Edmund G. Brown Jr.
Governor

CONJUNCTIVE USE OF AQUIFERS AND RESERVOIRS: TRADEOFFS BETWEEN ENERGY GENERATION AND WATER SUPPLY

PIER PROJECT REPORT

Prepared For:
California Energy Commission
Public Interest Energy Research Program

Prepared By:
Lawrence Berkeley National Laboratory
University of California, Berkeley

April 2011
CEC-500-2010-023

Prepared By:
Lawrence Berkeley National Laboratory
University of California, Berkeley
John Dracup
Larry Dale
Berkeley, California 94720
Commission Contract No. 500-02-004
Commission Work Authorization No: 040

Prepared For:
Public Interest Energy Research (PIER)
California Energy Commission

Joseph O'Hagan
Contract Manager

Guido Franco
Program Area Lead
Energy-Related Environmental Research

Linda Spiegel
Office Manager
Energy Generation Research Office

Laurie ten Hope
Deputy Director
ENERGY RESEARCH and DEVELOPMENT DIVISION

Melissa Jones
Executive Director

DISCLAIMER

This report was prepared as the result of work sponsored by the California Energy Commission. It does not necessarily represent the views of the Energy Commission, its employees or the State of California. The Energy Commission, the State of California, its employees, contractors and subcontractors make no warrant, express or implied, and assume no legal liability for the information in this report; nor does any party represent that the uses of this information will not infringe upon privately owned rights. This report has not been approved or disapproved by the California Energy Commission nor has the California Energy Commission passed upon the accuracy or adequacy of the information in this report.

Preface

The California Energy Commission's Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

The PIER Program conducts public interest research, development, and demonstration (RD&D) projects to benefit California.

The PIER Program strives to conduct the most promising public interest energy research by partnering with RD&D entities, including individuals, businesses, utilities, and public or private research institutions.

PIER funding efforts are focused on the following RD&D program areas:

- Buildings End-Use Energy Efficiency
- Energy Innovations Small Grants
- Energy-Related Environmental Research
- Energy Systems Integration
- Environmentally Preferred Advanced Generation
- Industrial/Agricultural/Water End-Use Energy Efficiency
- Renewable Energy Technologies
- Transportation

Conjunctive Use of Aquifers and Reservoirs: Tradeoffs between Energy Generation and Water Supply is the final report for the Development and Application of a California Basin Water and Energy Model project (Contract Number 500-02--004, Work Authorization Number 040) conducted by Lawrence Berkeley National Laboratory. The information from this project contributes to PIER's Energy Related Environmental Research Program.

For more information about the PIER Program, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

Please cite this report as follows:

Dracup, J., and L. Dale. 2011. *Conjunctive Use of Aquifers and Reservoirs: Tradeoffs Between Energy Generation and Water Supply*. California Energy Commission, PIER Energy-Related Environmental Research Program. CEC-500-2010-023.

Table of Contents

Preface……...i

Table of Contents iii

Abstract v

Executive Summary 1

1.0 Introduction 5

1.1. Problem Formulation and Solution Method 7

1.1.1 Problem Formulation 77

1.1.2. Solution Method 10

2.0 Case study of the Merced River Basin. 15

2.1. Description of Merced River Basin.....15

2.2. The Groundwater Model 15

2.3. Calibration of the SDP/NLP Model 16

3.0 Conjunctive Use of Reservoir and Aquifer: Comparison of Different Scenarios and Sensitivity Analysis. 19

3.1. Social Optimum and Electric Power Solutions.....19

4.0 Summary of the Results 24

4.1. Scenario Analysis.....24

4.2. Results of the Scenario Analysis 26

5.0 Conclusion 30

6.0 References 32

Appendix A. Detailed Problem Formulations

Appendix B. Groundwater Model

Appendix C. Calibration of the SDP/NLP model

Appendix D. Additional Figures

List of Tables

Table 1. Summary of scenarios used in calibration phase 17

Table 2. Value for parameters resulting in the calibration phase 17

Table 3.A. Comparison of results under different scenarios (summary of operations) 20

Table 3.B. Comparison of results under different scenarios (summary of costs and benefits) 20

Table 4.A. Comparison of results under different scenarios and changes in parameters/conditions: summary of operations 26

Table 4.B. Comparison of results under different scenarios and changes in parameters/conditions: summary of benefits and costs (base case and net changes) 27

List of Figures

Figure 1. Basic System representation 8

Figure 2. Algorithm flow chart: Annual SDP Model with non-linear optimization model embedded (SDP/NLP) 13

Figure 3. Comparison of aquifer head levels for different scenarios 21

Figure 4. Comparison of average reservoir storage for different scenarios 22

Figure 5. Comparison of simulated operations: A. Releases; B. River Diversion; C. Groundwater Pumping 23

Abstract

In a typical Central California water basin, water may be stored in a reservoir and in a groundwater aquifer. An aquifer is an underground layer of water-bearing rock or unconsolidated materials such as gravel, sand, or clay. Typically, these sources of water are managed separately, but the coordinated management of surface water and groundwater supplies, referred to as conjunctive use, can be used to maximize the energy and supply yield of both resources. *Conjunctive use* of surface and groundwater supplies must contend, however, both on a seasonal and annual basis with conflicting demands for retaining surface water for hydropower generation later and increasing reliance on energy-intensive groundwater pumping or releasing surface water for agricultural needs, reducing groundwater demands but forgoing hydropower generation.

As water supplies diminish due to an increasing population and a warming climate, the cost of water, as well as the cost of the energy generated by reservoir releases or the energy used to pump groundwater, is likely to increase. To evaluate how best to balance these conflicting demands with increasing energy and water costs, an optimization model (that chooses the best solution from a set of alternatives) was developed and applied to a case study in the Merced River Basin, located in the eastern San Joaquin Valley. In the case study, the benefits of different management approaches to conjunctive use surface and groundwater supplies were evaluated.

Although the model is used to evaluate operations in one region, the results suggest lessons for other regions as well. In particular, the results suggest that the benefits of conjunctive reservoir and aquifer storage under historic conditions may now be relatively low. However, as energy and water prices rise and the need for careful management of resources grows, the analysis suggests an approach to more efficiently manage water in the state. The largest gains from water management are likely to come from more careful controls on access to groundwater in dry years and on the ability of districts to deliver excess irrigation water for storage in wet years. These gains may be relatively small at present but they are likely to grow in the future, as water and energy become increasingly scarce and valuable.

Keywords: conjunctive use, groundwater, hydropower, reservoir, Merced River Basin, San Joaquin Valley

Executive Summary

Introduction

In a typical Central California water basin, water may be stored in a reservoir and in a groundwater aquifer. An aquifer is an underground layer of water bearing rock or unconsolidated materials such as gravel, sand or clay. There are three conflicting water use demands on this stored water. First, there is a yearly conflict between energy generators and farmers over the timing of reservoir releases. Generators usually prefer reservoir releases late in the summer, when energy prices are high, while farmers prefer releases to be earlier, when crop irrigation needs are highest. Second, there is a long running conflict between generators and farmers regarding the carryover storage from year to year. Generators tend to prefer higher carryover storage levels to increase future period electricity generation. Farmers usually prefer lower carryover storage and higher surface water deliveries. Third, there is a long running conflict among farmers over groundwater pumping. Individually, farmers want to pump enough water to irrigate all their crops. However, farmers have an incentive to lower groundwater pumping to prevent groundwater overdraft.

In this paper, a conjunctive use model was developed to explore these water use conflicts in the Merced basin and suggest potential solutions. *Conjunctive use* refers to the coordinated management of surface water and groundwater supplies to maximize the yield of the overall water resource. The Merced Irrigation District region is described. Then a water storage model is presented and used to evaluate water use conflicts and potential solutions.

The Region

The Merced River basin is located east of the San Joaquin River in California's Central Valley. Two groups of farmers are identified in the Merced River Basin, including farmers in the Merced Irrigation District and farmers that are outside the district. The Merced Irrigation District operates New Exchequer Dam so that farmers in the district have access to surface water and control, to some extent, the timing of reservoir releases. Farmers outside the district rely mostly on groundwater and have no access or control over reservoir releases.

Lake McClure, the reservoir regulating stream flow in Merced River behind New Exchequer Dam, has a capacity of 1,025,000 acre feet, slightly above the annual inflow to the reservoir, which has a capacity of approximately 950,000 acre feet. The Merced Irrigation District diverts water released from New Exchequer to irrigate an agricultural area that overlays part of what is known as the Merced Groundwater Basin. This groundwater aquifer encompasses an area of more than 400,000 acres and provides water to farmers both within and outside the district.

The Model

A common agricultural water system in California includes a river, a reservoir, farmland, and an aquifer. The water that is released from the reservoir generates energy and irrigates agricultural crops. The groundwater pumped from the aquifer also irrigates crops, but energy costs are incurred to obtain this water.

In this project, this system is modeled using C2VSIM, a non-linear programming intra-annual model, a computer program developed by the California Department of Water Resources which is used to identify system optimization. This is embedded in another model (Stochastic Dynamic Programming/Non-linear Program) that can depict how economic factors may change over time, including changes in both demand and cost. The model addresses surface and groundwater storage (the aquifer and the reservoir) and two economic outputs, the value of crop and of the hydroelectricity (sales). Hydroelectricity sales are adjusted to show net value by subtracting the costs for groundwater pumping. The user adjusts management variables in the model, including groundwater pumping, reservoir releases, reservoir spills, and diversions to calculate the resulting effect on crop and electricity sales.

Management Scenarios and Sensitivity Analysis

In this section, the conjunctive use model is used to evaluate the effect of changing prices and management scenarios on system water use in the Merced Basin. First, the model is run to determine the effect of a rise in the relative price of electricity (compared to the value of irrigation water) on reservoir operations. In this example, the model is run once assuming historical electricity prices and a zero irrigation water price (high energy price scenario). The outputs of this model run are compared with the outputs of a second model run, which was run assuming historic period electricity and irrigation water prices (historic energy price scenario). The results indicate that when the relative price of electricity rises, storage should be managed to increase end of year carryover storage (27 percent) and lower surface diversions during the irrigation season (26 percent). Interestingly, the total amount of hydropower generation is little affected by the rise in relative electricity price, but the value of hydropower generation is increased (16 percent). Apparently in the high electricity price scenario, the main focus is to shift reservoir release times to coincide with late summer peak prices.

These model runs are made assuming joint management of reservoir releases and aquifer pumping. Historically, few basins have been managed in this way. More often, reservoirs are managed independently of aquifers, and controls on groundwater pumping are rare. The benefits of moving towards conjunctive use controls in the Merced Basin are evaluated in a second set of model runs. In this second case, one model run is made assuming conjunctive use controls, and a second model run is made assuming no conjunctive use controls, holding prices constant. The price of electricity and the value of irrigation water are set in both runs to match historical crop and electricity prices.

The results of these runs indicate that a move toward conjunctive use controls in the Merced Basin provides only a slight improvement (0.1 percent) in annual net benefits. These improvements come from a combination of reduced pumping costs (12 percent) and slightly increased hydropower benefits (0.1 percent). This increase in hydropower benefits arises mostly due to a change in the timing of operations to take advantage of the variability in energy prices; this is where reservoir releases are slightly delayed in the year whereas pumping is occurring earlier in the year.

Although the benefits of conjunctive use controls are small assuming historical values for water and electricity, this conclusion may change as resources become scarcer in the future. In

particular, a climate change scenario assuming rising crop prices and energy prices may increase the pressures for and the cost of groundwater overdraft.

Conclusion

In this project the benefits of conjunctive use of surface water storage and groundwater pumping were evaluated by applying a novel monthly non-linear programming model embedded in another model that depicts how economic factors may change over time, including changes in both demand and cost, to simulate reservoir and aquifer operations in the Merced River Basin.

The model is used to estimate the effect of different management and price scenarios on reservoir operations, hydropower benefits and agricultural benefits. Not surprisingly, the price scenarios indicate that the Merced River Basin has flexibility to trade off irrigation deliveries and electricity revenue against one another. It is also not surprising that system benefits increase when reservoir operators assume full conjunctive use controls over extractions of ground and surface water.

However, when comparing system benefits across the different scenarios, it is somewhat surprising that current operations at the Merced River Basin appear to be reasonably close to the conjunctive use optimum. Since the district does not now have control over groundwater pumping, this study concludes that the benefits of controlling groundwater pumping are currently small, assuming existing economic conditions.

Benefits to California

In this paper, a conjunctive use model is used to evaluate operations in one California region but the results suggest lessons for other regions as well. In particular, the results suggest that the benefits of conjunctive reservoir and aquifer storage may now be relatively low. However, as energy and water prices rise and the need for careful management of resources grows, the analysis suggests an approach to more efficiently manage water in the state. The largest gains from water management are likely to come from more careful controls on access to groundwater in dry years and on the ability of districts to deliver excess irrigation water for storage in wet years. These gains may be relatively small at present, but they are likely to grow in the future, as water and energy becomes increasingly scarce and valuable.

Note: Unless otherwise noted, all figures and tables included in this report were created by the authors for this report.

