate scenarios. The assessments are based on various combinations of inflow forecasting models, decision rules, and climate scenarios and demonstrate that (1) reliable inflow forecasts and adaptive decision systems can substantially benefit reservoir performance and (2) dynamic operational procedures represent effective climate change coping strategies.

1. Introduction

What are the conditions under which inflow forecasts can improve reservoir management? What is the value of adaptive forecast-decision systems relative to traditional reservoir operating rules? Are climate model predictions potentially useful for reservoir management? What are the potential impacts of climate change on reservoir performance? Can such impacts be mitigated by adaptive forecast-decision systems? These are the questions addressed in this article using as a case study the Folsom Lake on the American River in California.

Our approach is to conduct detailed comparative assessments using various combinations of inflow forecasting models, decision rules, and climate scenarios. Relevant recent studies aiming to quantify the impacts of climate change on managed water resources systems include *Chao, 1999,* and *Lettenmaier et al., 1999*, among others. These assessments assume that reservoirs are operated using traditional release rules and simulate their response under present and future climate scenarios. In this work, adaptive and dynamic decision schemes are shown to have distinct advantages over traditional practices, their value increasing with climate change. These findings are consistent with those of *Georgakakos et al., 1998a*. The value of different forecast forms is investigated, demonstrating that forecast uncertainty characterization is important for reservoir management. Forecast uncertainty is quantified using likely inflow realizations (forecast ensembles), and a new approach is developed to incorporate it within the decision system. A new inflow forecasting scheme is introduced and evaluated together with the forecasting schemes described in the companion article of *Carpenter and Georgakakos, 2000*. The complexity and data needs of the forecasting models vary, including models based on streamflow, models based on watershed hydrology, and models also based on climate (General Circulation Model) predictions (*Georgakakos et al., 1998b*).

In the following sections, the modeling framework is outlined first and its individual components are described; subsequently, the assessment findings are discussed for the historical and a potential future climate.

2. Modeling Framework

Figure 1 depicts the modeling framework used in this assessment. The principal modules pertain to (a) inflow forecasting, (b) reservoir management, and (c) system assessment. The inflow forecasting options to be tested include operational forecasts, historical analog ensemble forecasts, hydrologic ensemble forecasts, GCM-conditioned hydrologic ensemble forecasts, and perfect forecasts, all of which are further discussed in the following section. Reservoir management is based on a decision system which includes three coupled models pertinent to turbine load dispatching, short-range energy generation scheduling (hourly time steps), and long/mid-range reservoir management (daily time steps). The assessment process quantifies the response of the system over a long time horizon, assuming that reservoir releases are made based on the use of a particular combination of forecast-control models. The assessment is performed for three different inflow realizations: (a) a historical inflow realization from 1965 to 1993, (b) a potential inflow realization from 1993 to 2050 generated by the General Circulation Model (GCM) of the Canadian Center for Climate Modeling and Analysis assuming no CO_2 increase, and (c) a potential inflow realization from 1993 to 2050 generated by the same GCM assuming 1% CO_2 annual increase.

In the following sections, we first describe or provide references for the previous models and then discuss the results of the assessment.

*(**Figure 1:** Folsom Forecasting/Decision/Assessment Modeling Framework)*

3. Inflow Forecasting Models

Inflow forecasting is critical for reservoir management. Reliable multi-lead forecasts could increase energy generation, mitigate severe droughts, and provide reliable flood protection. However, forecast benefits depend on the skill of the forecasting models as well as on the form in which forecast information is presented to and used by the decision models and management processes. To assess the effectiveness of coupled forecast-decision schemes in a changing climate, several forecasting models of varying complexity were evaluated.

The "*Operational Forecasts*" scheme is a three-month inflow forecast sequence (consisting of a single trace) developed by the reservoir management authority at the beginning of each month. These sequences will herein be assumed as representative of those used in practice.

The *Historical Analog Extended Streamflow Prediction (Analog ESP*) forecasts are based on information contained in the historical streamflow record. The underlying premise of this model is that streamflows materialize as a result of a nonlinear hydro-climatic process orbiting around an unknown attractor set. Although this set is not easily definable, this premise leads to the following conjecture: If the process is presently at a certain point in its orbit, its position in the near future can potentially be inferred by observing the movement it experienced on similar occasions in the past. More specifically, streamflows are the result of the rainfall-runoff process, and the values they assume over a certain time period depend on various hydro-climatic factors including watershed rainfall, temperature, and soil moisture conditions. Thus, if the climate-watershed system tends to revisit the neighborhood of certain conditions (states), it should also tend to generate similar streamflow patterns.

In keeping with this intuitive conjecture, the historical analog ESP model "searches" the historical record and selects several inflow traces which, at some time in the past, have started from conditions similar to those of the current inflow sequence. Each one of these traces is a possible future realization of the inflow process, and all together constitute a set on which to base probabilistic, multi-lead forecasts.

Thus, suppose that the present time is April 1st, and the previous days' inflows were W_1,

$W_2,...,W_n$, where subscript "1" represents the last day in March, "2" the day before that, etc., and n is a parameter related to the process memory. Namely, $[W_1, W_2,...,W_n]$ is the most recent inflow sequence to April 1st. The next step in the implementation of the analog ESP model is to retrieve all inflow traces of the same month and date as the $W_1, W_2,...,W_n$ from the historical record and compute their Euclidian distance, E_j , from the current sequence:

$$E_j = \sqrt{\sum_{i=1}^{n} [\, W_i - W_i^j]^2} \quad , \quad j = 1 \, , \, ... \, , \, m \tag{1}$$

where W_i^j is the historical inflow of year j at the same calender date as W_i; m is the number of years in the historical record; and E_j measures the proximity of $[W_i^j , i=1, 2, ..., n]$ to the most recent inflows $[W_i , i=1, 2, ..., n]$. A small value of E_j implies that the W_i^j sequence is in the neighborhood of W_i . The inflows following W_i^j are known (as part of the historical record) and can be used as the forecasts of the inflows following W_i. To generate multiple forecast traces, one can rank the E_js from smallest to largest, select the top portion of the ranked list, and use the corresponding historical inflows following W_i^j as possible future inflow realizations. It is noted that several other ways may be used to measure the proximity of the historical to the most recent streamflow sequences. The reasons for using this particular scheme are that it is easy to implement and it has been effective in several other applications.

The analog ESP model has two parameters: (**1**) the length of the historical matching period [n], and (**2**) the number of inflow realizations. In this study, sensitivity analysis showed that model forecasting ability is optimized when the historical matching period is from three to seven days, and the forecast ensemble includes 10 to 15 inflow realizations. The model forecasting ability was measured by the criteria described below.

An example of a 60-day forecast ensemble is shown on Figure 2. Whether such forecast ensembles contain any useful information for reservoir management depends on their attributes of bias, reliability, and skill. A forecast ensemble is ***biased*** if its median (or mean) consistently over- or under-estimates actual inflow. A forecast ensemble is ***reliable*** if it contains the actual inflow sequence most of the time. Forecast ***skill*** is related to the range of the ensemble. The most desirable forecast ensembles are those that maintain a narrow (but reliable) range for long lead times. A series of retrospective simulations were conducted to assess the forecast attributes of the analog ESP model.

In these simulations, a forecast ensemble similar to the one on Figure 2 was generated for each day of the 1965 to 1993 historical period (29 years), with the actual inflow sequence excluded from the ensemble. At the end of the simulation process, 29 forecast ensembles (each consisting of 15 realizations and extending over 60 days) were generated for each calendar day of the year. For a particular calendar day and lead time, forecast bias was estimated by first computing the median (across the ensembles) difference between the ensemble median (across the ensemble traces) and the actual inflow. This quantity was then normalized by the median of the historical inflows. Forecast reliability was estimated as the percentage of the ensembles that contained the actual inflow. Lastly, forecast skill was measured by the ratio of the forecast ensemble range to the historical inflow range. The ratio distribution (29 sample points) was characterized by its minimum, maximum, and mean values. Figures 3 and 4 show these forecast measures for forecasts issued at the beginning of the first six months of the year when streamflow volume is most significant. The figures support the following observations:

- For most months and lead times, forecast bias is less than 10% of the median flow. The results are especially good for March through June, while for January and February they indicate that forecasts tend to underestimate inflow for short lead times. Overall, the analog ESP model provides fairly unbiased forecasts.

- Forecast reliability ranges from 85 to 97% for all months and lead times. This implies that forecast ensembles manage to contain the actual inflows approximately nine out of ten years.

- The ratio of forecast to historical inflow range suggests that the model also exhibits forecast skill. This conclusion follows by the wide and consistent separation of the minimum and maximum ratios as well as by the skewed position of the mean toward the minimum ratio. To put these results in perspective, complete lack of forecast skill would be indicated by all ratios (minimum, maximum, and mean) being close to 100%, while near-perfect forecasts would result in all ratios being close to zero. As can be seen in the figures, forecast skill varies with lead time but stays significant throughout the 60-day forecast horizon. The model performs particularly well in May.

All three forecast attributes are very important for reservoir management. Biased forecasts would result in misestimation of reservoir levels; forecasts of low reliability would cause frequent violations of minimum and maximum reservoir levels and releases; and forecasts of low skill would fail to anticipate wet and dry periods and would not fully utilize the reservoir regulation capability. To be most useful in reservoir management, inflow forecasting models should perform well with respect to all three criteria.

The next two inflow forecasting models include more detailed representations of the basin response to climate inputs. The *hydrologic ESP (H-ESP)* uses a physically-based representation of the Folsom watershed, while the *GCM-conditioned ESP (GCM-ESP)* additionally assumes that GCM climate forecasts (from the GCM of the Canadian Center for Climate Modeling and Analysis) are available and used as described by Carpenter and Georgakakos (companion article).