1.0 Introduction

Water in a basin has several potential uses and different users have different goals for using that water. The water basin management problem is compounded because of negative externalities associated with the use of water, where agents use water without taking into account the costs their use imposes on others. For example, in a typical Central California water basin, water is stored in a reservoir and an aquifer managed by different groups facing different incentives. The reservoir is used to generate energy and to supply irrigation water to farmers during dry periods. Farmers may also pump aquifer water for irrigation, but they generally prefer surface water, which does not require pumping. Often, the reservoir is managed by utilities to maximize energy generation (subject to minimum irrigation releases) while the aquifer is unmanaged, and exploited to supply residual crop irrigation requirements.

There are three principal water use conflicts facing users in such a basin. The short run conflict is caused by the high price of electricity late in the summer irrigation season, relative to the high (shadow) value of irrigation water early in the irrigation season. In this case, energy generators prefer to release reservoir water in late summer, when energy prices are high while farmers prefer reservoir releases to be made during the spring and early summer when water is important for irrigation purposes.

There is another long-run conflict between generators and farmers over the optimal level of water storage in the reservoir and in the aquifer. The storage level affects the potential energy generated by the release of water in the reservoir and the costs of pumping water from the aquifer. Generators tend to prefer higher carryover storage levels as a way to increase future period electricity generation but this could affect water supplies to farmers who would be concerned with the effect that this has on aquifer levels and future pumping costs. The preference of the two groups for carryover storage varies according to the relative price elasticity of water demand and the relative drop in water storage level caused by additional reservoir releases. For example, a farmer's preference for low carryover storage goes up the more inelastic his demand for water and the more responsive his aquifer level, to changes in reservoir releases.

Finally, there is a conflict between farmers over the amount of groundwater pumping. Individually, farmers have little incentive to limit groundwater pumping, because the cost of lower groundwater levels is shared with other farmers. Collectively farmers have an incentive to lower groundwater pumping of other farmers.

Many irrigation districts in the Central Valley manage reservoirs for irrigation because they do not fully realize gains from energy generation, which is controlled by long term contracts. Alternatively, electric utilities usually manage reservoirs for electricity generation, because they don't receive payment for irrigation releases. Finally, farmers often draw down their aquifers because they don't receive payment from other farmers for preserving higher groundwater levels.

The economic literature suggests that farmers and generators can increase their welfare by organizing to jointly manage conflicts and eliminate externalities. The gains from organizing

depend on the current allocation of water use benefits to farmers and generators. But most importantly these benefits will depend on the level of water scarcity in the basin. If surface water was abundant none of the tradeoffs discussed earlier would be significant. Groundwater pumping would be small, and hence pumping costs small, reservoirs and aquifer would be close to their storage capacity and the timing of reservoir releases would be constrained by factors such as turbine capacity with little influence of the variability of energy prices throughout the year.

The conjunctive use literature is extensive (refer for example to Burt (1964), Dracup (1966), Bredehoeft and Young (1970, 1983), Maddock (1974), Gisser and Sánchez (1980), Provencher and Burt, (1993, 1994), Knapp and Olson (1996), Feinerman and Knapp (1983), Tsur and Graham-Tomasi (1991), Worthington et al. (1985), Noel and Howitt (1982), Reichard (1995) or Koundouri (2004) for a complete review in this literature). However, only a few papers have analyzed the coordination problem from both a surface and a groundwater perspective. Examples of the later are Hooper et al. (1991), Matsukawa et al. (1992), Peralta et al., (1995), Chatterjee et al., (1998), Philbrick and Kitanidis (1998), Pulido-Velasquez et al. (2006) and Schoups et al. (2006).

These works differ in their approach to the conjunctive use optimization problem in four ways: the level of groundwater detail, the time horizon, the treatment of streamflow uncertainty, and the modeling of water storage level. Matsukawa et al. (1992), Peralta et al. (1995), Pulido-Velasquez et al. (2006) and Schoups et al. (2006) all considered detailed (distributed) ground-water system hydraulics. However the optimization approach in these papers is deterministic, with a monthly timestep. Hooper et al. (1991), Chatterjee et al. (1998) and Philbrick and Kitanidis (1998) all use simplified groundwater models ("bathtub" models). The optimization approach of Chatterjee et al. (1998) is deterministic, with a focus on the seasonal trade-offs existing in reservoir and groundwater operations over a single irrigation season. On the other hand the models developed by Hooper et al. (1991) consider stochastic inflows, but restricted to the average value for each month in the historical record. As a result, the model estimates optimal trajectories rather than optimal operating rules. Finally Philbrick and Kitanidis (1998) developed an annual stochastic model with uncertain reservoir inflows. However this paper does not explicitly consider the effects of pumping on aquifer head. In summary none of these studies includes a model with all the features included in the research team's model which are: a detailed stochastic, non-linear, monthly model of the conjunctive operations of an aquifer and reservoir with explicit representation of the effects that reservoir releases and groundwater pumping have on storage levels of both sources of water.

In this paper the authors construct an interannual stochastic model of the operations of a conjunctive use system that includes a reservoir as a source of surface water and an aquifer. The model incorporates monthly variability in energy prices and crop water requirements. The basic structure of the model is a monthly non-linear programming model (NLP) embedded in an annual Stochastic Dynamic Programming (SDP) model (SDP/NLP). As part of the of SDP/NLP configuration the authors include a lumped hydrological model of groundwater hydraulics to take into account the way farmers affect groundwater levels when pumping and applying irrigation water. This hydrologic model is calibrated to the conditions simulated in a distributed model of the California Central Valley (C2VSIM). Some of the parameters of the

SDP/NLP model are calibrated to reflect historical conditions in the Merced Irrigation District in California. The authors compare the benefits associated with this calibrated scenario with two levels of coordination between the farmers in the valley who perceive benefits when their lands are irrigated and the reservoir operator who perceives benefits by selling energy to an electric utility. Depending on the level of coordination, the authors have two possible cases:

Uncoordinated case (or electric power solution): In this case the authors assume the reservoir is operated by an electric power company with consideration only of the hydropower benefits (present and future) as part of its objective function. Farmers then decide how much water to divert from the river and pump from the underlying aquifer depending on their irrigation needs for current period.

Coordinated case (or social planner solution): in this case the reservoir is operated to generate electricity and to supply irrigation water. This operator (social planner) has also control over groundwater pumping taking into account future pumping costs. The calibrated or historical case will fall in between these two cases and will allow the research team to compare current operations against the social optimum.

The remainder of the paper is organized as follow. In the second section the authors formulate the problem and suggest a solution algorithm (SDP/NLP model). Following, the case study of the Merced Irrigation District in California is introduced and the calibration process used to determine some of the parameters of the problem formulation is described. In a fourth section, the authors compare the benefits associated with the three coordination scenarios and extend the analysis by performing a sensitivity analysis on some key parameters. The authors conclude with a discussion of the potential benefits of conjunctive use of surface and groundwater in California under different economic conditions.

1.1. Problem Formulation and Solution Method

1.1.1. Problem Formulation

The basic unit of analysis considers a basin with two sources of water; a reservoir and an aquifer. See Figure 1. The water in the basin is used for two purposes, energy generation and crop irrigation. The water that is released in the reservoir generates energy and as it becomes available in the river it is also used to irrigate agricultural crops. The farmers also have an aquifer as a secondary source for irrigation, but energy costs are incurred to obtain this water.

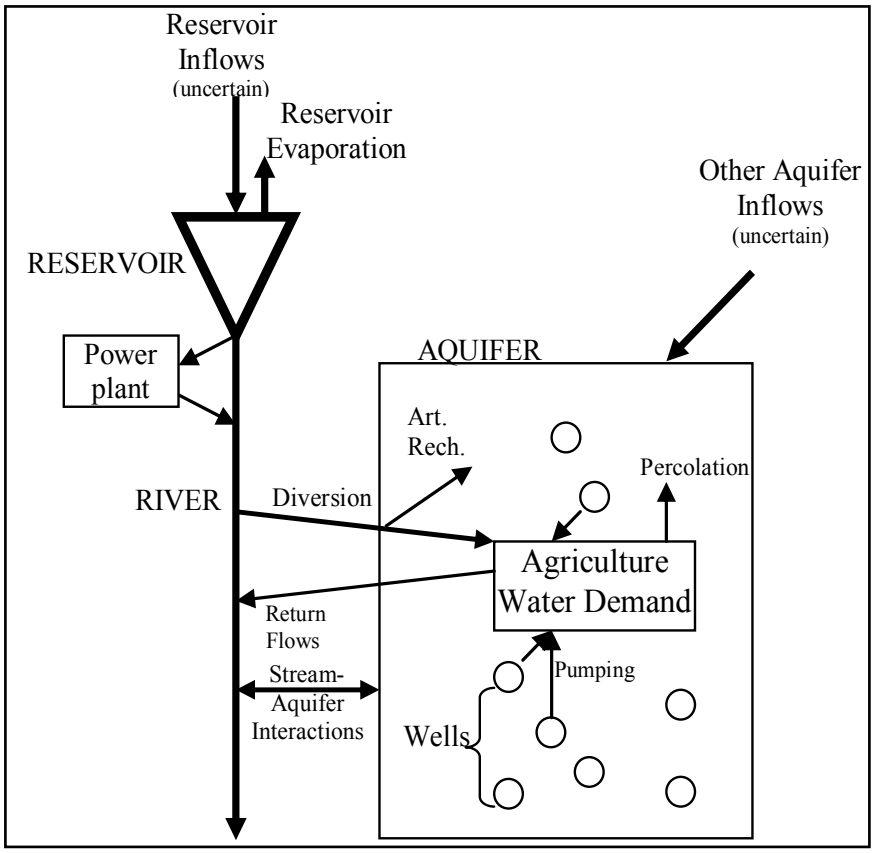

Figure 1. Basic system representation

There are two state variables in this problem represented by vector $\mathbf{X}_t$ and four control variables represented by vector $\mathbf{U}_t$. The state variables are defined as H_m^A and S_m^R, the stock of water in the aquifer (represented by the aquifer head) and in the reservoir (represented by volumetric storage) in month *m*. And the three control variables are P_m^{A}, the amount of water pumped by farmers in the aquifer, R_m^t releases through turbines, R_m^s spills and D_m^{ag} river diversions for agriculture in month *m*. The benefits of using water in the basin include the benefits of crop irrigation (AgBenefits) and the benefits of water used to generate electricity (GenBenefits). The only costs considered correspond to pumping costs (PumpCosts). Each one of this expression is related to stock and control variables just mentioned.

$$AgBenefits_m = \beta_m^{ag} * (P_m^A + \varepsilon D_m^{ag}) - \frac{\gamma_m^{ag}}{2} * (P_m^A + \varepsilon D_m^{ag})^2 \quad (1)$$

$$GenBenefits_m = \alpha_m^R * f(R_m^t) * H^{\mathrm{R}}(S_m^R) \quad (2)$$

$$PumpCosts_m = P_m^A * K_1 * (Surface - H_m^A) * c_m \quad (3)$$

Where,

$\beta_m^{ag}, \gamma_m^{ag}$	=	Are parameters related to the linear demand function for water in the farm.
ε	=	1 – percent of recoverable losses (seepage)
$P_m^A + \varepsilon D_m^{ag}$	=	Total water delivery at farm
α_m^R	=	$K_2 * c_t$ is a parameter that takes into account monthly energy prices c_t and the appropriate unit transformation
$f(R_m^t)$	=	Effect of releases in energy generation considering efficiency
$H^{\mathrm{R}}(S_m^R)$	=	Head in the reservoir as a function of storage (look up table)
$Surface$	=	Surface elevation
K_1	=	Unit conversion to obtain energy requirements
c_m	=	Pumping energy price

The relationship between state (stock) and the control variables is expressed through a set of transition equations. For example for the reservoir the transition equation for reservoir storage has the following form:

$$S_{m+1}^R = S_m^R + Q_m - R_m^t - R_m^s - NetEvap_m(S_m^R) \tag{4}$$

Where Q_m corresponds to monthly inflow to the reservoir, a stochastic variable at the annual timescale but deterministic at the monthly timescale, and $NetEvap_m(S_m^R)$ corresponds to net evaporation of water in the surface of the reservoir, a function of the amount of water stored.

Similarly the relationship between groundwater aquifer head, pumping and applied irrigation water is described in general by the following equation:

$$H_{m+1}^A = H_m^A + \frac{\Delta S_m^A(P_m^A, D_m^{ag})}{A * S^y} \tag{5}$$

where ΔS_m^A corresponds to the change in storage in the aquifer, a function of the amount of pumping and applied water at the farm, and A and S^y are the area and specific yield/storage of the aquifer respectively that permit the estimation of changes in head/water level for a change in storage.