The last inflow forecast option, "*Perfect Forecasts*," assumes perfect knowledge of the upcoming inflows and is used to provide an upper bound of system performance.

*(**Figure 2:** Analog ESP Forecast Example (April 1st)*
*(**Figure 3:** Analog ESP Forecast Statistics (January, February, and March)*
*(**Figure 4:** Analog ESP Forecast Statistics (April, May, and June)*

4. Decision Models

The Folsom decision module is designed to support reservoir management decisions pertaining to multiple time scales. Specifically, this module consists of (**a**) a long/mid-range control model with a horizon of 60 days and daily time steps, (**b**) a short-range control model with a horizon of one day and hourly time steps, and (**c**) a turbine commitment and load dispatching model pertaining to each hour. The concept of this decision hierarchy for reservoir management has been introduced by *Georgakakos et al., 1997a,b,c*, and its operational implementation for actual reservoir systems are described by *Georgakakos and Yao* (articles in review, *Water Resources Research*). Thus to avoid duplication, in what follows we only provide a summary discussion, focusing on the formulation elements particular to Folsom.

4.1 Turbine Dispatching Model

Folsom's hydropower station includes three turbines, each with a power range of 15 to 70.5 MW. The turbine characteristic curves relate power generation to turbine discharge and hydraulic head as shown in Figure 5. The purpose of the turbine commitment and load dispatching model is to determine the most efficient plant operation (i.e., the turbine load schedules) such that for a given hourly total outflow (from all active turbines, spillways, and outlet conduits) power is maximized. Reservoir levels and outflows are determined by the higher decision levels and are inputs to this model. In addition to solving the turbine commitment and load dispatching problem, the model also generates a function that relates total power to reservoir level and total release, under best efficiency plant operation. This function (Figure 6) is determined using dynamic programming (*Georgakakos et al., 1997a*), and is used by the short-range decision model. For a particular combination of reservoir elevation and total release, Figure 6 provides the maximum possible power that can be produced by Folsom's hydroelectric facility.

*(**Figure 5:** Folsom Turbine Characteristic Curves)*
*(**Figure 6:** Best Efficiency Plant Power Function)*

4.2 Short-Range Decision Model

After scheduling the plant operation within each hour, the next level of decisions pertain to the hourly energy generation scheduling (and reservoir release) during each day. Depending on power system requirements, this decision level should consider dependable capacity commitments (hours during which the plant is committed to operate at capacity), minimum flow requirements, and energy prices as a function of power demand. Two common management objectives are to maximize the value of daily energy *(Georgakakos et al., 1997c*) or to maximize the daily energy itself *(Georgakakos et al., 1997b)* subject to all relevant operational requirements. The present study uses the second objective due to the unavailability of the marginal power generation cost curve of the power system to which Folsom contributes.

Denoting u the total daily release; H the reservoir elevation at the beginning of the day; T_D the number of peak generation hours for that day; P_{max} the total power capacity at reservoir level H; Q_{max} the corresponding discharge (P_{max} and Q_{max} are determined from the power function shown on Figure 6 for elevation H); Q_i the plant discharge for the i^{th} hour of the day; Q_{min} the minimum hourly release; P the optimal plant power generation function of Figure 6; and $g_E[u,H]$ the daily energy generation, the short-term decision problem can be stated as follows:

$$\underset{Q_i, i=1,2,...,24-T_D}{Maximize} \quad \{ g_E[u,H] = P_{\max} T_D + \sum_{i=1}^{24-T_D} P(Q_i, H) \} \ , \tag{2}$$

subject to

$$\begin{aligned} u &= Q_{\max} T_D + \sum_{i=1}^{24-T_D} Q_i \, , \\ Q_{\min} &\leq Q_i \leq Q_{\max} \ , \ i = 1,2,\ldots,24 \ . \end{aligned} \tag{3}$$

For a particular daily release u and reservoir level H (provided by the long/mid-range decision model), the solution of the above problem yields the maximum daily energy that can be generated subject to the stated constraints. The solution can be obtained via an one-dimensional dynamic programming algorithm. We note that elevation H is assumed to be constant because the daily elevation variation can usually be neglected. If significant level changes occur during the day, then the reservoir water balance equation (hourly time steps) should also be included in the constraint set.

In addition to the optimal hourly generation and release schedule, the short-range decision model also develops the optimal daily energy function by solving the previous problem for many combinations of u, H, and T_D. Figure 7 shows a plot of this function for T_D equal to zero. The optimal daily energy generation function is used by the long/mid-range decision model as described below.

(***Figure 7:*** *Optimal Daily Energy Generation Function)*

4.3 Long/Mid-Range Decision Model

The short-range decision level addresses hourly operational decisions within each day *given* a reservoir level and a daily release volume. The purpose of the long/mid-range decision model is to determine reservoir release and level sequences that satisfy Folsom's long-term objectives–flood control, hydropower generation, water supply, environmental protection, and drought management. This model has a control horizon of 60 days, thus combining long- and mid-range features. Reservoir level changes are incorporated through the water balance equation:

$$\begin{aligned} S(k+1) &= S(k) - u(k) + w(k) - e(k)\ A[S(k)] - d(k)\ , \\ H(k) &= H[S(k)]\ , \\ k &= 0, 1, \ldots, N-1\ , \end{aligned} \tag{4}$$

where S(k) is the reservoir storage at the beginning of day k, u(k) is the total daily release, w(k) is reservoir inflow, e(k) is the evaporation rate, A[S(k)] is the water surface area, d(k) is the water demand, and N is 60 days (control horizon). In the above equation, reservoir inflow is uncertain, causing future reservoir storage to be uncertain too. However, inflow forecast ensembles can serve to quantify this uncertainty and define reliable reservoir operation policies.

Reservoir level and release variables are constrained by physical capacity and operational limitations:

$$\begin{gathered} H^{\min}(k) \le H[S(k)] \le H^{\max}(k)\ , \\ k = 0, 1, \ldots, N, \end{gathered} \tag{5}$$

where $H^{min}(k)$, $H^{max}(k)$, $u^{min}(k)$, and $u^{max}(k)$ are lower and upper level and release limits. In view of the inflow uncertainty, a more appropriate representation of the reservoir level

$$u^{min}(k) \leq u(k) \leq u^{max}(k)\,, \\ k = 0, 1, \ldots, N-1\,. \tag{6}$$

constraints is as follows:

$$\begin{aligned} &Prob[H[S(k)] \leq H^{min}(k)] \leq \varepsilon^{min}\,, \\ &Prob[H[S(k)] \geq H^{max}(k)] \leq \varepsilon^{max}\,, \\ &k = 0, 1, \ldots, N, \end{aligned} \tag{7}$$

$$u^{max}(k) = u^{max}_{Trbn}(k) + u^{max}_{Splwy}(k)\,, \\ k = 0, 1, \ldots, N-1\,. \tag{8}$$

where ε^{min} and ε^{max} are user-specified risk thresholds (e.g., 1% or 10%) at which reservoir level would be acceptable to exceed its specified limits. For Folsom, $H^{min}(k)$ and $H^{max}(k)$ correspond to the lower and upper levels of the active storage zone, extending from 327 to 466 feet.

The minimum release, $u^{min}(k)$, is set at 1000 cfs to accommodate downstream environmental and water supply requirements, while the maximum release, $u^{max}(k)$, is taken as the combined turbine and spillway outflow capacity, and depends on reservoir level as well as on power generation limits. It is noted that $u^{min}(k)$ could also accommodate *seasonally variable* instream flow requirements that are better suited for environmental and fish and wild life protection.

Though the reservoir outlet structures can release at very high discharge rates (200,000 to 300,000 cfs), the cost of flood damage to the downstream areas (Figure 8) rises sharply for outflows exceeding 115,000 cfs.

Folsom's primary regulation objectives include flood protection, power generation, and the provision of dependable downstream releases for water supply and environmental and ecosystem protection (drought management). From a long-range management standpoint, these objectives would be optimized if the regulation policy realizes *all* of the following conditions:

- Maintain reservoir level as high as possible (for hydropower and drought management);
- Avoid excessive outflows (for flood protection and hydropower); and
- Meet minimum flow requirements (for drought management and hydropower).

Some of these conditions are build into the long/mid-range control model through the above-stated constraints [e.g., Constraint (6)], while the rest are incorporated through the performance index (or objective function). Thus, the rationale and role of the performance index is to realize (to the extent possible) these desirable operational conditions. The formulation is as follows:

$$\begin{aligned} J = E\{ \sum_{k=0}^{N-1} \{ & \alpha\, g_H[S(k)] + \beta\, g_{spl}[u(k), S(k)] + \gamma\, g_{fldmg}[u(k)] \\ & + \delta\, g_{H-trgt}[S(k)] - \varepsilon\, g_E[u(k), H(S(k))] \} \\ & + \zeta\, g_H[S(N)] + \eta\, g_{H-trgt}[S(N)] \} . \end{aligned} \tag{9}$$

E{ } denotes expectation with respect to the joint probability distribution of the reservoir inflows. The first term enforces the requirement that reservoir levels should be kept within H^{min} and H^{max} [Constraints (7)]. Function g_H[ ] has the continuously differentiable form introduced by *Georgakakos et al., 1997a*, assigning a high penalty to reservoir level fluctuations outside the permissible range. The second term concerns reservoir spillage. Spillage is defined as release exceeding turbine capacity but being less than $u^{max}(k)$ [Equation (8)]. This term adds a quadratic penalty when spillage occurs and thus favors sequences that avoid it. In addition to the spillage penalty, the third term penalizes releases over 115,000 cfs that accrue flood damage.