As mentioned above, there are several possible organizational structures for managing such basins and the optimization problem differs for each organizational structure. Details of these different formulations are found in Appendix A. In general, however, the authors can describe this optimization problem using the following notation:

$$\begin{aligned}
&\underset{\mathbf{U}_t}{Max}\left\{\underset{\mathbf{Q}}{\mathrm{E}}\left[\sum \mathrm{NetBenefits}_t(\mathbf{X}_t,\mathbf{U}_t)\right]\right\} \\
&st \\
&\mathbf{U}_t \in (\Theta \bigcup \Pi) \text{ (constraints)} \\
&\mathbf{X}_{t+1} = \mathbf{T}(\mathbf{X}_t,\mathbf{U}_t,Q_t) \text{ (transition equations)}
\end{aligned} \tag{6}$$

Where, $\mathbf{X}_t$ represents the vector of state variables, $\mathbf{U}_t$ represents the vector of controls variables, $(\Theta \bigcup \Pi)$ represent the set of constraints that has to be satisfied by the control variables, $\mathbf{T}(\mathbf{X}_t,\mathbf{U}_t,Q)$ are the transition equations expressing the change in the state variables and $\underset{\mathbf{Q}}{\mathrm{E}}[\cdots]$ is the expectation operator over future hydrologic conditions (Q_t), stochastic in nature.

1.1.2. Solution Method

The authors suggest in this paper an algorithm to solve this non-linear stochastic optimization problem. To capture the stochastic and non-linear characteristics of the problem the authors use an annual Stochastic Dynamic Programming (SDP) model. SDP models have been used extensively in the water resources (see Yakowitz (1982); Yeh (1985) for reviews) and conjunctive use literature (e.g. Burt (1964), Onta and Gupta (1991), Philbrick and Kitanidis (1998) and Provencher and Burt (1993, 1994)). To represent monthly operations and explore some of the tradeoffs existing in a conjunctive use setting the authors embed a non-linear monthly model within the annual SDP (Vedula and Kumar, 1996). The resulting model, described hereafter as SDP/NLP is described as follows.

The basic interannual SDP can be represented by the following Bellman Equation;

$$\begin{aligned}
&F^t(\mathbf{X}_t,Q_t^h) = \underset{\mathbf{U}_t\in(\Theta\bigcup\Pi)}{Max}\left\{\mathbf{B}_t(\mathbf{X}_t,\mathbf{U}_t,Q_t^h) + \beta \underset{Q_{t+1}}{\mathrm{E}}\left[F^{t+1}(\mathbf{X}_{t+1},Q_{t+1})\right]\right\} \\
&\forall \mathbf{X}_t, Q_t^h \\
&\mathbf{X}_{t+1} = \mathbf{T}(\mathbf{X}_t,\mathbf{U}_t,Q_t^h)
\end{aligned} \tag{7}$$

In order to represent monthly operations, the authors embed a monthly non-linear programming model within the interannual SDP model. With this approach, the authors implicitly represent the control variable $\mathbf{U}_t$ (e.g. annual releases in the reservoir) by annual changes in the state variable (e.g. reservoir storage). The structure of the annual SDP with the embedded monthly non-linear programming model is shown below:

$$F^t(\mathbf{k}, Q_h^t) = \underset{feasible\ control\ (\mathbf{l})}{Max} \left\{ \mathbf{B}_t^a(\mathbf{k}, \mathbf{l}, Q_h^t) + \beta \underset{\mathbf{Q}_{t+1}}{\mathrm{E}} \left(F^{t+1}(\mathbf{l}, Q^{t+1}) \right) \right\}$$

Where,

$$\mathbf{B}_t^a(\mathbf{k}, \mathbf{l}, Q_h^t) = \underset{\mathbf{U}_1, \mathbf{U}_2 .. \mathbf{U}_{12}}{Max} \left(\sum_{m=1}^{m=12} \left(\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) \right) \right)$$

$$st: \qquad (8)$$

$$\mathbf{X}_{m+1} = \mathbf{T}(\mathbf{X}_m, \mathbf{U}_m, Q_m^h)$$

$$Q_m^h = f(Q_h^t)$$

$$\mathbf{X}_m \in \Theta_m;\ \mathbf{U}_m \in \Pi_m$$

$$\mathbf{X}_1 \in \mathbf{k};\ \mathbf{X}_{12} \in \mathbf{l}$$

And,

k, l	=	Initial and final state vector conditions
$\mathbf{B}_t^a(\mathbf{k}, \mathbf{l}, Q_h^t)$	=	Maximum benefit attainable if state at the beginning of the cycle is **k** and at the end of the cycle is **l**, and annual inflow category is equivalent to Q_h^t. Is the result of a non-linear optimization problem that is solved earlier.
t, m	=	Temporal indices, *t* at annual and *m* at monthly scale
Q_m^h	=	Annual flow distributed monthly using function *f*
β	=	Discount factor

The expectation term in the SDP algorithm can be transformed into its deterministic equivalent using transition probability matrices:

$$\underset{\mathbf{Q}_{t+1}}{\mathrm{E}} \left(F^{t+1}(\mathbf{l}, Q^{t+1}) \right) = \sum_{k=1}^{k=n} p\left(Q_{t+1} = Q_k \right) * F^{t+1}(\mathbf{l}, Q_k) \qquad (9)$$

$$\text{More compactly} = \mathbf{P}_{Q_k}^t F^{t+1}(\mathbf{l}, Q_{t+1,k})$$

The authors approximate current period benefits and the value function using cubic splines, which permit a solution of this problem using non-linear programming (see Johnson et al.,

(1993) and Tejada-Giibert et al., (1993) for a discussion on the use of splines within a water resources SDP model).

The steps that need to be followed in the algorithm development are laid out in Figure 2. First (Step 1), $\mathbf{B}_t^a(\mathbf{k},\mathbf{l},Q_h^t)$ is estimated for discrete values of $\mathbf{k},\mathbf{l}$ and Q_h^t. A continuous function of these benefits is estimated using cubic splines. In Step 2 this function is introduced in the annual SDP model to determine optimal operating rules for all possible states. Finally (Step 3) these operating rules are used to simulate optimal system operations over a sequence of actual hydrologic conditions.

In the next section the authors apply this SDP/NLP to explore the operations of different organizational structures in the Merced River Basin.

Step 1. Reduced form of Annual Benefits For a discrete set of possible combinations of initial and final states and different inflow conditions determine optimized benefits ($\mathbf{B}_t^a(\mathbf{k},\mathbf{l},Q_h^t)$. See Appendix I.B. Convert to a continuous function using spline approximation ($\tilde{B}_t^a(k,l,Q)$).

Step 2. Solve Annual SDP Model using historical inflow probability distributions

Step 2.1: Obtain a spline approximation of future value function. Step 2.2: For a discrete set of initial states and inflow conditions solve non-linear optimization problem:

$F^t(\mathbf{k},Q_h^t) = \underset{feasible\ control}{Max} \left\{ \tilde{B}_t^a(\mathbf{k},l,Q_h^t) + \beta \underset{\mathbf{Q}_{t+1}}{\mathrm{E}} \left(\tilde{F}^{t+1}(l,Q^{t+1}) \right) \right\}$. Step 2.3 Check convergence criteria.

If not met go to Step 2.1. If met, result is optimal release rule (carryover storage) $l^* = l(k,Q_h^t)$.

Step 3. Simulate conditions using historic hydrologic time series. Using optimal carryover rule, monthly decisions are determined using the same non-linear optimization used in Step 1.

Step 4. Analyze results

Figure 2. Algorithm flow chart: Annual SDP Model with non-linear optimization model embedded (SDP/NLP)

2.0 Case study of the Merced River Basin

2.1. Description of Merced River Basin

The Merced River basin is located east of the San Joaquin River in the California Central Valley. Two groups of farmers are identified in the Merced River Basin, including farmers in the Merced Irrigation District (MID) and farmers outside MID. The district (MID) operates New Exchequer dam so that farmers in the District have access to surface water and control, to some extent, the timing of reservoir releases. Farmers outside the district rely mostly on groundwater and have no control over reservoir releases.

Lake McClure, the reservoir regulating streamflow in Merced River behind New Exchequer dam, has a capacity of 1,025 TAF (thousand acre feet), slightly above the annual inflow to the reservoir which is approximately 950 TAF. New Exchequer was built in 1967 expanding an already existing dam built in 1926. To build this dam the Merced Irrigation District contracted with Pacific Gas and Electric Company to sell all electric energy produced by the Project at a price that would allow the district to finance the project at no cost to district taxpayers or growers[1]. This contract will expire in 2014 when MID needs to apply for a new Federal Energy Regulatory Commission operation license. MID diverts water released from New Exchequer to irrigate an agricultural area that overlays part of what is known as the Merced Groundwater Basin (DWR, 2003). This groundwater aquifer encompasses an area of over 400 thousand acres and supplies pumped water to farmers in MID and some farmers outside the district.

Using the SDP/NLP model described above, the authors developed two optimization models of the New Exchequer operations and groundwater extractions corresponding to two organization structures described above. Appendix A lays out the nomenclature and mathematical structure of these two optimization models.

2.2. The Groundwater Model

A first step towards development of the conjunctive use model is the construction of a groundwater model to simulate the hydraulic dynamics of the Merced Groundwater Aquifer. The research team's groundwater model is constructed by reducing a comprehensive set of groundwater head-groundwater stress relationships (pumping, applied water at farm) into a simplified set of physically based statistical relationships. The authors used C2VSIM, a distributed groundwater model developed by the California Department of Water Resources (CDWR), to simulate changes in groundwater head associated with historic stress in the Merced Groundwater Aquifer. The authors used regression analysis to calibrate the parameters of a physically based set of simplified relationships between this head changes and stresses. A thorough description of the approach used and is presented in Appendix B.

---

1 http://www.mercedid.org/district_news/history.html, accessed May 31, 2007.

http://ca.water.usgs.gov/archive/waterdata/99/11269500.html, accessed May 31, 2007.

2.3. Calibration of the SDP/NLP Model

Following Howitt et al. (2002) and Cai and Wang (2006), the authors calibrate the SDP/NLP model by estimating key parameters of the optimization problem and organizational structure. The key parameters include the discount rate parameter, the irrigation demand benefit function parameters (β_m^{ag} and γ_m^{ag} in Eq. 1) and the organizational type parameter. One assumption supporting this calibration process is that reservoir release decisions are independent of groundwater pumping decisions. This assumption implies that farmers make groundwater pumping decisions after they learn how much surface water is available for diversion from the reservoir. Another related assumption is that reservoir operators have no control over groundwater pumping. To choose among the different alternative parameters the authors compare reservoir storage, aquifer head levels and reservoir releases with the historic conditions and select the set that results in the lowest weighted sum of squared errors.

The first of the parameters considered is the discount rate used in the annual SDP model. The discount rate is equivalent to $(1-\beta)/\beta$, where β is the discount factor used in *Eq. 7*. The discount rate, which represents the intertemporal preferences of reservoir operators, has a substantial impact on optimal carryover storage, or the amount of storage left in the reservoir at the end of the water year. Higher discount rates represent more "myopic" reservoir operations, and less concern about future period benefits. In the extreme an infinite discount rate would result in an operating rule that empties the reservoir for any given initial storage and inflow condition.

The agricultural water demand function is assumed to be linear and is represented by two different parameters: the maximum annual demand of water (at a 0 price) and the maximum willingness to pay for water (at zero quantity). The authors estimate these parameters for 12 different demand functions, one for each month of the year[2]

In general, increasing the value of the water demand parameters leads to reservoir release schedules that closely match the monthly distribution of physical crop water requirements (i.e. spring and early summer). Alternatively, decreasing the value of the water demand parameters results in reservoir releases that closely match the pattern of energy prices throughout the year. A high relative value of irrigation benefits also implies higher end of year storage (end of September) and increased groundwater pumping

Finally, the authors include a fourth parameter in the calibration process to represent the relative weight given by reservoir operators to hydropower benefits and to irrigation benefits. The authors allow this parameter to have six discrete values including two extreme and four intermediate values. The extreme values represent the pure hydropower case (with irrigation

2 The authors assume that water needs are distributed uniquely throughout the year and the maximum willingness to pay is considered the same for all months. With these assumptions the parameters for each one of these demand functions can be determined by knowing just the two parameters considered in the calibration process. If the distribution of water needs assumed is the same as the distribution for the most valuable crops this is a reasonable assumption.

benefits coming as a side benefit of hydropower releases) and the pure irrigation case (where hydropower benefits are a side benefit of irrigation releases). The four intermediate values represent different relative preferences given to hydropower and irrigation (ϕ). Table 1 summarizes the objective functions used to represent this parameter.

Table 1. Summary of scenarios used in calibration phase

Scenario	Objective Function
Pure Hydropwer	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = EnergyB_m(\mathbf{X}_m, \mathbf{U}_m)$
Pure Irrigation	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = AgB_m(\mathbf{U}_m)$
Both Hydropower and Irrigation	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = AgB_m(\mathbf{U}_m) + \phi EnergyB_m(\mathbf{X}_m, \mathbf{U}_m)$, with $\phi = [0.25\ 1]$

Table 2 presents the parameters estimated in this calibration phase (a more detailed discussion of the results in the calibration phase is presented in Appendix C). The discount rate derived from the calibration exercise is 3% , a value consistent with previous studies (*Feinerman and Knapp, 1983*). The irrigation demand curve parameters include maximum willingness to pay, estimated at 75$/AF, and the maximum demand quantity was estimated at 20% above observed historical levels. Both these values are consistent with results of similar studies in the region (e.g. use of Central Valley Production Model (CVPM) model in the San Joaquin Basin). Finally, the irrigation hydropower tradeoff parameter derived from the calibration exercise is 1.0 (Table 1). This value indicates that the reservoir is managed to obtain an even balance of hydropower and irrigation benefits.