The functional form is a smooth approximation of the flood damage function of Figure 8. The fourth term aims at maintaining the reservoir near the top of the conservation pool [$H^{max}(k)$] to conserve water, enable recreation activities, and optimize power generation efficiency. The fifth term is the daily generation function derived by the short-range control model (Figure 7), with a negative sign to conform to a minimization formulation. Lastly, the sixth and seventh terms relate to the reservoir levels at the end of the control horizon and are functionally similar to the first and fourth terms.

Penalty parameters α, β, γ, δ, ε, ζ, and η are used to weigh the significance of the various performance index terms and are distinguished in three clusters. Parameters α, β, γ, and ζ impose the highest weights to guide the control algorithm to first identify sequences which meet the level constraints and avoid spillage and flood damage. Parameter δ assigns an intermediate weight to limit the previous sequences to those that maintain high feasible reservoir levels. Lastly, parameter ε introduces the lowest relative weight to further restrict the identified sequences to those that additionally optimize power generation efficiency. The actual numerical values of these parameters are selected so that the terms in the different clusters differ by a factor of 100. Sensitivity analysis shows that these specifications identify release policies that generate desirable reservoir sequences.

The control problem formulated here is solved using the Extended Linear Quadratic Gaussian (ELQG) control method which was developed by *Georgakakos 1989, 1993, Georgakakos et al., 1997a,b,c,* and *Georgakakos et al., 1998a*. ELQG is an iterative optimization procedure starting from an initial control sequence {$\mathbf{u}(k)$; k = 0, 1, 2, .., N-1} and subsequently generating increasingly better sequences until convergence. Convergence is achieved when the value of the performance index cannot be reduced any further. ELQG is reliable, computationally efficient, and especially suited for uncertain, multi-reservoir systems. For a more detailed discussions of the ELQG algorithmic features, the reader is referred to the previously cited references.

***(Figure 8:** Food Damage Curve)*

4.4 Uncertainty Characterization

ELQG is an optimization method that constructs the storage probability distributions using a number of statistical moments, usually the mean, covariance, and possibly third order moments (*Georgakakos, 1989*). These probability distributions are then approximated by normal or log-normal functions (or other probability models as appropriate) and used to establish the feasible solution space. Though this procedure generally works well, some discrepancies still arise, especially in cases where control (release) constraints alternate between a binding and a non-binding status, changing the shape of the storage probability distributions. To correct for these discrepancies, *Georgakakos and Yao, 2000 (article in review)*, introduced an ELQG modification that ensures the fidelity of the reliability constraints (7) through a full uncertainty characterization. We next discuss the main idea of this modification.

As part of the solution process, ELQG generates linear approximations of the problem's feedback control laws $\{u(k) = \mu_k[S(k)],\ k=0,1,...,N-1\}$:

$$\begin{aligned} u(k) &= \Lambda(k)\ S(k) + \lambda(k) \\ k &= 0, 1, \ldots, N-1\,, \end{aligned} \tag{10}$$

where $\{\Lambda(k)$, and $\lambda(k)$, $k=0,1,...,N-1\}$ are control gains computed analytically. The idea is to use these approximate linear feedback laws together with the inflow forecast traces to generate possible *storage (elevation)* realizations over the control horizon. For each inflow trace, this computation can be performed efficiently by substituting the linear feedback functions (10) into the system dynamics (4) and iterating in time. Repeating the process for all inflow traces in the forecast ensemble, several storage (elevation) realizations can be computed and used to characterize the entire probability distribution for all time periods. *Georgakakos and Yao, 2000*, discuss the details of this approach and demonstrate (through Monte Carlo analysis) that it provides reliable characterizations of the storage probability distributions. Figure 9 shows the reservoir elevation and release ensembles that may materialize over a period of two months as a result of decision process and the inflow ensemble of Figure 2. In this run, the regulation objective is to maintain high reservoir levels, ensure that 90% of them are below 466 feet (the upper elevation limit), generate as much energy as possible, minimize spillage, and meet the downstream flow requirements.

In an operational application of the decision system, the release derived for the first day would be implemented, and a new run would be performed at the beginning of the following day after updating the inflow forecasts and reservoir level. This sequential operation would ensure that decisions are always made using current information.

Figure 9 exemplifies the importance of good inflow forecasts. Forecast bias, reliability, and skill directly affect the location and shape of the possible reservoir level and release ensembles, and thus enhance or undermine the effectiveness of the decision process. The figure also illustrates the objective of the decision system. The objective is to create reservoir level and release ensembles desirable in shape as well as in location.

*(**Figure 9:** An Example Run of the Folsom Decision Model)*

4.5 Decision Model Linkages

The three models of the decision system constitute a multilevel control hierarchy with an operational flow that follows two directions: The lower level models are activated first to generate information that is used by the upper levels regarding performance functions and bounds. In the course of this upward flow, the decision system simulates the Folsom response for various hydrologic and water use scenarios, selecting those that optimize system performance. Once the most desirable policies are identified, the control levels are activated in the reverse order to generate the best turbine hourly sequences and loads implementing these decisions consistently across all relevant time scales. The decision system is designed to operate sequentially, at the beginning of each day, continually updating its release policies in keeping with the most current inflow forecasts and operational conditions.

The Folsom decision support system (Folsom DSS) is implemented within a user-friendly, PC-based interface and can be used for planning and operational purposes.

5. Assessment Model

The last element of the Folsom DSS (Figure 1) is the assessment model. Its purpose is to quantify the Folsom response for a specified inflow sequence, streamflow forecasting scheme, and operational policy. The assessment model replicates the sequential operation in which the decision system is designed to work in practice. Thus, at the beginning of each day in the assessment period, the inflow forecasting scheme is invoked first to generate a forecast ensemble for the upcoming inflows. As discussed, a good forecast ensemble has the potential to fully characterize the uncertainty of future inflows. However, this information may or may not be utilized, depending on the nature of the management system. If, for example, reservoir release policies are derived by deterministic management schemes (as are most current reservoir operating rules relating water level to release), the inflow ensemble is usually reduced to a single time sequence such as the median or the average trace, and the uncertainty implied by the ensemble is ignored. In this work, we will consider and evaluate both deterministic and full ensemble forecasts.

Next, the decision system uses the forecast information to determine the most desirable reservoir release sequences over the forecast-control horizon as described in the previous sections. The response of the reservoir is then simulated for the current day, and the process is repeated at the beginning of the next day. At the completion of the forecast-decision-simulation process, the program generates sequences of all relevant system performance measures including reservoir levels, releases, energy generation, flood damage, and low flow violations. These sequences can be used to compare the benefits and consequences of various inflow scenarios, forecast-decision configurations, and operational policies. For example, Figure 10 shows the reservoir level and release sequences that would result over the 1965-1993 historical time period under (**a**) the "Operational Forecast" option and a decision rule derived from current management practices (to be discussed in the following section), and (**b**) the "Perfect Forecast" option and the Folsom DSS. These different scenarios can be viewed as two extreme cases, with the former using heuristic forecasts and fixed decision rule curves and the latter using perfect forecasts and adaptive decision policies. The figure shows that the heuristic management scenario keeps lower reservoir levels and avoids flooding, but it also causes minimum flow violations and generates about 18% less energy. By contrast, the adaptive scenario uses the forecasts to derive dynamic release policies drawing the reservoir down in anticipation of high floods and allowing it to refill as flood waves pass. As a result, flood damage is avoided, reservoir levels and energy generation are higher, and minimum flow requirements are met always. Perfect forecasts, however, are unattainable, and the adaptive scenario can only serve to define an upper performance limit. A question of practical interest is "How close can Folsom get to this optimal performance using *realistic* forecast procedures and adaptive management schemes?" This question is taken up next.

*(**Figure 10:** Example Runs of the Folsom Assessment Model)*

6. Historical Climate Assessments

Assessments for the 1965 to 1993 historical period were performed for various forecast-decision model combinations. The results on Table 1 were obtained using a simplification of the current decision rule coupled with three different forecasting models. The decision rule (which is shown on Figure 11 and will be referred to as "rule curve") sets high reservoir level targets for the dry season (from June to October) and lower level targets for flood-prone winter and early spring. In operational practice, a different target curve is selected depending on the available storage at three smaller upstream reservoirs. The simplification used herein is that the *same* upstream storage availability is assumed *throughout* the assessment horizon, and curve switching is not permitted. However, assessments are performed for all four rule curves. Inflow forecasts are obtained using the operational forecast, analog ESP, and perfect forecast schemes.

Table 1 reports model performance relative to energy generation, energy value (based on 1995 California monthly energy prices), spillage (release volume in excess of turbine capacity), minimum flow violations, and flood damage. Comparing the results for different rule curves, we note that all four avoid flood damage. However, the curves corresponding to 100 and 130 thousand acre feet (TAF) of upstream storage lead to minimum flow violations. This happens because the prescribed drawdown cannot always be refilled by the end of the wet season, leaving the reservoir vulnerable to droughts. (The reservoir level and release sequences corresponding to the 100 TAF rule curve are shown on Figure 10.) With respect to energy generation, the rule curves with higher reservoir levels perform better, increasing energy revenues by approximately 0.8 to 1.8 million dollars per year. Considering that no rule curve causes flood damage, it can be concluded that the rule curve corresponding to 200 TAF of upstream storage performs best.

Comparing the results for different forecasting options, we note that model performance is not sensitive to forecast quality. The reasons for this are that (1) the rule curves are overly conservative relative to flood control and (b) the dominant decision factor is the position of the reservoir relative to the rule curve. Thus, even perfect inflow forecasts do not accrue appreciable improvements.

The results on Table 2 were obtained using the Folsom DSS and various forecast schemes including the operational forecasts, analog ESP, hydrologic ESP, GCM-conditioned ESP, and perfect forecasts. The reliability parameter indicates the type of forecast information utilized by the decision system. The "deterministic" and "50%" indications imply the use of a single sequence. For the ESP schemes, this sequence corresponds to the median trace. The "90%" indication implies the use of the full forecast ensemble and a probabilistic tolerance threshold of 90% for the reservoir level constraints (7).

The assessment results support several notable conclusions. First, the full forecast ensemble cases consistently outperform the deterministic forecast cases (with the exception of the perfect forecasts). More specifically, the full forecast ensemble methods increase energy generation by 11 to 17 GWH per year (2 to 3% increase), increase energy revenues by 1.3 to 1.8 million dollars per year (also a 2 to 3% increase), decrease annual spillage by 50%, and decrease flood damage by 622 to 841 million dollars. These improvements occur because forecast ensembles forewarn the decision model of the potential inflow range, helping it to avoid excessive releases while maintaining high reservoir levels. Thus, inflow forecast ensembles coupled with stochastic dynamic management schemes can substantively improve reservoir management. By contrast, deterministic forecasts provide incomplete information for future inflows and (in the long term) lead to over-confident and risky management policies.

The differences among the forecast ensemble methods (cases labeled 90%) are related to their attributes of bias, reliability, and skill. The results show that the GCM-conditioned ESP outperforms the hydrologic ESP, with the former incurring 114.7 million less flood damage than the latter. Thus, in Folsom's case, climate information helps extend the foresight of hydrologic forecasts and improves reservoir management. Both models, however, exhibit lower forecast reliability than the analog ESP model which manages to eliminate flood damage, spill less, and generate an additional 2 to 4 GWH per year. On the other hand, the results for the 50% cases show that the GCM-conditioned ESP performs somewhat better than the analog ESP and hydrologic ESP, due to less forecast bias. Thus, although physically-based models have the potential to improve forecast accuracy (especially for conditions outside their calibration range), they do not necessarily improve reservoir management unless their forecast ensembles exhibit high reliability. Compared to the "perfect forecast" case, the full ensemble analog ESP generates only 4% less hydropower and is equally effective with respect to flood protection.

Comparing the results of Table 2 with those of Table 1, we conclude that dynamic decision schemes using reliable forecast ensembles can substantively improve reservoir management. Specifically, the Folsom DSS using analog ESP forecasts generates 55 GWH per year more energy than the 200-rule curve, increasing the annual energy revenue by 4.7 million dollars (an 8.9% increase). Both schemes fully avoid flood damage and always meet the minimum flow requirements.

*(**Figure 11:** A Schematic of Folsom's Rule Curve)*

7. Future Climate Assessments

A future climate/hydrology scenario for Folsom was generated using the GCM of the Canadian Center for Climate Modeling and Analysis, assuming a 1% annual CO_2 increase (Carpenter and Georgakakos, *companion article)*. A direct comparison of this scenario with the historical scenario would not be appropriate, however, because GCM skill to simulate regional climate conditions is limited. Thus, a GCM-*control* run for the historical period was also generated. The annual average inflows for the three scenarios are 106.6 billion cubic feet (historical), 116.4 billion cubic feet (GCM control run for the historical period), and 150.3 billion cubic feet (1% CO_2 annual increase). The maximum daily inflows for the three scenarios are 121,837 cubic feet per second (historical), 81,700 cubic feet per second (GCM control run for the historical period), and 149,736 cubic feet per second (1% CO_2 annual increase). Thus, the Canadian GCM suggests that Central California will experience wetter and more variable climate under a CO_2 increase. Comparing the GCM-control scenario for the historical period with the GCM CO_2-increase scenario, annual average flow is expected to increase by 30% while daily maximum flow is expected to increase by 80%. A comparison of the GCM-control with the true historical scenario shows that the Canadian GCM over-estimates average flows and under-estimates extremes.

Tables 3 and 4 summarize the assessment results for the GCM control and CO_2 increase scenarios for various decision-forecast model combinations. Comparing the results of the two tables, we note that Folsom's energy generation and revenue (based on 1995 electricity prices) would increase by 20 to 24%, spillage would increase by 65 to 80%, and flood damage would, in some cases, increase by more than 4.3 billion dollars.

Comparing the Folsom DSS with the rule curves (for the analog ESP forecast case), we note that the performance improvements due to the former decision scheme are expected to increase. Specifically, the energy value difference of the two schemes amounts to 8.3% for the historical climate, 10.5% for the GCM-controlled climate, and 13% for the CO_2 increase climate. Neither scheme causes flood damage or minimum flow violations. These results imply that adaptive management schemes can mitigate the effects of climate change and improve system performance. By contrast, the performance of heuristic operational procedures degrades as climate changes away from its current state.

As in the historical assessments, using full forecast ensembles to derive adaptive management policies also improves system response. This improvement is most notable in flood control (Table 4). Using the Folsom DSS with a median analog ESP forecast sequence (1% CO_2 increase scenario) would cause 4.3 billion dollars flood damage, while the same decision-forecast scheme with the full forecast ensemble would completely avoid flood damage. The improvement is also significant for the other forecasting schemes. For example, using the Folsom DSS with the full hydrologic ESP forecast ensemble would incur 219 million dollars flood damage compared to 4.3 billion dollars accrued by the median hydrologic ESP sequence. Full forecast ensembles also benefit energy generation. In this regard, the potential improvements range from 4.5 to 8.5%, more than twice the percent improvement for the historical climate (both observed and GCM controlled). Thus, the value of full forecast ensembles increases in wetter and more variable climates. If the GCM tendency to over-estimate average and under-estimate extreme conditions applies to the future climate scenario, climate change impacts would intensify and adaptive forecast-decision schemes would become even more attractive.

The relative performance of the various model combinations is similar to that of the historical period. Namely, for deterministic forecasts, the GCM-conditioned ESP performs better than the hydrologic ESP and the analog ESP, while for full forecast ensembles, the analog ESP performs best.

To establish an upper performance bound, a run was also conducted with perfect streamflow forecasts. In this case, flood damage is prevented, energy generation attains a maximum value, and spillage is minimized. These results are within 3% of those obtained with the Folsom DSS and the analog ESP forecasts.

8. Conclusions

This work assesses the value of integrated forecast-decision systems for reservoir management under historical and future climate scenarios. Though the assessment results are strictly valid for Folsom Lake on the American River in California, they support several general qualitative conclusions.

- To be useful in reservoir management, inflow forecasting models should exhibit good unbiassness, reliability, and skill attributes. Models that quantify forecast uncertainty, such as models based on forecast ensembles, are most effective and can clearly improve system performance. Furthermore, the use of climate models can enhance hydrologic forecasting. However, the overall value of the forecasting scheme depends on its bias, reliability, and skill, and simpler models (such as the analog ESP introduced in this work) can be equally or even more effective.

- Forecasting models do not *necessarily* improve reservoir management. For improvements to occur, the management process (or model) must also use forecast information *effectively*. Perfect forecasts, for example, used within traditional rule curves were found to accrue no appreciable improvements. By contrast, adaptive decision systems utilizing reliable forecast ensembles to determine dynamic operational policies were found to be highly effective.

- The General Circulation Model of the Canadian Center for Climate Modeling and Analysis predicts that further atmospheric CO_2 increases will lead to a wetter and more variable climate in Central California. Assessment investigations with this potential climate scenario indicate that traditional reservoir operation rules will gradually downgrade reservoir performance as the climate changes away from its current state. Furthermore, the assessments show that adaptive forecast-decision schemes can effectively mitigate the effects of climate change and even improve reservoir response.