These parameter values provide the best fit between the SDP/NLP optimization model outputs and historic operations in the Merced River Basin. Of course, the precision of the calibration process is limited by how well the optimization model reproduces historical operations in the basin (as discussed in Appendix C). In the next section, the authors compare historical agricultural and hydropower benefits, as estimated with the base calibrated model, against benefits that might be achieved under different operational scenarios (coordinated and uncoordinated operations scenarios). With this comparison, the authors are able to estimate how close historical operations have been to the social optimum associated with the fully coordinate scenario.

Table 2. Value for parameters resulting in the calibration phase

Parameter	Parameter Value
Discount Rate	3%
Maximum Willingness to Pay	75 $/AF
Demand at 0 price	1.2*Average Historic Applied Water
Objective Function	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = AgB_m(\mathbf{U}_m) + \phi EnergyB_m(\mathbf{X}_m, \mathbf{U}_m)$, with $\phi = 1$

3.0 Conjunctive Use of Reservoir and Aquifer: Comparison of Different Scenarios and Sensitivity Analysis.

3.1. Social Optimum and Electric Power Solutions

In this section, the authors explore the benefits of achieving different levels of coordination between reservoir and aquifer operations. The historical scenario, introduced in the previous section, assumed a reservoir operator with control over reservoir releases but no control over groundwater pumping. In this next section, the authors estimate the potential additional benefits of controlling groundwater pumping as well as reservoir releases (the social optimum scenario). Following, the authors estimate the potential losses from controlling reservoir releases only to maximize the value of hydropower (electric power solution), ignoring the demand for water by downstream farmers. Together, these three scenarios suggest some of the operating tradeoffs faced by reservoir owners.

The mathematical description of this optimization problem is presented as Configuration 2 in Appendix A. The algorithm used to solve the problem is similar to that presented schematically in Figure 2. In this case however the number of state variables is increased to include groundwater and hence the computational requirements also increase. The computational requirements increase exponentially with the number of states variables in a SDP optimization approach. This computational requirement is also dependant on the number of discrete levels representing the state variables: the higher the number of levels, the higher the computational requirements and the more accurate the solution.

In the case of the reservoir operations, a good degree of accuracy is achieved with less than 10 discrete levels. In the case of the aquifer however, the storage capacity is larger and more discrete levels are needed to properly represent this state variable. In the SDP/NLP model, the authors chose 6 discrete levels to represent the end of September reservoir storage (state variable in the SDP) and 27 discrete levels to represent groundwater aquifer head (second aquifer layer). The authors believe that this number of discrete levels is sufficient to represent the system, particularly given the author's use of cubic splines to approximate reservoir and aquifer storage between discrete levels (Philbrick and Kitanidis [2001]; Johnson et al., [1993]). [3]

The social optimum run assumes the same discount rate, water use benefit parameters and electricity prices used in the calibration run. Unlike the calibration run, where the authors focus only on the recent historical conditions (1970-1998), the social optimum and electric power solutions include a more extended hydrologic time series including reservoir inflows starting in 1922 and ending in 1998.[4]

---

3 Obviously, the introduction of a second state variable in this simplified manner introduces additional inaccuracies into the model.

4 New Exchequer Dam was built to its actual conditions in 1967, and great changes in land uses have occurred since 1922 in the Merced River Basin so these results should be seen as the hypothetical consequence of operating the system under such hydrologic conditions more than the actual historical conditions themselves.

The types of results the authors are interested in here are those related to system operations such as: aquifer head, reservoir storage, reservoir releases, river diversion and groundwater pumping and three associated monetary benefits/costs: irrigation and hydropower benefits and pumping costs. Table 3 summarizes the results of the historical, the social optimum and electric power scenario runs and Figures 3, 4, and 5 provide a graphic comparison of these results.

Table 3.A. Comparison of results under different scenarios (summary of operations)

Scenario	Annual Release (TAF/yr)	Annual Diversion (TAF/yr)	Annual Pumping (TAF/yr)	EoS Storage (TAF)	EoS Head (ft)
Uncoordinated (Only HP)	950	457	412	640	-60
Historical (Calibrated)	954	614	298	490	36
Coordinated	953	614	283	504	48

Table 3.B. Comparison of results under different scenarios (summary of costs and benefits)

Scenario	Hydropower (MWh/yr)	Hydropower ($/yr)	Pumping Costs (MWh/yr)	Pumping Costs ($/yr)	Ag Benefits ($/yr)	All Benefits ($/yr)	?% from Coordinated
Uncoordinated (Only HP)	2.78E+05	9.37E+06	1.46E+05	8.74E+06	2.42E+07	2.483E+07	-13.4%
Historical (Calibrated)	2.78E+05	8.06E+06	6.94E+04	4.16E+06	2.47E+07	2.864E+07	-0.1%
Coordinated	2.79E+05	8.10E+06	6.13E+04	3.68E+06	2.42E+07	2.868E+07	N/A

Figure 3 compares aquifer head levels for the three scenarios, Figure 4 presents average monthly reservoir storage, and Figure 5 includes three panels, the first showing average reservoir releases, the second average river diversions, and the third average pumping levels.