Acknowledgments

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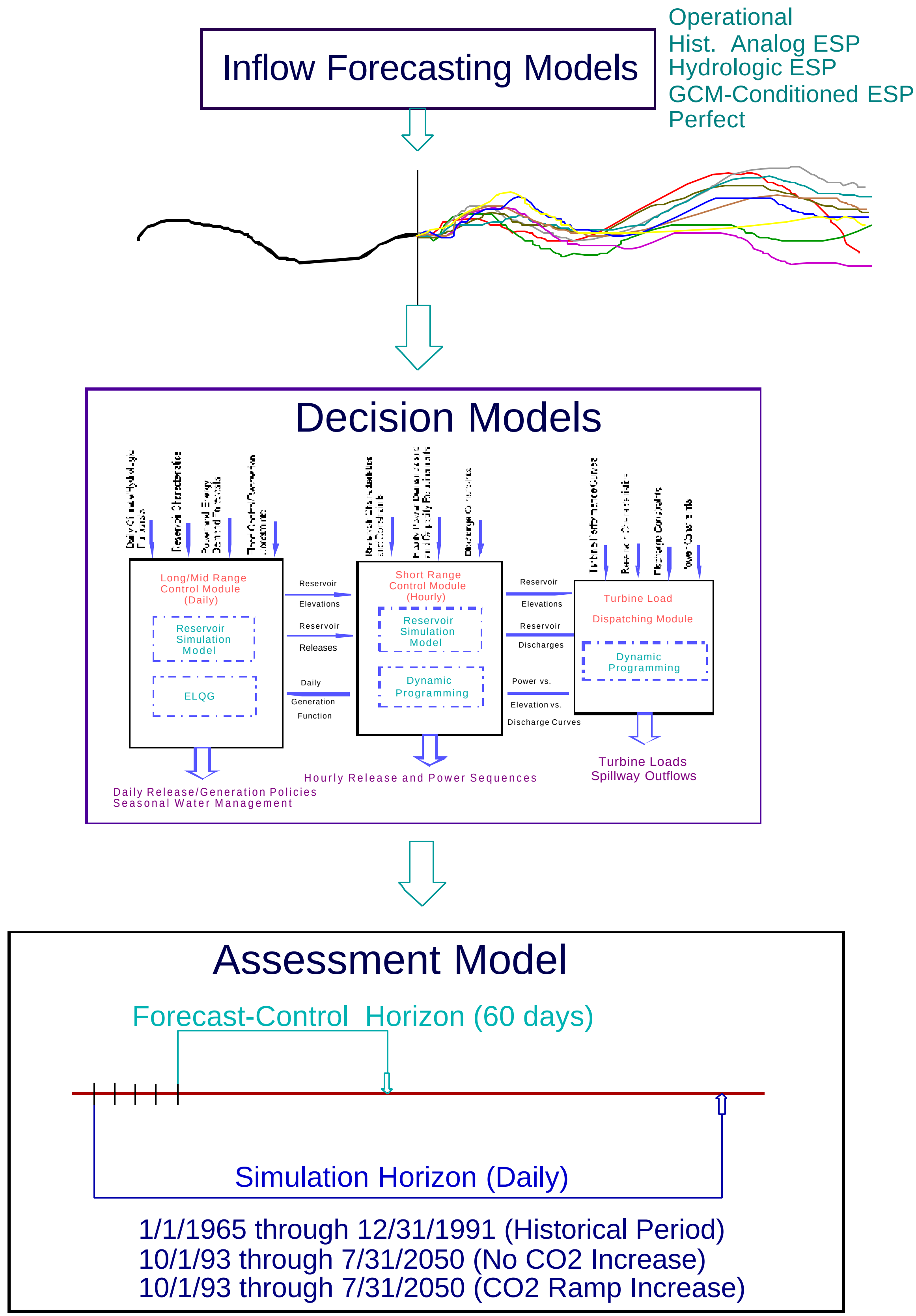


Figure 1: Folsom Forecast/Decision/Assessment Modeling Framework

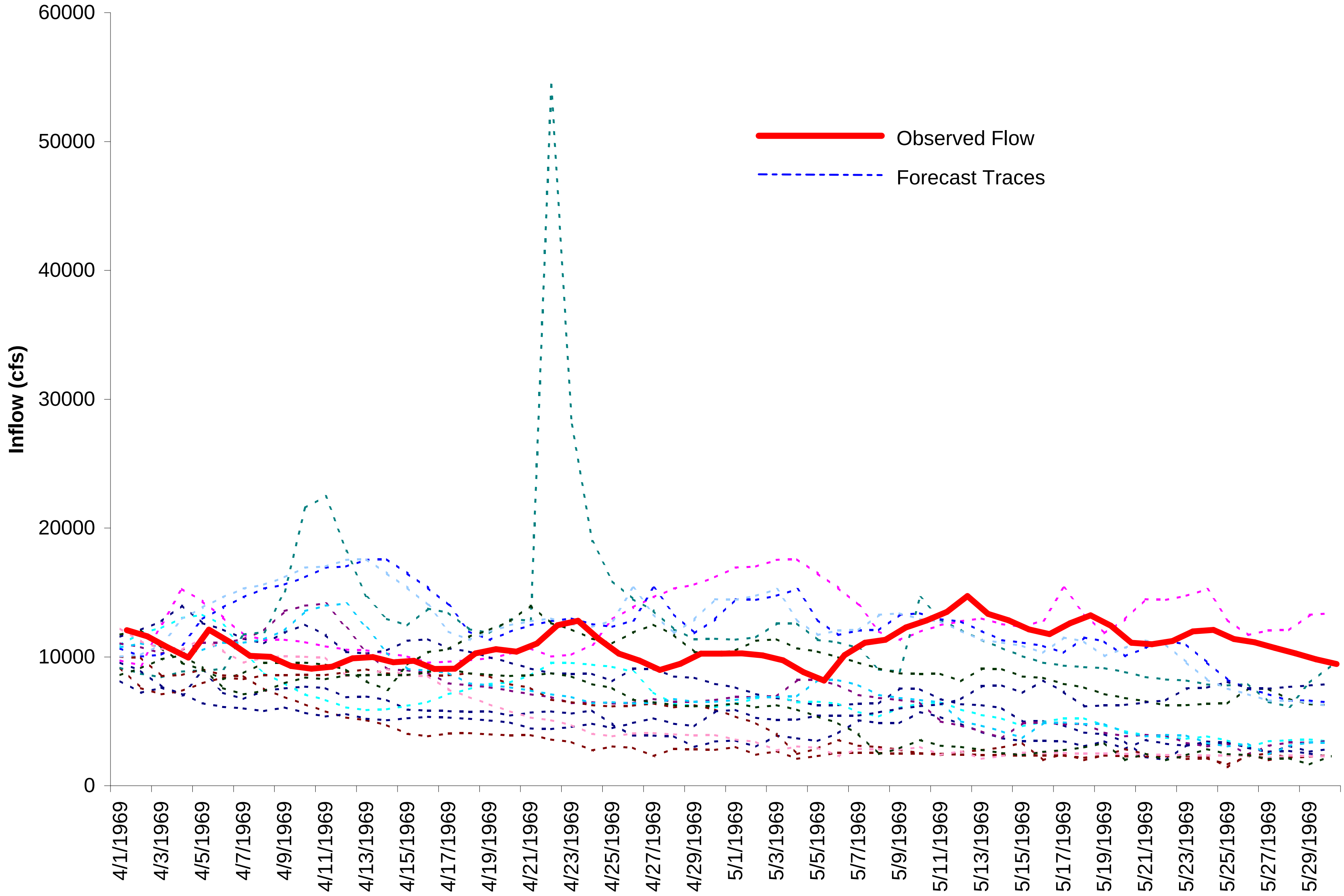


Figure 2: Analog ESP Forecast Example (April 1st)

Figure 3: Historical Analog ESP Model Forecast Assessment

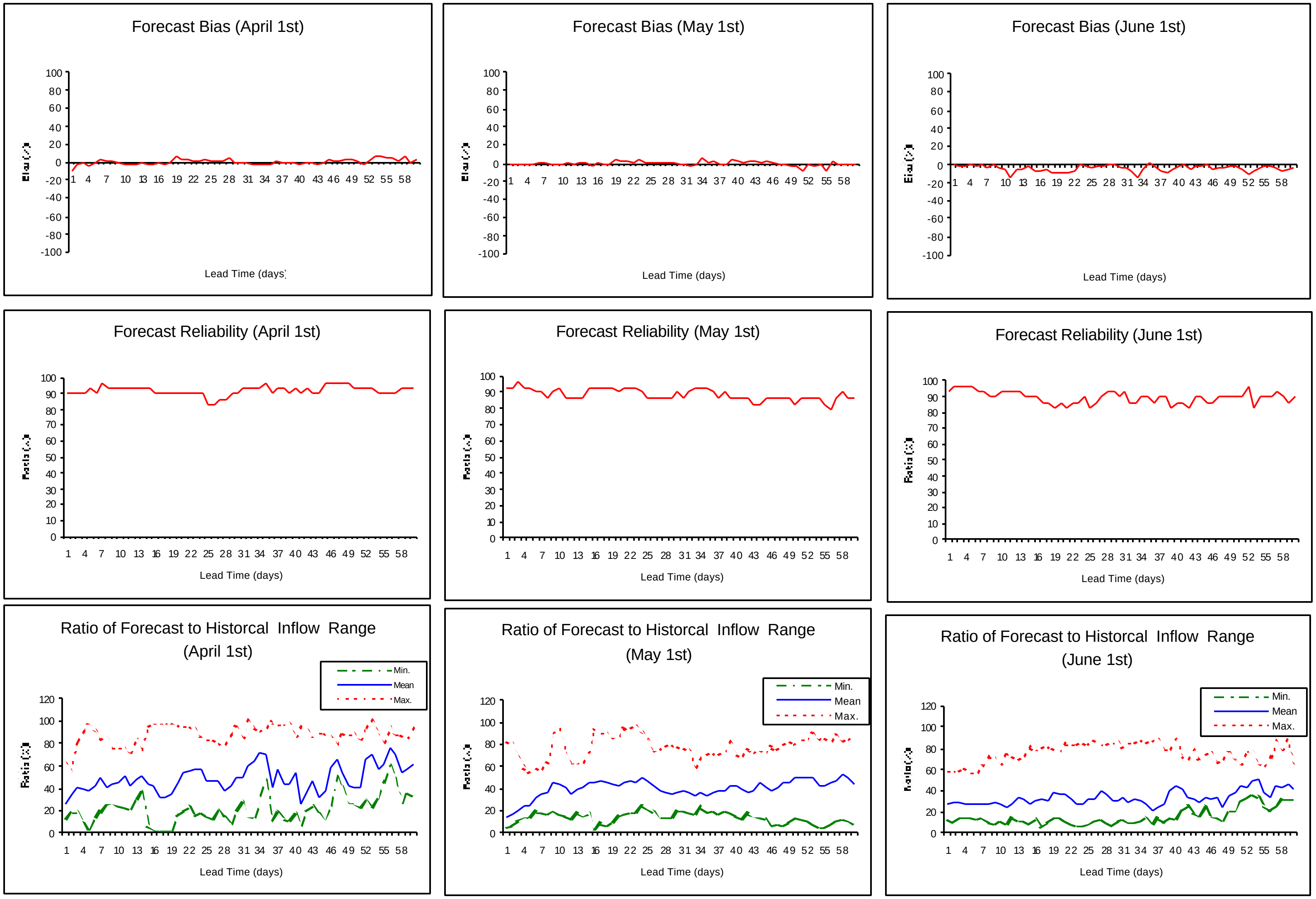


Figure 4: Historical Analog ESP Model Forecast Assessment

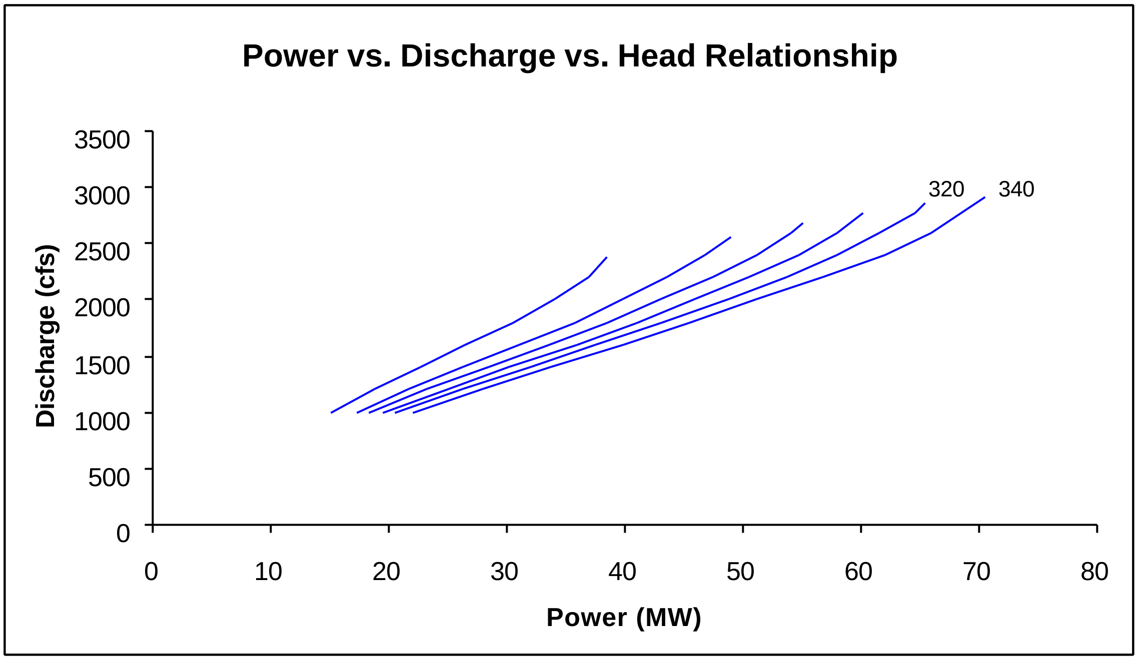


Figure 5: Folsom Turbine Characteristic Curves

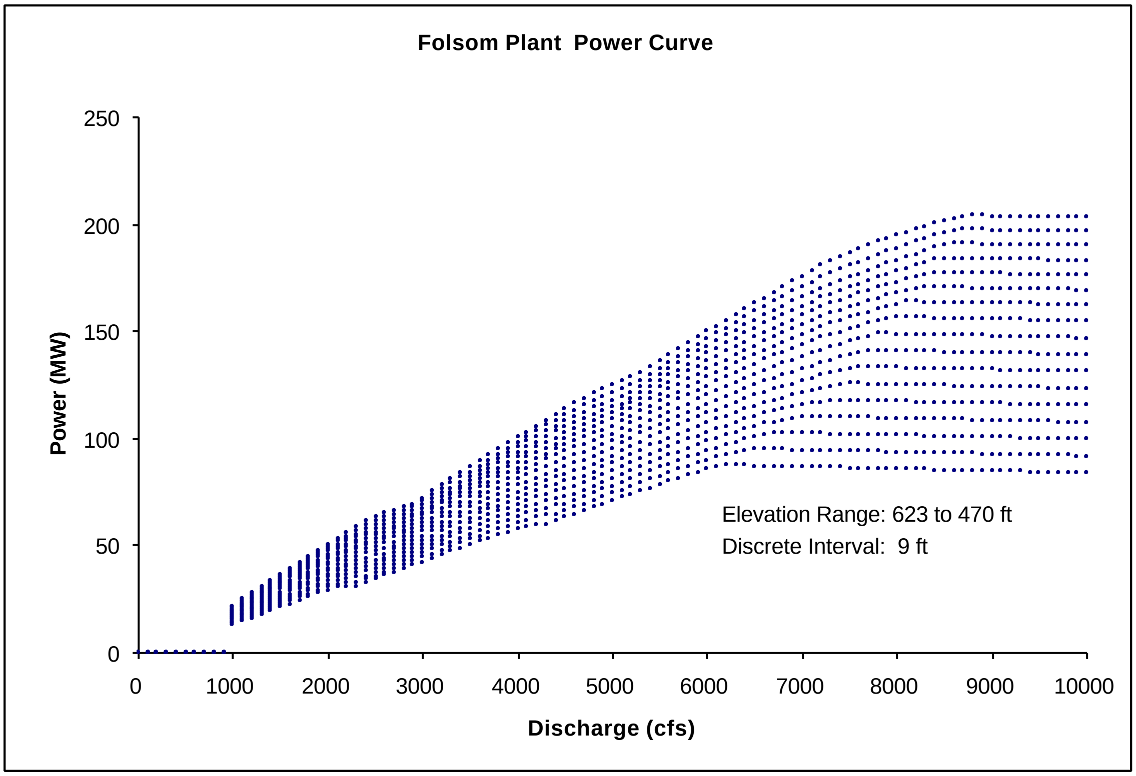