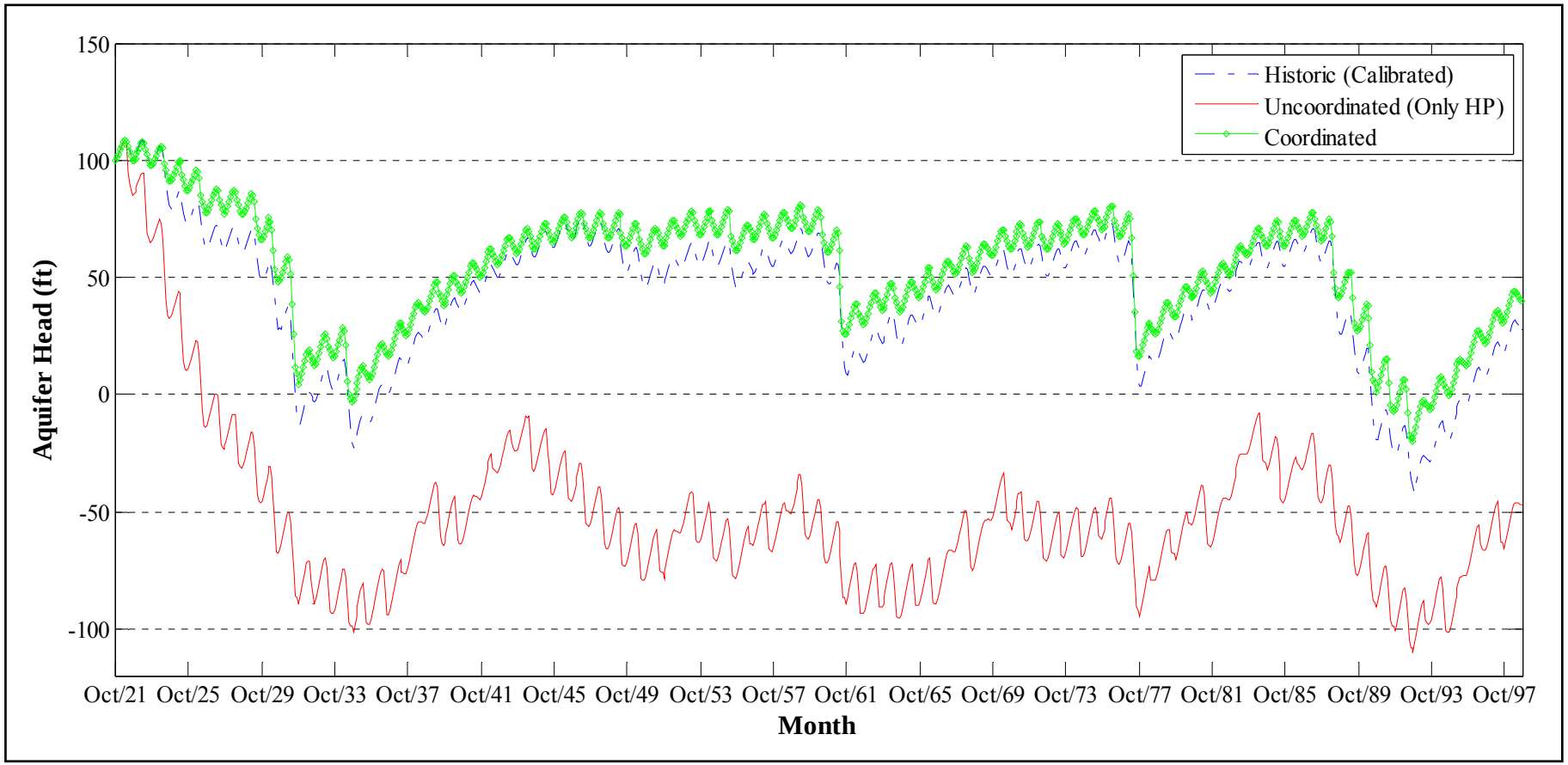

Figure 3. Comparison of aquifer head levels for different scenarios

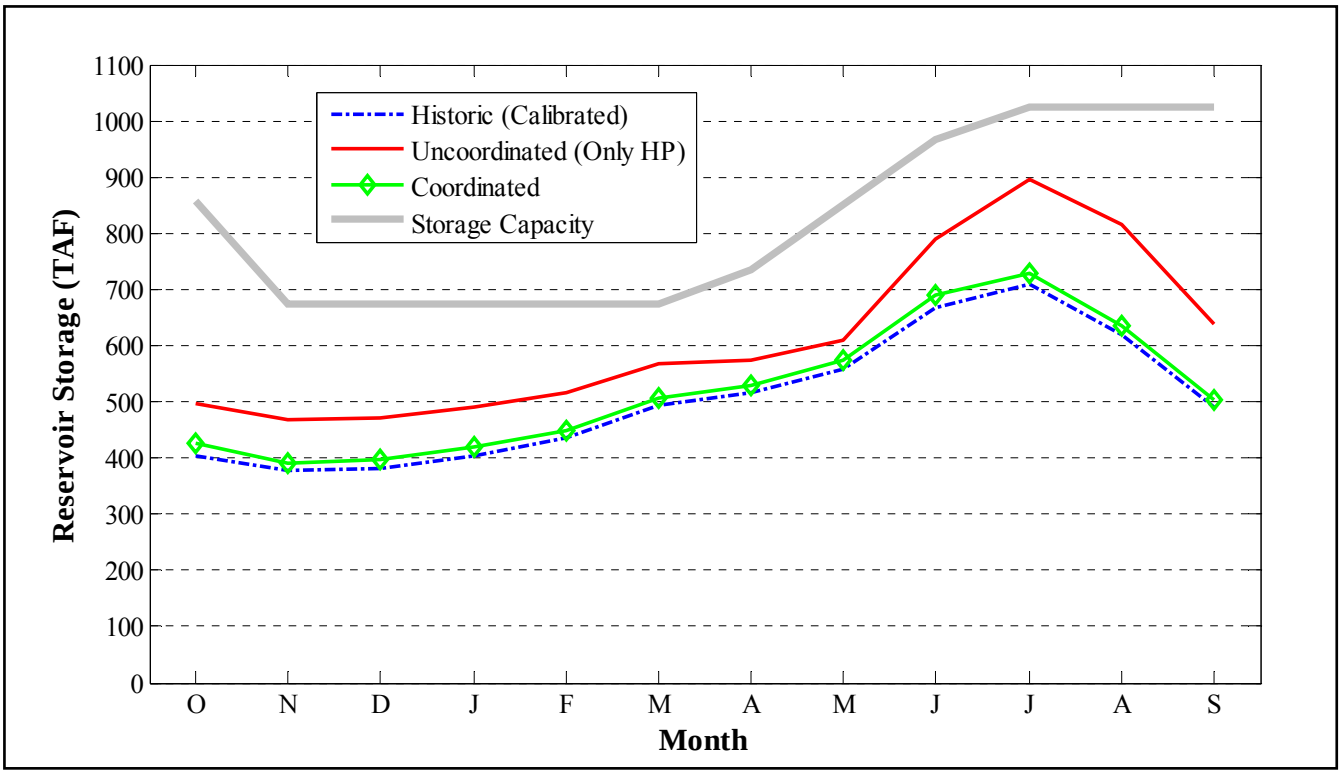

Figure 4. Comparison of average reservoir storage for different scenarios

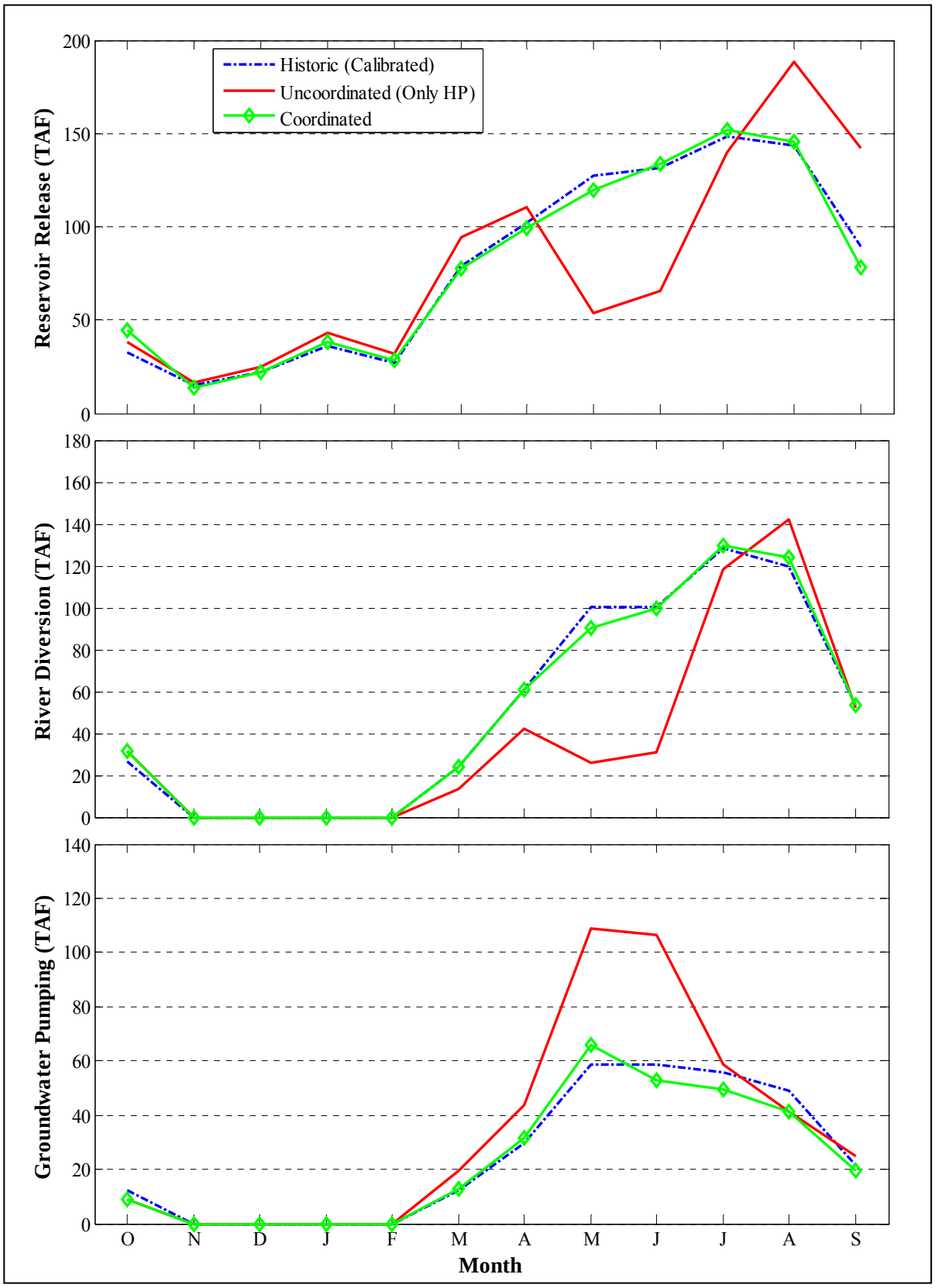

Figure 5. Comparison of simulated operations: A. Releases; B. River Diversion; C. Groundwater Pumping

4.0 Summary of the Results

These results indicate that historical reservoir operation are reasonably close to the social optimal and suggest that control over groundwater pumping will provide only a slight improvement (0.1%) in annual net benefits to MID. These improvements come from a combination of reduced pumping costs (at the expense of agriculture benefits) and increased hydropower generation benefits.[5] [6]

These results also indicate that net benefits to MID will decrease if reservoir operations are directed to increase hydropower production, at least at current electricity prices. When reservoir operations are directed to maximize hydropower benefits, reservoir releases are delayed to a great extent to the end of the summer when energy prices are higher (See Figure 5.A), and reservoir storage is kept at a higher level. (See Figure 4). This decreases surface irrigation diversions (See Figure 5.B), and increases groundwater pumping. See Figure 5.C.

The loss in benefits in this scenario reflects a tradeoff between hydropower and agricultural benefits coupled with a groundwater pumping externality. The timing of reservoir releases affects farm benefits and decreases the amount of surface water available for irrigation. This results in an increase in costly groundwater pumping. Since farmers have no control over regional groundwater pumping, over time groundwater levels decline, and the cost of groundwater pumping rises steadily.

4.1. Scenario Analysis

The analysis conducted in this study suggests that the region will benefit to a limited degree from control over groundwater pumping. However, it is possible that this result may apply only to the peculiar historical conditions and practices existing in the Merced basin and the authors are interested to find out how this conclusion may change for other regions. In this section, the authors performed a scenario analysis to determine how this result might vary under a wider set of conditions and practices. The scenario analysis includes evaluations of different structures for the level of operational authority granted to the decision making agent (MID or social planner). One of such levels includes a change in irrigation practices that allows the use of artificial recharge practices. Another included changing the agricultural service area under the control of the decision making agent. The authors also perform a more classic sensitivity analysis on a couple of key parameters: the stream inflow quantity (level of scarcity) and electricity prices.

The first scenario the authors introduce is the idea of artificial recharge. In the present problem formulation, farms are not allowed to apply more than the current period crop water use

---

5 The later arises mostly due to a change in the timing of operations to take advantage of the variability in energy prices; where the authors see that reservoir releases are slightly delayed in the year whereas pumping is occurring earlier in the year. (See Figure 5.A. and Figure 5.C).

6 The authors find that coordination of reservoir and aquifer operations confers only a small financial benefit to the region is consistent with the results reported in the literature (*Gisser and Sánchez, 1980; Feinerman and Knapp, 1983; Knapp and Olson, 1995*).

requirement. This condition is expressed by the following constraint (See Appendix A for more detail):

$$P_m^A + \varepsilon D_m^{ag} \leq Demand_m(\mathbf{Q}^i) \quad (10)$$

Under an artificial recharge scheme, farms may apply more water than is used by crops, in one period to replenish groundwater aquifer levels for use in subsequent periods. The Merced Irrigation District is currently evaluating this practice and has initiated a series of artificial recharge studies (Corneliusm et al., 2003). Under this new scenario, an option for artificial recharge in the model is included by discarding the constraint limiting applications to current period crop water use (Eq. 10). The existing groundwater model determines the replenishing effect of this excess applied water on groundwater levels without further model formulation changes (see Appendix B). Introducing artificial recharge makes sense only within a conjunctive use scheme were the access to groundwater is controlled and hence there are incentives to replenish the aquifer (at some cost as for example leaving some land without cultivation) with some surplus water. Therefore the benefits estimated with the inclusion of this practice should be associated with the benefits of a conjunctive use approach.

The hydrologic conditions in the second scenario were modified to evaluate the benefits of conjunctive use under a drier set of conditions. In this case, the authors reduce reservoir inflows (a fixed proportion), decreasing surface supplies and increasing the demand for groundwater pumping. The increase in groundwater pumping raises the value of groundwater storage and the potential benefits of coordinated operations.

A third sensitivity analysis tests the impact of increasing the district surface area on conjunctive use. Currently, a large amount of the groundwater pumping in the Merced Basin region occurs outside the formal district service area, and outside the sphere of influence of the optimization model. This condition is represented in the model by a fixed pumping constraint that reflects pumping by a group of non-district farmers (Eq. 11 and Appendix A). This constraint is removed from the base cases, to allow surface water deliveries to supply land the previously received fixed amount of water pumped from the aquifer. The constraint is replaced in this new case by a condition without the minimum pumping requirement (Eq. 12).

$$P_m^A \geq P_{m,\min}^A(\mathbf{Q}^i) \quad (11)$$

$$P_m^A \geq 0 \quad (12)$$

In a final sensitivity analysis, the authors explore the effect of changing energy prices on conjunctive use benefits and management. In this analysis, the benefits of conjunctive use are evaluated assuming an increase in energy prices for pumping and hydropower generation. This should increase the potential benefits of controlling groundwater pumping, encourage more reservoir storage and shift reservoir release times toward periods of high energy prices.

4.2. Results of the Scenario Analysis

The results of the sensitivity analysis comparing benefits assuming reservoir operators have full control of surface and groundwater storage and assuming control only over surface storage are presented below. A summary of the results is presented in Table IV-4. The authors present for each comparison first the results for the partially coordinated case (the calibrated scenario but with changes in some of the parameters/conditions modified in the scenario analysis) and then the difference for each output for the coordinated case for the same change in parameters. The only exception is the comparison for the artificial recharge case, where the results for the coordinated scenario without artificial recharge are presented. In Appendix D, the results of the scenario analysis are summarize in a series of figures.

Table 4.A. Comparison of results under different scenarios and changes in parameters/conditions: summary of operations

Sensitivity Analysis	Scenario	Annual Release (TAF/yr)	Annual Diversion (TAF/yr)	Annual Pumping (TAF/yr)	EoS Storage (TAF)	EoS Head (ft)
Aritifical Recharge	Part. Coord.* (Base)	954	614	298	490	36
	Coordinated (Base)	-1	1	-15	14	12
	Coordinated (Recharge)	-1	86	-15	10	15
Low Inflows	Part. Coord.	712	494	358	409	-16
	Coordinated	-2	1	-19	-1	15
No fixed pumping outside MID	Part. Coord.	955	665	230	455	88
	Coordinated	-3	-11	-10	61	6
High Energy Price	Part. Coord.	954	610	289	495	43
	Coordinated	-1	0	-13	14	10

* Part. Coord. = Partially Coordinated. Equivalent to the calibrated scenario presented before but with changes in some parameters in some cases

Table 4.B. Comparison of results under different scenarios and changes in parameters/conditions: summary of benefits and costs (base case and net changes)

Sensitivity Analysis	Scenario	Hydropower (MWh/yr)	Hydropower ($/yr)	Pumping Costs (MWh/yr)	Pumping Costs ($/yr)	Ag Benefits ($/yr)	All Benefits ($/yr)	Δ% from P. Coord.
Aritifical Recharge	Part. Coord. (Base)	2.78E+05	8.06E+06	6.94E+04	4.16E+06	2.47E+07	2.864E+07	
	Coordinated (Base)	944	42,886	-8,088	-485,250	-490,012	38,124	0.1%
	Coordinated (Recharge)	786	46,381	-9,067	-544,005	-481,022	109,364	0.4%
Low Inflows	Part. Coord.	1.95E+05	5.73E+06	1.07E+05	6.42E+06	2.46E+07	2.387E+07	
	Coordinated	205	124,759	-11,989	-719,367	-658,032	186,093	0.8%
No fixed pumping outside MID	Part. Coord.	2.76E+05	8.00E+06	3.87E+04	2.32E+06	3.33E+07	3.895E+07	
	Coordinated	4,115	1,011,051	-4,498	-269,888	-382,123	898,816	2.3%
High Energy Price	Part. Coord.	2.79E+05	1.02E+07	6.45E+04	4.84E+06	2.45E+07	2.986E+07	
	Coordinated	1,195	39,071	-6,864	-514,837	-546,812	7,095	0.0%

This scenario analysis indicates that conjunctive use benefits are positively correlated with increased district authority (over irrigation quantity and groundwater pumping). Given authority to artificially recharge the aquifer, reservoir operators are able to achieve higher aquifer levels and lower pumping costs. See Figure D.3.B. Reducing the pumping costs allows the replacement of some surface water delivered with groundwater pumping increasing late summer release and hydropower benefits.

As expected, conjunctive use and authority over groundwater pumping are particularly important when water is scarce. In the dry scenario (when inflows are reduced by 25%), reservoir operators can check groundwater overdraft and better match releases to times of high energy prices. In this case, conjunctive use leads to a decrease in groundwater pumping costs and an increase in hydropower benefits, compared to the base case. See Figures D.5.A.-C.

The largest gains from coordinated operations are evident when the decision making agent (social planner) is granted full authority to check groundwater overdraft outside the district. When the authors incorporate all surface area (including those that are not currently served by MID) into the social planner's optimization problem, reservoir operators can more efficiently increase water storage and better synchronize pumping and releases with seasonal energy price patterns. Increasing the amount of land traduces into a more effective use of surface water availability. In years that are sufficiently wet, there would be no need for groundwater pumping and aquifer levels would go up. See Figure D.6. In the coordinated case, when surface water deliveries are needed, they are released from the reservoir at times to fully exploit the hydropower benefits leaving the still needed groundwater pumping to happen only on those months with low energy price (see Figure D.8.A-C). Also in the coordinated case, which relies on groundwater pumping as a second source of water, the reservoir operator decides to leave more water stored in the reservoir thereby increasing the hydropower benefits. See Figure D.7.

Finally, rising energy prices seem to have no major effect on the value of conjunctive use. As expected, reservoir operators seek to raise storage levels when energy prices are high, in order to reduce pumping costs and increase hydropower benefits. However, the benefits of groundwater controls are fairly limited despite higher prices, presumably because water is not scarce and the benefits of groundwater controls are small, in the high energy price scenario. It is also possible that this negligible effect is impacted by the fact that not all irrigable land is covered by surface water supplies. In a future set of runs, the authors will combine some of the different scenarios presented here. (For example, increase energy price but also introduce all irrigable area into the decision-making process.) This new set of runs could be used to test this statement.