Figure 6: Best Efficiency Plant Power Function

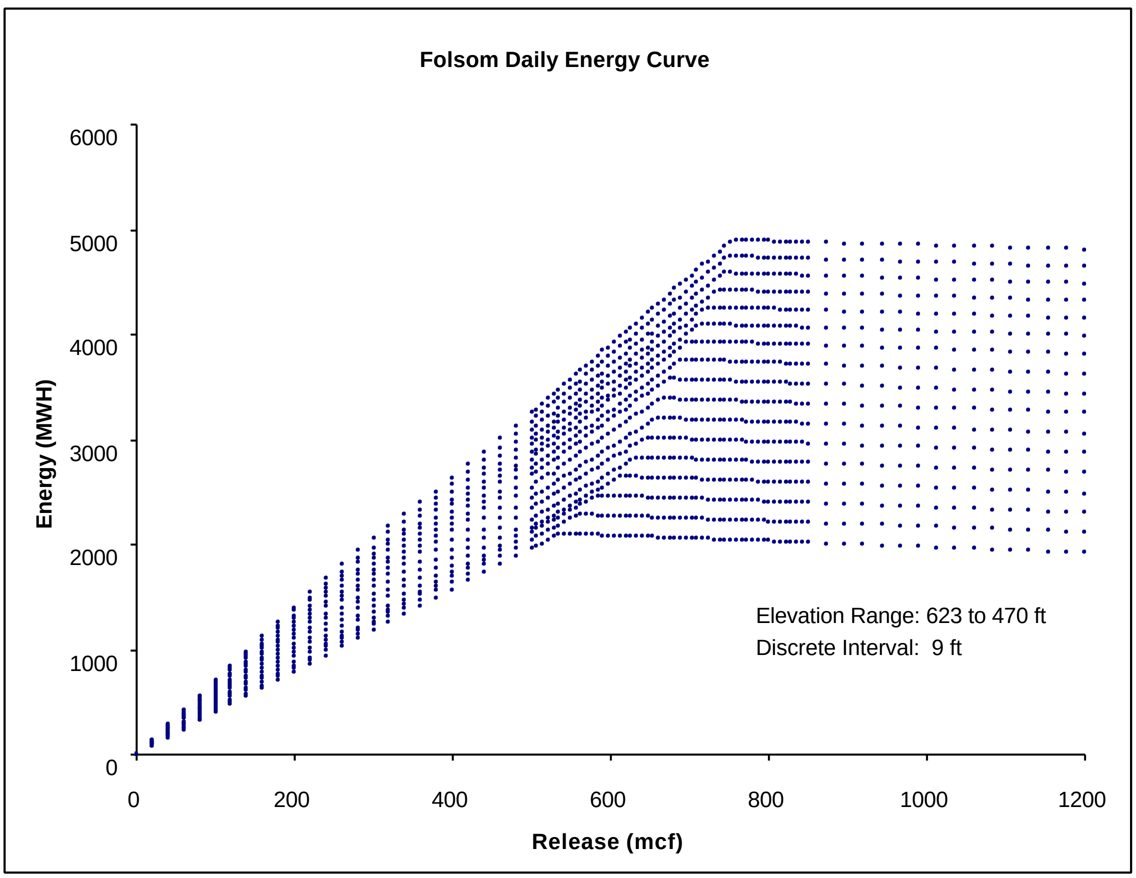


Figure 7: Optimal Daily Energy Generation Function

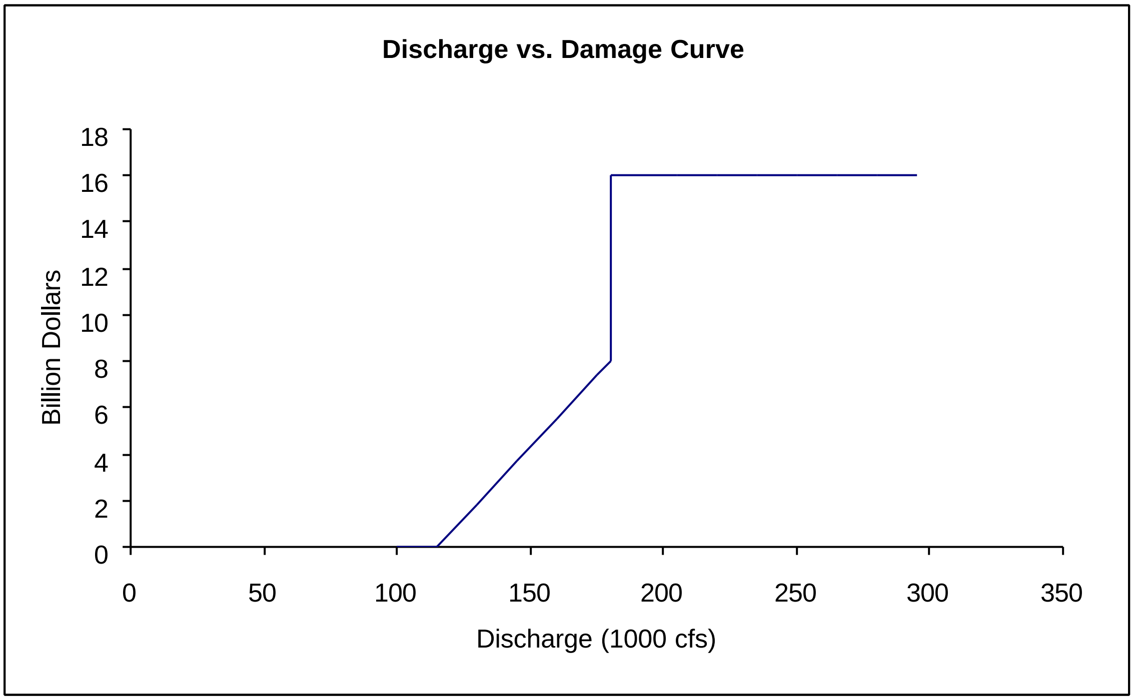


Figure 8: Flood Damage Curve

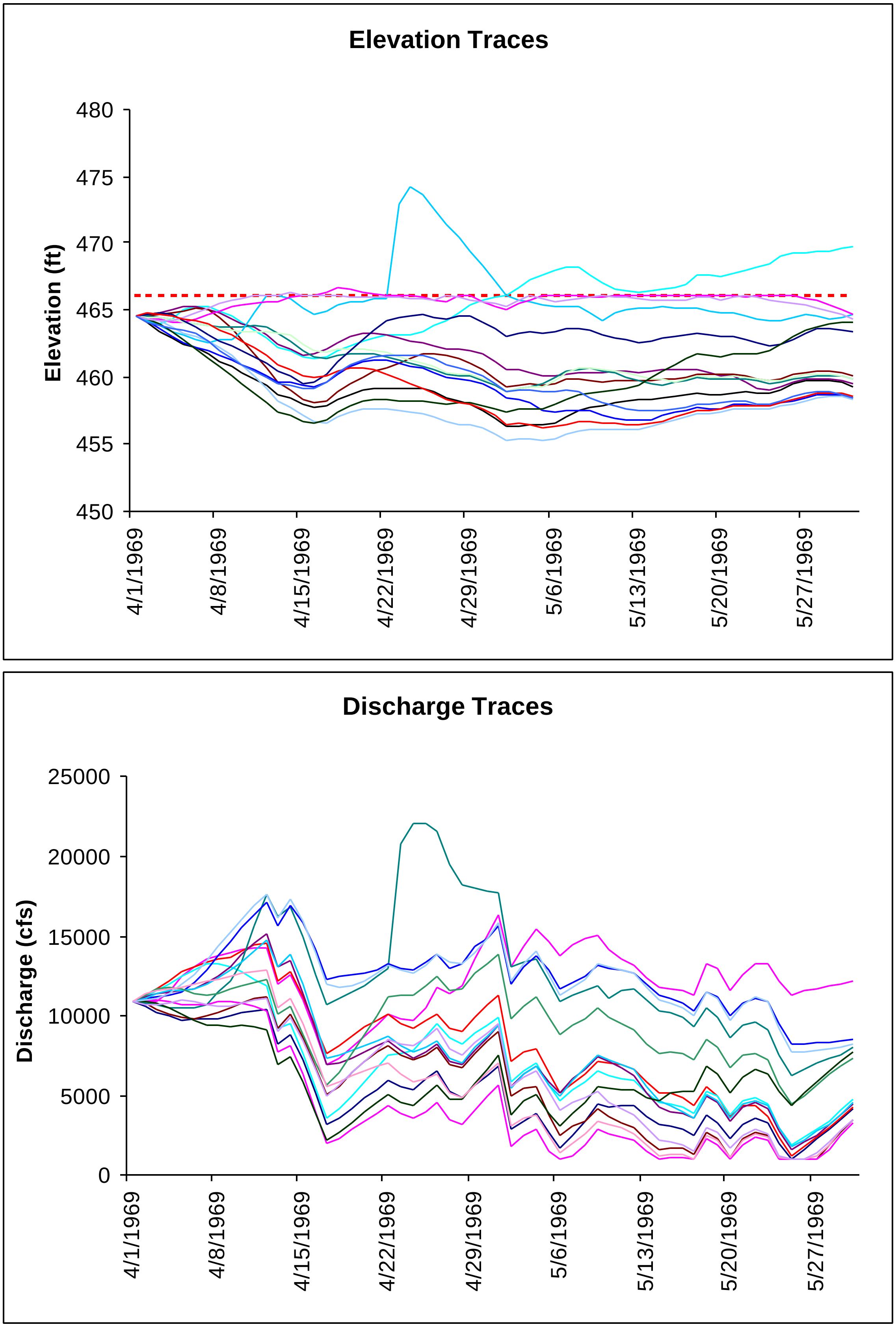
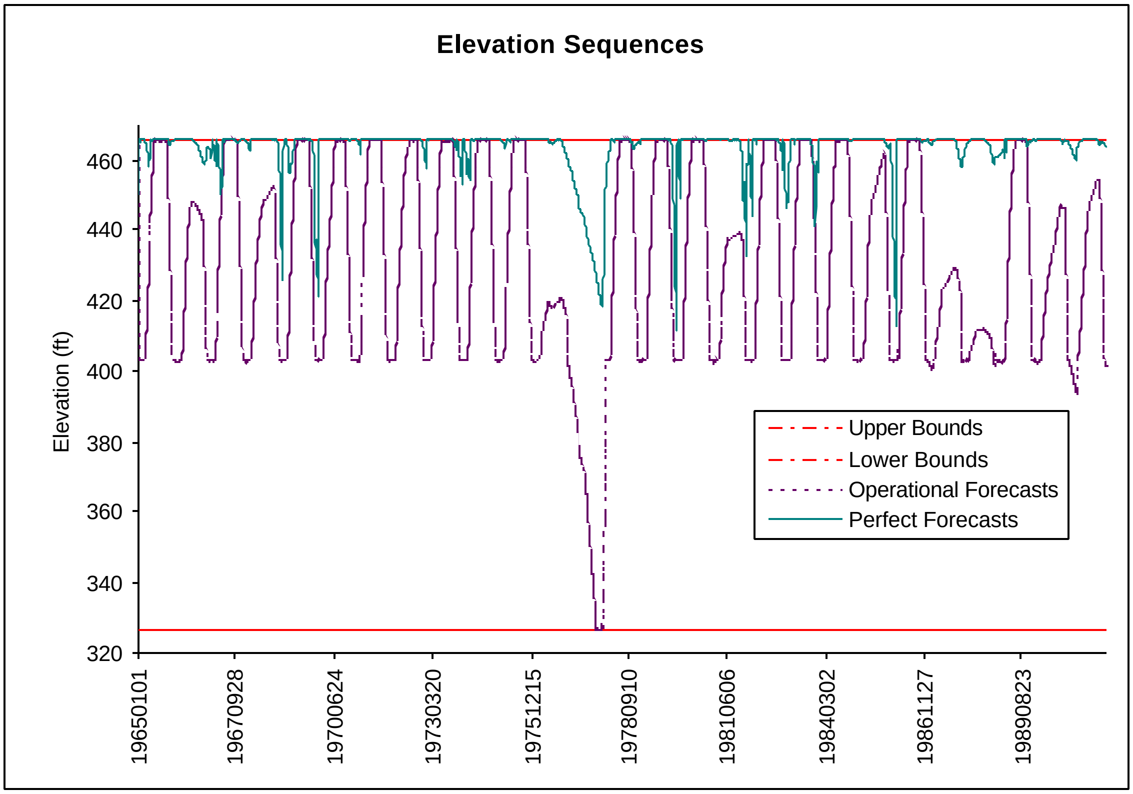