5.0 Conclusion

In this paper, the authors explore the benefits of conjunctive use applying a novel monthly non-linear programming model embedded into an annual stochastic dynamic programming model (SDP/NLP model) to simulate reservoir and aquifer operations in the Merced River Basin. The authors calibrated some parameters of the SDP/NLP model to reflect historic operations (historic model run). The model was then used to estimate the impact of different reservoir management structures and incentives on hydropower and agricultural system benefits. Not surprisingly, system net revenues increase when reservoir operators act as social planners and assume full control over ground and surface water storage and releases (coordinated run). Similarly, system net revenues decline substantially when reservoir operators act only to maximize the value of hydropower (hydropower run).

Comparing system benefits across the different scenarios, operations at the Merced River Basin appear to be reasonably close to the "social planner" optimum. In any case, it is apparent that historical district reservoir operations have not been directed solely to maximize hydropower revenues. Since the district does not now have control over groundwater pumping, this study, in line with most of the previous literature, concludes that the benefits of controlling groundwater pumping are currently small, assuming existing economic conditions.

The impact of changing these economic conditions is explored in a scenario analysis. For example, the analysis indicates groundwater controls are particularly valuable when the decision making agent (district or social planner) is given full authority over irrigation levels (including artificial recharge) and outside of the district groundwater pumping. An increase in water scarcity also enhances the value of groundwater controls. Increasing energy prices has little effect on the value of coordinated operations, but there are reasons to believe that they could be larger under a different structure than the one existing in Merced River Basin today.

Thus, this conjunctive use model is adapted to operations in one California region, but scenario runs and sensitivity analysis with the model suggest water storage lessons for other regions as well. In particular, the benefits of conjunctive reservoir and aquifer storage may now be relatively low in many regions. However, as energy and water prices rise in future, and the need for careful management of resources grows, the model presented in this paper may be used to explore ways to more efficiently manage water in the state. The largest gains from water management appear to come from more careful controls of access to groundwater. Additional gains may come from the ability of districts to deliver excess irrigation water for storage in wet years. These gains may be relatively small at present. This may change in future, as water and energy becomes increasingly scarce and valuable.

6.0 References

Bredehoeft, J.D. and R.A.Young. (1970). "The Temporal Allocation of Ground Water – A Simulation Approach." *Water Resources Research*, *6*(1):3-21.

Bredehoeft, J.D. and R.A.Young. (1983). "Conjunctive Use of Groundwater and Surface Water for Irrigated Agriculture: Risk Aversion." *Water Resources Research*, *19*(5):1111-1121.

Burt, O.R. (1964). "The Economics of Conjunctive Use of Ground and Surface Water." *Hilgardia, 36*(2) 31-111.

Cai X. and D. Wang. (2006). "Calibrating Holistic Water Resources–Economic Models." *J. Water Resources Planning and Management*, *132* (6), 414-423.

Chatterjee, B., R.E. Howitt, and R.J. Sexton (1998). "The Optimal Joint Provision of Water for Irrigation and Hydropower." *J. Environ. Econ. Manage.*, *36*(3), 295-313.

Corneliusm M., A.Taghavi, and J. Blanke. (2003). Merced Area Groundwater Pool Interests. Conjunctive Use Site Assessment. Prepared for: Merced Area Groundwater Pool Interests (MAGPI). In Coordination with: California Department of Water Resources; Division of Planning and Local Assistance; Conjunctive Water Management Branch. Prepared by: Water Resources and Information Management Engineering, Inc. (WRIME). May 2003

Dracup, J.A. (1966). "The Optimal Use of Ground-Water and Surface Water System: A Parametric Linear Programming Approach." *Tech. Pap. 6-24, Contrib. 107*, Hydraulic. Lab., Water Resour. Center, Univ. of Calif., Berkeley.

Feinermann, E. and K. C. Knapp. (1983). "Benefits From Groundwater Management: Magnitude, Sensitivity, and Distribution." *American Journal of Agricultural Economics*, *65*, 703–710.

Gisser, M., and D. A. Sánchez. (1980). "Competition Versus Optimal Control in Groundwater Pumping." *Water Resources Research*, *16*, 638–642.

Hooper, E.R., A.P. Georgakakos, and D.P. Lettenmaier. (1991). "Optimal Stochastic Operation of Salt River Project Arizona." *J. Water Resources Planning and Management*, *117*(5), 566-587.

Howitt, R. E., A. Reynaud, S. Msangia, S., and K. C. Knapp. (2002). "Calibrated Stochastic Dynamic Models For Resource Management" *World Congress of Environmental and Resource Economists* – Monterey California. June 24-27, 2002 (http://weber.ucsd.edu/~carsonvs/).

Johnson, S.A., J.R. Stedinger, C.A. Shoemaker, Y. Li, Y. and J.A. Tejada-Guibert. (1993). Numerical Solution of Continuous-State Dynamic Programs Using Linear and Spline Interpolation." *Operations Research*, *41*, 484-500.

Knapp, K.C. and L.J. Olson. (1996). "The Economics of Conjunctive Groundwater Management with Stochastic Surface Supplies." *J. Water Resources Planning and Management*, *28*(3), 340-356.

Koundouri, P. (2004). "Potential for Groundwater Management: Gisser-Sanchez Effect Reconsidered." *Water Resources Research*, 40, W06S16, doi:10.1029/2003WR002164.

Maddock III. T. (1974). "The operation of a Stream-Aquifer System Under Stochastic Demands." *Water Resources Research*, *10*(1):1-10.

Matsukawa, J., B.A. Finney, and R. Willis. (1992). "Conjunctive-Use Planning in Mad River Basin, California." *J. Water Resources Planning and Management*, *118*(2), 115-132.

Noel, J. E. and R. E. Howitt. (1982). "Conjunctive Multibasin Management: An Optimal Control Approach." *Water Resources Research*, *18*(4), 753-763.

Onta, P.R. and A.D. Gupta. (1991). "Multistep Planning Model for Conjunctive Use of Surface and Ground Water Resources." *J. Water Resources Planning and Management*, *117*(6), 662-678.

Peralta, R.C., R.A. Cantiller, and J.E. Terry. (1995). "Optimal Large-Scale Conjunctive Water-Use Planning: Case Study." *J. Water Resources Planning and Management*, *121*(6), 471-478.

Philbrick, C.R. and P.K. Kitanidis. (1998). "Optimal Conjunctive-Use Operations and Plans." *Water Resources Research*, *34*(5), 1307-1316.

Philbrick, C.R. and P.K. Kitanidis. (2001). "Improved Dynamic Programming Methods for Optimal Control of Lumped-Parameter Stochastic Systems." *Operations Research*, *49*(3), 398–412.

Provencher, B. and O. Burt. (1993). "The Externalities Associated With the Common Property Exploitation of Groundwater." *J. Environ. Econ. Manage.*, *24*, 139-158.

Provencher, B. and O. Burt. (1994). "Approximating the Optimal Groundwater Policy in a Muliaquifer Stochastic Conjunctive Use Setting." *Water Resources Research*, *30*(3), 833-843.

Pulido-Velázquez, M., J. Andreu, and A. Sahuquillo. (2006). "Economic Optimization of Conjunctive Use of Surface Water and Groundwater at the Basin Scale." *J. Water Resources Planning and Management*, *132* (6), 454-467.

Reichard, E. (1995). "Groundwater-Surface Water Management With Stochastic Surface-Water Supplies: A Simulation Optimization Approach." *Water Resources Research*, *31*(11), 2845-2865.

Schoups, G., C. L. Addams, J. L. Minjares, and S. M. Gorelick. (2006). "Sustainable Conjunctive Water Management in Irrigated Agriculture: Model Formulation and Application to the Yaqui Valley, Mexico." *Water Resources Research*, *42*, W10417, doi:10.1029/2006WR004922.

Tejada-Guibert, J., Johnson, S. A. and J. R. Stedinger. (1993). "Comparison of Two Approaches for Implementing Multireservoir Operating Policies Derived Using Stochastic Dynamic Programming." *Water Resources Research*, *29*(12), 3969-3980.

Tsur, Y. and T. Graham-Tomasi. (1991). "The Buffer Value of Groundwater With Stochastic Surface Water Supplies." *J. Environ. Econ. Manage.*, *21*, 201-224.

Vedula, S., and D. N. Kumar. (1996). "An Integrated Model for Optimal Reservoir Operation for Irrigation of Multiple Crops." *Water Resources Research*, *32*(4), 1101-1108.

Worthington, V.E., O.R. Burt, and R. Brustkern. (1985). "Optimal Management of a Confined Groundwater System." *J. Environ. Econ. Manage.*, *12*, 229-245.

Yakowitz, S. (1982). "Dynamic Programming Applications in Water Resources." *Water Resources Research*, *18*(4), 673-696.

Yeh, W.W.G. (1985). "Reservoir Management and Operations Models–A State-of-the-Art Review." *Water Resources Research*, *21*(12), 1797-1818.

Appendix A

Detailed Problem Formulations

Appendix A.

Detailed Problem Formulations

When water is released from the reservoir hydropower is generated as this water flows through the turbines. Later, water in the river could be diverted to be used to irrigate farms in the valley. The first configuration explained below correspond to a situation where reservoir operations occur independent of groundwater pumping decisions. After a release decision is made (Step 3 in the optimization algorithm, see Figure 2), farmers decide how much water to divert from the river and how much water to pump considering the marginal costs (pumping costs) and benefits of using that water in the farm. The second configuration is the case of a social planner which has complete control on both groundwater pumping levels and reservoir release. It represents the case of full coordination between reservoir and aquifer operations.

Configuration 1: Independent reservoir and aquifer operations

This condition is composed of two parts. In a first phase, the authors solve an SDP/NLP problem for the operations of the reservoir independently of farm level decisions. In this scenario, the authors have the following variables: **X**, the vector of state variables in this case represents storage in reservoir, S_t^R; the vector of control variables, **U** is represented by R_t^t, releases through turbines, R_t^s uncontrollable spills and D_t^{ag} river diversions for agriculture. The other components of the problem formulation are defined as:

$$\mathbf{B}_m^R(\mathbf{X}_m,\mathbf{U}_m) = AgB_m(\mathbf{U}_m) + \phi EnergyB_m(\mathbf{X}_m,\mathbf{U}_m)$$

$$= \beta_m^{ag} * \varepsilon D_m^{ag} - \frac{\gamma_m^{ag}}{2} * (\varepsilon D_m^{ag})^2 + \alpha_m^R * f(R_m^t) * H^{\mathrm{R}}(S_m^R)$$

$$\mathbf{X}_{m+1} = \mathbf{T}(\mathbf{X}_m,\mathbf{U}_m,Q_m^i) \longrightarrow S_{m+1}^R = S_m^R + Q_m^i - R_m^t - R_m^s - NetEvap_m$$

$$Q_m^i = f(\mathbf{Q}^i) = \mathbf{Q}^i * D_m(\mathbf{Q}^i)$$

$$\mathbf{X}_m \in \Theta \longrightarrow S_{\min}^R \le S_{m+1}^R \le S_{m,\max}^R$$

$$\mathbf{U}_m \in \Pi \longrightarrow D_m^{ag} - R_m^t - R_m^s \le -q_{\min,m}; \text{ (Minimum flow requirements)}$$

$$\varepsilon D_m^{ag} \le Demand_m(\mathbf{Q}^i); \text{ (Surface water delivery} \le Demand_m(\mathbf{Q}^i)$$

$$R_m^t \le R^{\max}; \text{ (Maximum Release through turbines)}$$

$$K_2 * f(R_m^t) * H^{\mathrm{R}}(S_m^R) \le Gen^{\max}; \text{ (Maximum Generation Capacity)}$$

$$D_m^{ag}, R_m^t, R_m^s \ge 0$$

where,

$\mathbf{B}_m^R(\mathbf{X}_m, \mathbf{U}_m)$	=	Monthly benefits from the reservoir operator perspective.
ϕ	=	Relative weight given to hydropower and irrigation benefits in the reservoir operator objective function.
$\beta_m^{ag}, \gamma_m^{ag}$	=	Are parameters related to the linear demand function for water in the farm (parameters that need to be calibrated, see section 4). Demand of water is a function of overall wetness of the season as represented by annual inflows.
ε	=	1 – percent of recoverable losses (seepage)
α_m^R	=	$K_2 * c_t$ is a parameter that takes into account monthly energy prices c_t and the appropriate unit transformation
$f(R_m^t)$	=	Effect of releases in energy generation considering efficiency
$H^{\mathrm{R}}(S_m^R)$	=	Head in the reservoir as a function of storage (look up table)
Q_m^i	=	Monthly inflow corresponding to annual inflow bin *i*
$D_m(\mathbf{Q}^i)$	=	Monthly percent distribution of bin *i* of historical annual inflows
$S_{\min}^R, S_{m,\max}^R$	=	Minimum and maximum reservoir storage respectively
$q_{\min,m}$	=	Minimum streamflow requirements

The solution of the SDP/NLP problem yields a set of operating rules of the form: $S_{12}^{R,*} = \mathrm{Rule}(S_1^R, \mathbf{Q}^i)$. This rule is then applied considering historic conditions (inflows to the reservoir) to obtain the boundary conditions for the NLP monthly model which when solved creates a series of optimal monthly reservoir releases through the turbines ($R_{m,t}^{t,*}$), and spills ($R_{m,t}^{s,*}$) (*Step 3* in SDP/NLP algorithm, see Figure 1).

Finally the farmers make a decision on the amount of water to divert from the river and the amount of groundwater pumping by solving the following single period NLP optimization problem:

$$\underset{\mathbf{U}_1,\mathbf{U}_2..\mathbf{U}_{12}}{Max}\left(\sum_{m=1}^{m=12}\left(\mathbf{B}_m^F(\mathbf{X}_m,\mathbf{U}_m)\right)\right)$$

With,

$$\mathbf{B}_m^F(\mathbf{X}_m,\mathbf{U}_m) = AgB_m(\mathbf{U}_m) - PumpingCosts_m(\mathbf{X}_m,\mathbf{U}_m)$$

$$= \beta_m^{ag} * (P_m^A + \varepsilon D_m^{ag}) - \frac{\gamma_m^{ag}}{2} * (P_m^A + \varepsilon D_m^{ag})^2 - P_m^A * K_1 * (Surface - H_m^A) * c_m$$

$st:$

$$\mathbf{X}_{m+1} = \mathbf{T}(\mathbf{X}_m,\mathbf{U}_m) \longrightarrow H_{m+1}^A = H_m^A + \frac{\Delta S_m^A(P_m^A, D_m^{ag})}{AS^y}$$

$$\mathbf{X}_m \in \Theta \longrightarrow H_{\min}^A \le H_{m+1}^A \le H_{\max}^A$$

$$\mathbf{U}_m \in \Pi \longrightarrow D_m^{ag} - R_{m,t}^{t,*} - R_{m,t}^{s,*} \le -q_{\min,m}; \text{ (Minimum flow requirements)}$$

$$P_m^A + \varepsilon D_m^{ag} \le Demand_m(\mathbf{Q}^i); \text{ (Applied Water} \le Demand_m(\mathbf{Q}^i))$$

$$P_m^A \ge P_{m,\min}^A(\mathbf{Q}^i)$$

$$D_m^{ag} \ge 0$$

where,

$\mathbf{B}_m^F(\mathbf{X}_m,\mathbf{U}_m)$	=	Monthly benefits from the farmer perspective.
$Surface$	=	Surface elevation
$P_m^A + \varepsilon D_m^{ag}$	=	Total water delivery at farm
K_1	=	Unit conversion to obtain energy requirements
c_m	=	Pumping energy price (could be monthly varying)
$H_{\min}^A, H_{\max}^A$	=	Minimum and maximum aquifer head respectively
ΔS_m^A	=	Net storage change in aquifer. Takes into account applied water in the farm, Agriculture and Urban pumping and subsurface flow from surrounding aquifers (on top, below or on the sides). See Appendix B for more details.
$P_{m,\min}^A(\mathbf{Q}^i)$	=	Minimum pumping (pumping occurring outside MID's territory) a function of overall wetness)

Configuration 2: Conjunctive use setting, social planner

In this case, the authors can only solve one SDP/NLP problem which includes the operations of both the reservoir and aquifer in coordination. Following the general algorithm as presented in

Section 3, the following notations are used to fully describe the details of the objective function and constraints.

$\mathbf{X}_t$, the vector of state variables in this case represents aquifer head H_t^A and storage in reservoir, S_t^R; the vector of control variables, $\mathbf{U}_t$ is represented by R_t^t releases through turbines, R_t^s uncontrollable spills, D_t^{ag} river diversions for agriculture and groundwater pumping P_t^{A} also for agriculture. The other components of the problem formulation are defined as:

$$\begin{aligned}
\mathbf{B}_m^{SP}(\mathbf{X}_m,\mathbf{U}_m) &= AgB_m(\mathbf{U}_m) + EnergyB_m(\mathbf{X}_m,\mathbf{U}_m) - PumpingCosts_m(\mathbf{X}_m,\mathbf{U}_m) \\
&= \beta_m^{ag} * (P_m^A + \varepsilon R_m^{ag}) - \frac{\gamma_m^{ag}}{2} * (P_m^A + \varepsilon R_m^{ag})^2 \\
&\quad + \alpha_m^R * f(R_m^t) * H^{\mathrm{R}}(S_m^R) \\
&\quad - P_m^A * K_1 * (Surface - H_m^A) * c_m
\end{aligned}$$

$$\begin{aligned}
\mathbf{X}_{m+1} = \mathbf{T}(\mathbf{X}_m,\mathbf{U}_m,Q_m^i) &\longrightarrow S_{m+1}^R = S_m^R + Q_m^i - R_m^t - R_m^s - NetEvap_m \\
&\longrightarrow H_{m+1}^A = H_m^A + \frac{\Delta S_m^A(P_m^A, D_m^{ag})}{AS^y} \\
Q_m^i = f(\mathbf{Q}^i) = \mathbf{Q}^i * D_m(\mathbf{Q}^i) & \\
\mathbf{X}_m \in \Theta &\longrightarrow S_{\min}^R \le S_{m+1}^R \le S_{m,\max}^R \\
&\longrightarrow H_{\min}^A \le H_{m+1}^A \le H_{\max}^A \\
\mathbf{U}_m \in \Pi &\longrightarrow D_m^{ag} - R_m^t - R_m^s \le -q_{\min,m} \text{ (Minimum flow requirements)} \\
& \quad P_m^A + \varepsilon D_m^{ag} \le Demand_m(\mathbf{Q}^i); \text{ (Applied Water} \le Demand_m) \\
& \quad R_m^t \le R^{\max}; \text{ (Maximum Release through turbines)} \\
& \quad K_2 * f(R_m^t) * H^{\mathrm{R}}(S_m^R) \le Gen^{\max}; \text{ (Maximum Generation Capacity)} \\
& \quad P_m^A \ge P_{m,\min}^A(\mathbf{Q}^i) \\
& \quad D_m^{ag}, R_m^t, R_m^s \ge 0
\end{aligned}$$

With all variables and parameters as previously defined, except $\mathbf{B}_m^{SP}(\mathbf{X}_m,\mathbf{U}_m)$ which refers to the monthly benefits from the social planner perspective.

The solution of this SDP/NLP is two set of rules for both the reservoir and aquifer operations of the form $S_{12}^{R,*} = Rule^R(S_1^R, H_1^A, \mathbf{Q}^i)$ and $H_{12}^{A,*} = Rule^A(S_1^R, H_1^A, \mathbf{Q}^i)$. These rules are then applied considering historic conditions (inflows to the reservoir) to obtain the boundary conditions for the NLP monthly model which when solved creates a series of optimal monthly reservoir releases through the turbines ($R_{m,t}^{t,*}$), spills ($R_{m,t}^{s,*}$), river diversions for agriculture ($D_{m,t}^{ag,*}$) and groundwater pumping levels $P_{m,t}^{\mathrm{A},*}$.

Appendix B

Groundwater model

Appendix B

Groundwater model

One of the limitations of Stochastic Dynamic Programming models (*Labadie, 2004*) is the computational burden of including too many state variables in the problem formulation. Thus far there have been successful approaches (without too many approximations) to include as much as 9 state variables (*Chen et al., 1999*) without any clear technique going beyond that number without sacrificing in some accuracy. In this work the authors don't try to go beyond that limit and hence are limited to a small number of state variables. In the case of representing reservoir conditions this doesn't pose a problem because reservoir hydrology is well represented considering just one state. However, this is not true in the representation of aquifer conditions. Here the spatial heterogeneity in physical conditions and stimuli creates a spatial distributed condition in the aquifer, meaning that more than one state variable is needed to fully represent conditions in different locations (both in terms of depth and position). In this Appendix, the authors describe the methodology used to create a lumped (one state variable only) representation of the Merced Aquifer trying to incorporate as much as possible the details of the distributed nature of the problem.

The approach basically reduces the sate dimension, through a series of physical/statistical relationships, of the results of the C2VSIM model, a distributed surface and groundwater model of the California Central Valley developed by the California Department of Water Resources. These relationships were calibrated using the historic results (groundwater budgets and average head/water table) for the region under consideration. The final objective is to create a lumped representation of groundwater head of the following form (with variables defined before).

$$H_{m+1}^{A} = H_{m}^{A} + \frac{\Delta S_{m}^{A}(P_{m}^{A}, D_{m}^{ag})}{AS^{y}} \qquad \text{(B.1)}$$

This relationship dictates that the change in head is equal to the change in storage divided by the multiplication of the storativity and surface area of the aquifer. A first step of the approach consisted in calibrating a parameter to represent this storativity. To do this the authors compared changes in average aquifer head with changes in the groundwater budget for the region, both results obtained from an historic C2VSIM simulation. The authors focused on the second layer of the aquifer as represented in the model. This layer is not connected with the stream and it is where most groundwater pumping occurs. The water quality issues in this layer are less of a concern also as they are in the first layer.

The second step in the approach consisted in the statistical calibration of physically based equations used to estimate the different components of the groundwater budget in this second later based in the available variables in the optimization model. The different components of the groundwater budget are:

Direct pumping

Subsurface inflow from layer 1 above

Subsurface inflow from surrounding regions

It was assumed that subsurface inflow from layer 1 above was determined by the head difference between layer 1 and 2 and also by the amount of water applied in the farm (affecting deep percolation). Both terms were added together. Subsurface inflow from surrounding regions is a function of the relative heads between this aquifer its neighbors and it's not explicitly modeled here but it's effect should be represented in the final values for the parameters. With all these considerations the functional form for the change in storage is represented by the following equation:

$$\Delta S_m^{A,L2} = A_0 + A_1 * (\bar{H}^{A,L1} - H_m^{A,L2}) + A_2 * \varepsilon D_m^{ag} + A_3 * (1-\phi) P_m^A - P_m^{A,U} \quad \text{(B.2)}$$

Where,

$\bar{H}^{A,L1} - H_m^{A,L2}$	=	Difference in head between layer 1 (held constant) and layer 2
εD_m^{ag}	=	Applied surface water in the farm (excludes seepage losses, 1-ε)
$(1-\phi)P_t^A$	=	Fraction of pumping used for irrigation coming from layer 2
$P_m^{A,U}$	=	Urban pumping (a constant each month)

The parameters A_0, A_1, A_2 and A_3 are calibrated comparing historic changes in groundwater budget and historic values for D_m^{ag} and P_m^A. The following figure shows a comparison between historic as simulated through C2VSIM and historic as simulated using the reduced model shown in *eq. B.1* (with historic data on pumping and surface water deliveries) average head in layer 2 of Merced Aquifer. As can be shown in the figure the lumped representation of the aquifer through the physically based equations just described gives a very reasonable representation of the Merced aquifer head.

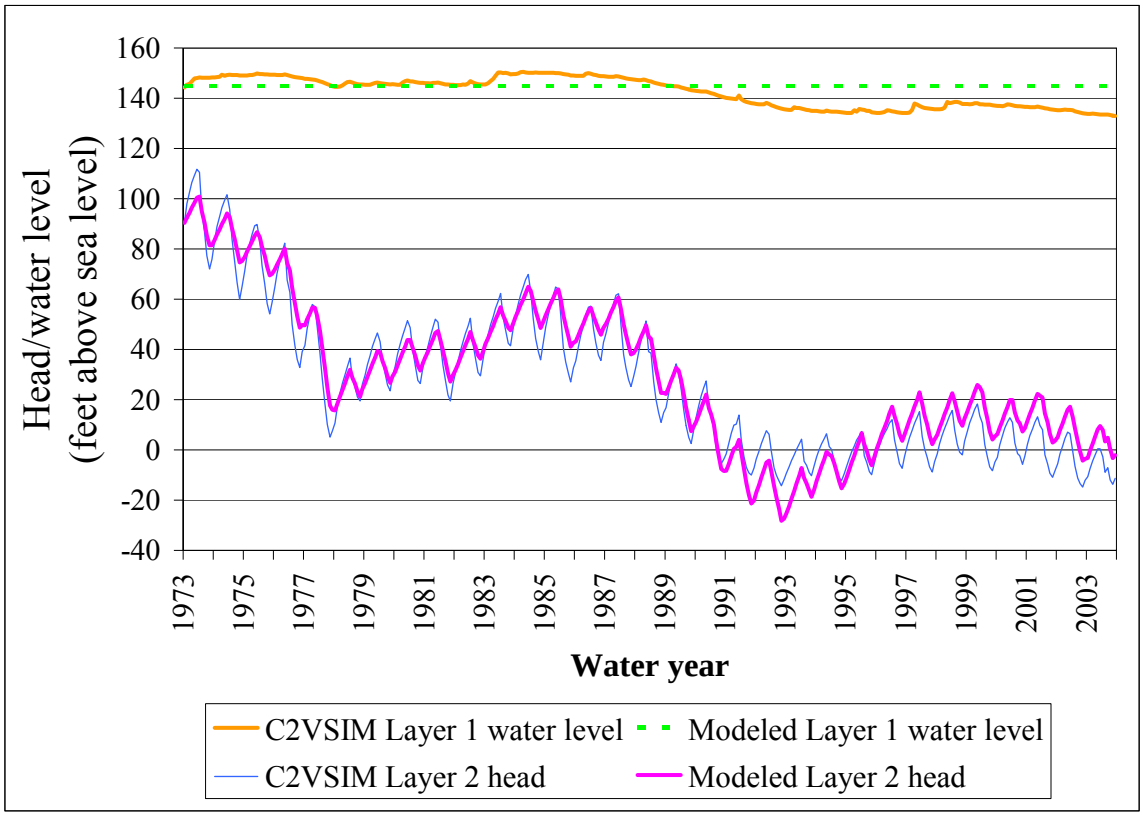

Figure B.1. Comparison between C2VSIM and modeled head/water level in layers 1 and 2 of Merced Aquifer

Appendix C

Calibration of the SDP/NLP model

Appendix C.