Figure 9: An Example Run of the Folsom Decision Model



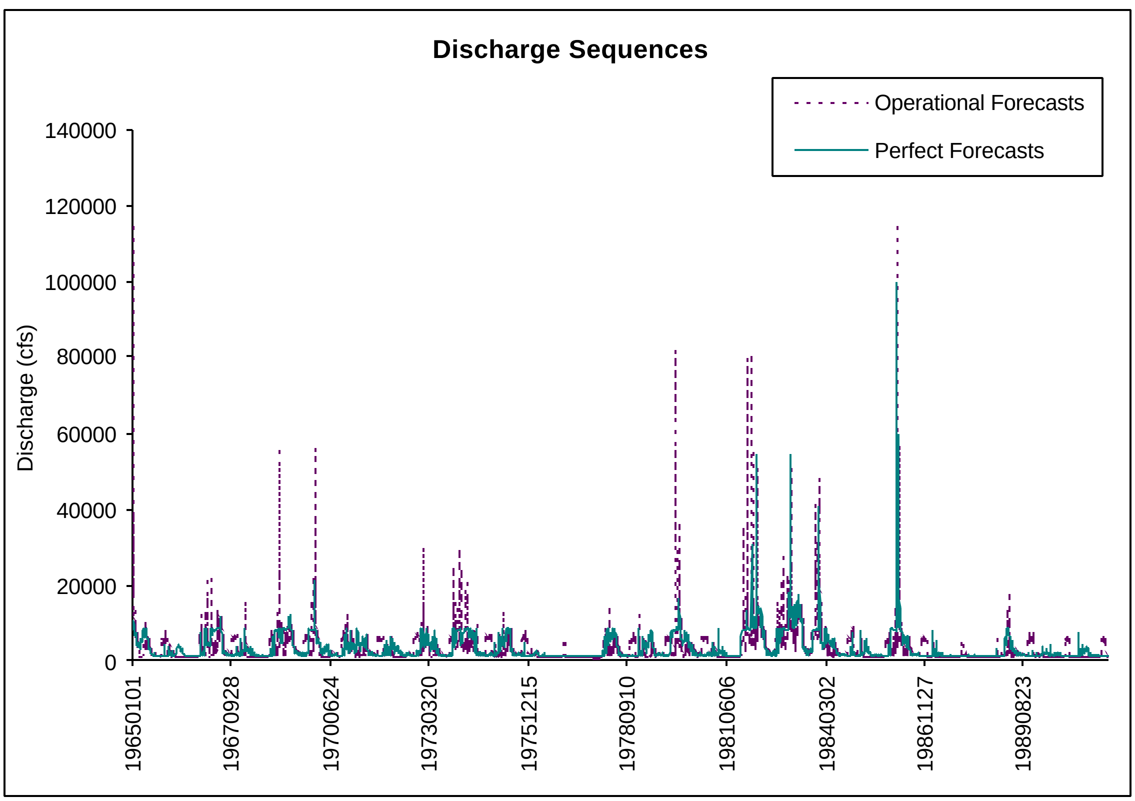


Figure 10: Example Runs of the Folsom Assessment Model

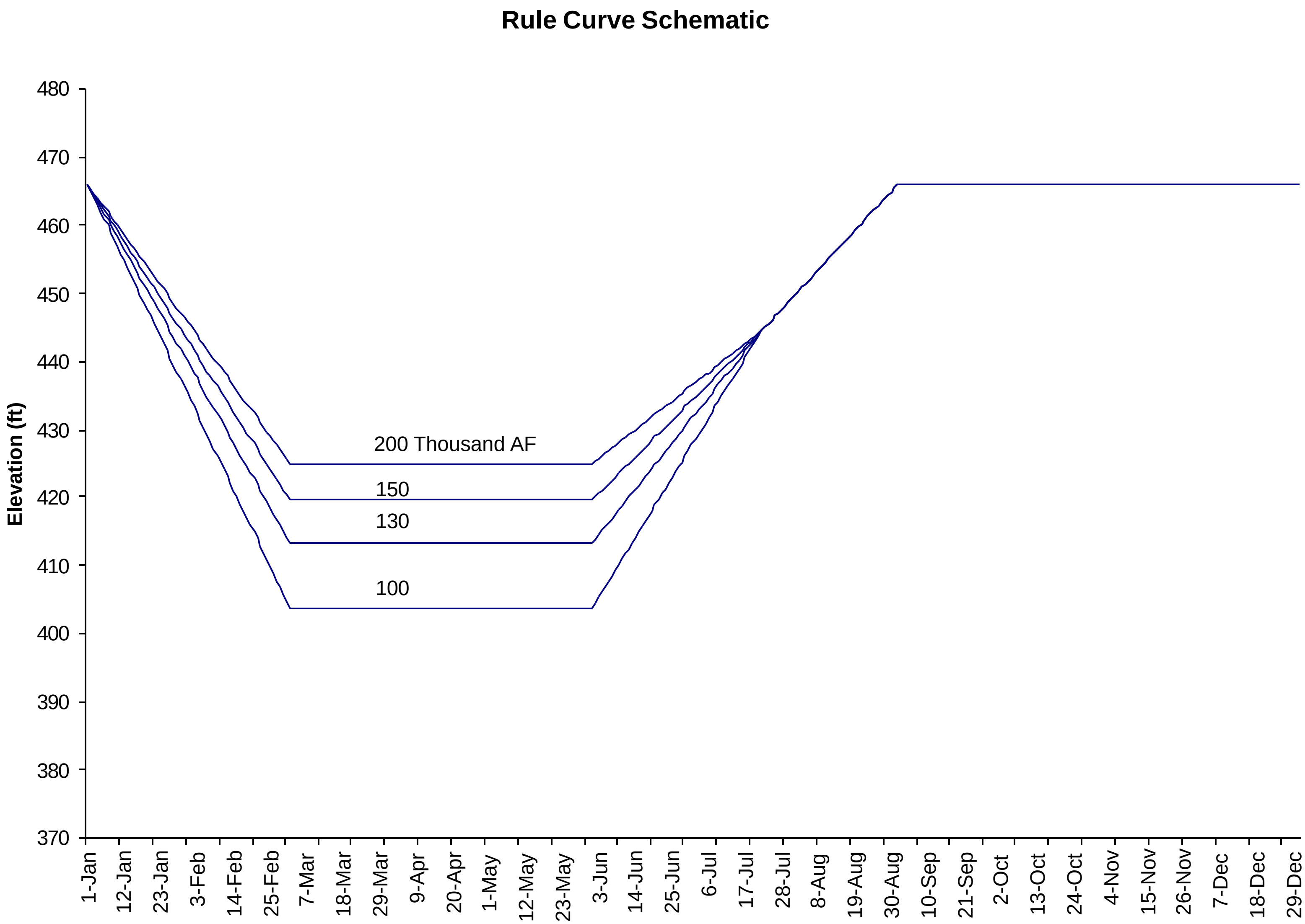


Figure 11: A Schematic of Folsom's Rule Curve

Table 1: Historical Climate Assessments Using a Rule Curve

Forecast Scheme	Upstream Storage (1000 Acre Feet)	Energy (GWH)	Energy Value (Million $)	Spillage (BCF)	Min. Flow Violations (Days)	Flood Damage (Million $)
Operational Forecasts	100	561.73	51.32	13.05	67	0
	130	570.95	52.14	12.88	18	0
	150	576.55	52.64	12.80	0	0
	200	581.67	53.08	12.77	0	0
Analog ESP	100	561.81	51.33	13.05	64	0
	130	570.99	52.14	12.88	16	0
	150	576.64	52.64	12.79	0	0
	200	581.81	53.09	12.75	0	0
Perfect Forecasts	100	561.9	51.33	13.07	63	0
	130	570.98	52.15	12.90	15	0
	150	576.65	52.65	12.80	0	0
	200	581.86	53.10	12.76	0	0

Table 2: Historical Climate Assessments Using the Folsom DSS

Forecast Scheme	Reliability	Energy (GWH)	Energy Value (Million $)	Spillage (BCF)	Min. Flow Violations (Days)	Flood Damage (Million $)
Operational Forecasts	Deterministic	620.06	56.37	11.57	0.00	841.48
Hydrologic ESP	50%	620.20	56.42	11.79	0.00	841.48
	90%	635.06	57.69	7.18	0.00	219.93
GCM-Conditioned ESP	50%	621.88	56.56	11.16	0.00	841.48
	90%	632.94	57.45	6.12	0.00	105.28
Analog ESP	50%	620.33	56.47	11.99	0.00	841.48
	90%	637.11	57.80	5.98	0.00	0.00
Perfect Forecasts	Deterministic	662.41	60.22	4.84	0.00	0.00

Table 3: Assessments for a GCM-Controlled Historical Period Climate

Decision-Forecast Scheme		Reliability	Energy (GWH)	Energy Value (Million $)	Spillage (BCF)	Min. Flow Violations (Days)	Max. Flood Damage (Million $)
Rule Curve	**Analog ESP**	Deterministic	610.50	55.67	16.85	0	0
	Perfect Forecasts	Deterministic	610.72	55.69	16.83	0	0
DSS	**Hydrologic ESP**	50%	653.63	59.40	16.44	0	0
		90%	678.88	61.60	10.37	0	0
	GCM-Cond. ESP	50%	654.47	59.46	15.98	0	0
		90%	675.12	61.21	9.59	0	0
	Analog ESP	50%	651.72	59.25	16.82	0	0
		90%	679.19	61.55	8.77	0	0
	Perfect Forecasts	Deterministic	706.26	64.15	7.79	0	0

Table 4: Assessments for a Potential Future Climate (1% Annual CO_2 Increase)

Decision-Forecast Scheme		Reliability	Energy (GWH)	Energy Value (Million $)	Spillage (BCF)	Min. Flow Violations (Days)	Max. Flood Damage (Million $)
Rule Curve	**Analog ESP**	Deterministic	745.24	67.87	27.98	0	0
	Perfect Forecasts	Deterministic	745.56	67.90	27.98	0	0
DSS	**Hydrologic ESP**	50%	788.26	71.56	28.67	0	4,275.20
		90%	839.48	76.08	18.06	0	219.90
	GCM-Cond. ESP	50%	797.83	72.40	26.78	0	4,275.20
		90%	833.78	75.54	17.87	0	841.44
	Analog ESP	50%	786.41	71.43	29.22	0	4,275.20
		90%	846.23	76.68	16.83	0	0.00
	Perfect Forecasts	Deterministic	868.92	78.77	15.09	0	0.00