Calibration of the SDP/NLP model

Following Howitt et al. (2002) and Cai and Wang (2006), the authors calibrated the SDP/NLP model by estimating key parameters of the optimization problem and organizational structure. The key parameters include the discount rate parameter, the irrigation demand benefit function parameters (β_m^{ag} and γ_m^{ag} in Eq. 1) and the organizational type parameter. One assumption supporting the author's calibration process is that reservoir release decisions are independent of groundwater pumping decisions. This assumption implies that farmers make groundwater pumping decisions after they learn how much surface water is available for diversion from the reservoir. Another related assumption is that reservoir operators have no control over groundwater pumping. To choose among the different alternative parameters, the authors compare reservoir storage, aquifer head levels and reservoir releases with the historic conditions and select the set that results in the lowest weighted sum of squared errors.

The first of the parameters considered is the discount rate used in the annual SDP model. The discount rate is equivalent to $(1-\beta)/\beta$, where β is the discount factor used in *Eq. 7*. The discount rate, which represents the intertemporal preferences of reservoir operators, has a substantial impact on optimal carryover storage (rule $l^* = l(k, Q_h^t)$ in *Step 2* of the algorithm), or the amount of storage left in the reservoir at the end of the water year. Higher discount rates represent more "myopic" reservoir operations, and less concern about future period benefits. In the extreme an infinite discount rate would result in an operating rule that empties the reservoir for any given initial storage and inflow condition.

The agricultural water demand function is assumed to be linear and is represented by two different parameters: the maximum annual demand of water (at a 0 price) and the maximum willingness to pay for water (at zero quantity). The authors estimate these parameters for 12 different demand functions, one for each month of the year. It is assumed that water needs are distributed uniquely throughout the year and the maximum willingness to pay is considered the same for all months. With these assumptions the parameters for each one of these demand functions can be determined by knowing just the two parameters considered in the calibration process. If the distribution of water needs assumed is the same as the distribution for the most valuable crops this is a reasonable assumption.

In general, increasing the value of the water demand parameters leads to reservoir release schedules that closely match the monthly distribution of physical crop water requirements (i.e. spring and early summer). Alternatively, decreasing the value of the water demand parameters results in reservoir releases that closely match the pattern of energy prices throughout the year. A high relative value of irrigation benefits also implies higher end of year storage (end of September) and increased groundwater pumping

Finally, the authors include a fourth parameter in the calibration process to represent the relative weight given by reservoir operators to hydropower benefits and to irrigation benefits. This parameter is allowed to have six discrete values including two extreme and four intermediate values. The extreme values represent the pure hydropower case (with irrigation benefits coming as a side benefit of hydropower releases) and the pure irrigation case (where hydropower benefits are a side benefit of irrigation releases). The four intermediate values represent different relative preferences given to hydropower and irrigation (ϕ). Table C.1 summarizes the objective functions used to represent this parameter.

Table C.1. Summary of scenarios used in calibration phase

Scenario	Objective Function
Pure Hydropwer	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = EnergyB_m(\mathbf{X}_m, \mathbf{U}_m)$
Pure Irrigation	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = AgB_m(\mathbf{U}_m)$
Both Hydropower and Irrigation	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = AgB_m(\mathbf{U}_m) + \phi EnergyB_m(\mathbf{X}_m, \mathbf{U}_m),$ with $\phi = [0.25\ 1]$

Summarizing these ideas that the authors have that the discount rate should affect carryover storage, the demand function parameters affect indirectly carryover storage, timing of releases and amount of pumping occurring in the basin and finally the objective functions considered will affect the timing of releases and carryover storage in the reservoir. The authors decided then to calibrate these parameters through their concurrent interrelated effect on operations by comparing historic with simulated (after using optimized operating rules, *Step 3* in optimization algorithm) conditions in the basin. The variables used in the calibration are historic carryover storage, historic average reservoir releases and historic average aquifer head (as simulated by the model C2VSIM under historic conditions). It's important to note that in this calibration process based on the historic aquifer head levels, a minimum amount of pumping occurring regardless of the available water in the reservoir (representing pumping outside the MID territory) was considering. Annual pumping (as a fraction of demand) for the wettest year in the record was chosen as this minimum pumping level. For the discount rate, the authors decided on a range of values starting on 0% discount to a 20% discount. The range of possible values for the "y intercept" was chosen based on the value of farming in this region (in terms of $/AF) based on Central Valley Production Model (CVPM) runs. The range of possible values for the "x intercept" (annual demand of water at 0 price) was chosen as positive multiples of the observed average water usage in the basin (this later corresponds to the lower bound for the parameter sought). To decide on the bests set of parameters, the authors calculated normalized squared errors for each parameters defined as:

$$r^2_{CO,\theta} = \frac{\sum_{t=1}^{t=end}\left(CO_t^{*,\theta} - CO_t^H\right)^2}{\sum_{t=1}^{t=end}\left(CO_t^H\right)^2}; \quad r^2_{R,\theta} = \frac{\sum_{m=1}^{m=12}\left(\bar{R}_m^{*,\theta} - \bar{R}_m^H\right)^2}{\sum_{m=1}^{m=12}\left(\bar{R}_m^H\right)^2}; \quad r^2_{H,\theta} = \frac{\sum_{t=1}^{t=end}\sum_{m=1}^{m=12}\left(H_{m,t}^{*,\theta} - H_{m,t}^H\right)^2}{\sum_{t=1}^{t=end}\sum_{m=1}^{m=12}\left(H_{m,t}^H\right)^2} \quad (C.1)$$

where,

$CO_t^{*,\theta}$	=	Reservoir carryover storage in year *t* as simulated using optimized operating rules for parameter set θ (just discount rate in this case)
CO_t^H	=	Historic reservoir carryover storage in year *t*
$\bar{R}_m^{*,\theta}$	=	Average reservoir releases in month *m* as simulated using optimized operating rules for parameter set θ (demand function parameters)
$\bar{R}_m^H$	=	Historic average reservoir releases in month *m*
$H_{m,t}^{*,\theta}$	=	Aquifer head in month *m* and year *t* as simulated using optimized operating rules for parameter set θ (demand function parameters)
$H_{m,t}^H$	=	Historic aquifer head in month *m* and year *t*

Then these squared errors are combined in a standardized measure of the errors considering all different parameters. The authors did these by calculating a weighted sum of normalized sum of squared errors based on average sum of square errors for all set of parameters.

$$r^2_{weighted,\theta_i} = \frac{r^2_{CO,\theta_i}}{\overline{\overline{r^2_{CO,\theta}}}} + \frac{r^2_{R,\theta_i}}{\overline{\overline{r^2_{R,\theta}}}} + \frac{r^2_{H,\theta_i}}{\overline{\overline{r^2_{H,\theta}}}}$$

(C.2)

In Table C.3, the authors present the values of $r^2_{weighted,\theta_i}$ for all different possible objective functions scenarios and different set of parameters considered in the calibration approach. The best combination of parameters arise when both objectives are considered as part of the optimization algorithm, an "x" intercept that is 20% higher than the observed applied water, a "y" intercept corresponding to a maximum willingness to pay of 75 $/AF and a discount rate of 0%. The difference between the results for this discount rate and those up to a 5% are very similar so to maintain some consistence with previous studies (e.g. Feinerman and Knapp, 1983), a discount rate of 3% is selected. Table C.2 presents the parameters estimated in this calibration phase.

Table C.2. Value for parameters resulting in the calibration phase

Parameter	Parameter Value
Discount Rate	3%
Maximum Willingness to Pay	75 $/AF
Demand at 0 price	1.2*Average Historic Applied Water
Objective Function	$\mathbf{B}_m(\mathbf{X}_m, \mathbf{U}_m) = AgB_m(\mathbf{U}_m) + \phi EnergyB_m(\mathbf{X}_m, \mathbf{U}_m)$, with $\phi = 1$

Figures C.1, C.2 and C.3, show graphically the results obtained in this step. Figure C.1 shows a comparison between historic and simulated reservoir storage for three different conditions. The first correspond to the chosen set of parameters, the second correspond to the same parameters for the demand function but a higher discount rate and the last correspond to the case where the authors assumed that the objective function only considered irrigation benefits. It's clear that a higher discount rate tends to reduce the carryover storage whereas a higher value for water used for irrigation as compared to the hydropower benefits increase the storage by the end of September.

Figure C.2 shows a comparison between the average historic releases and three simulated conditions. The first corresponds to the condition chosen as the calibrated set of parameters. The second and third correspond to the two extreme cases, one in which the authors have considered the operation of the reservoir with the only objective of fulfilling hydropower benefits and the other just the opposite, i.e. an operation oriented only to meet irrigation demand requirements. It can be clearly seen that by increasing the relative weight of hydropower benefits (lower values of either the "x" intercept or the "y" intercept will increase the relative weight of hydropower benefits) the timing of releases is affected moving towards a pattern that closely match the pattern of energy prices (shown in the upper panel of Figure C.2) instead of the pattern of irrigation water demand as occurs in the opposite case (shown also in the upper panel of Figure C.2). Although the operations are clearly closer to a condition where irrigation water demand drives reservoir operations there is still some effect of hydropower generation especially in the month of September as explained before where a pure irrigation operation is not enough to explain the higher release levels occurring in this month.

Finally Figure C.3 shows a comparison between historic aquifer head levels and again three simulated conditions, the first with the chosen set of parameters and the second and third considering the lowest and highest benefits associated with farm irrigation respectively. This figure clearly shows the effects that these parameters have on the amount of groundwater pumping (and hence aquifer head levels): as the maximum willingness to pay ("y" intercept) and the water demand at 0 price ("x" intercept) increase, the amount of groundwater pumping increases and hence aquifer levels fall. If they are "too" high though, aquifer levels fall more than the historic drawdown. And correspondingly, if they are "too" low aquifer levels stay at levels higher that the historic record suggests.

Table C.3. Comparison of $r^2_{weighted,\theta_i}$ for sets of parameters and objective functions

Objective Function	X Intercept (TAF/yr)	Y Intercept ($/AF)	Discount rate 0%	1%	3%	5%	10%
Pure Irrigation	Average Applied	50	4.10	4.07	3.96	3.83	3.63
		75	2.61	2.58	2.53	2.45	2.40
		100	2.20	2.19	2.17	2.15	2.12
		125	2.07	2.04	2.03	2.01	1.98
	1.2*Average Applied	50	2.23	2.21	2.18	2.17	2.14
		75	1.84	1.80	1.75	1.72	1.68
		100	1.68	1.68	1.68	1.68	1.73
		125	1.81	1.81	1.82	1.84	1.90
	1.4*Average Applied	50	1.70	1.70	1.72	1.74	1.83
		75	2.05	2.07	2.10	2.15	2.23
		100	2.78	2.80	2.82	2.85	2.96
		125	3.46	3.48	3.46	3.49	3.53
Irrigation+0.25*Hydropower	Average Applied	50	2.15	2.14	2.13	2.13	2.12
		75	1.74	1.75	1.75	1.75	1.76
		100	1.56	1.56	1.57	1.59	1.62
		125	1.47	1.48	1.49	1.50	1.54
	1.2*Average Applied	50	1.65	1.67	1.72	1.76	1.89
		75	1.39	1.41	1.46	1.50	1.63
		100	1.42	1.44	1.47	1.51	1.63
		125	1.53	1.55	1.58	1.61	1.73
	1.4*Average Applied	50	1.73	1.76	1.83	1.90	2.10
		75	1.96	1.99	2.05	2.12	2.31
		100	2.49	2.52	2.57	2.63	2.80
		125	3.02	3.05	3.09	3.15	3.31
Irrigation+0.5*Hydropower	Average Applied	50	2.01	2.01	2.01	2.01	2.09
		75	1.63	1.63	1.62	1.62	1.68
		100	1.48	1.48	1.48	1.48	1.52
		125	1.44	1.44	1.42	1.42	1.46
	1.2*Average Applied	50	1.54	1.57	1.65	1.71	1.86
		75	1.31	1.34	1.40	1.45	1.59
		100	1.36	1.39	1.43	1.47	1.61
		125	1.48	1.50	1.54	1.57	1.69
	1.4*Average Applied	50	1.62	1.67	1.75	1.81	2.02
		75	1.89	1.93	1.98	2.05	2.26
		100	2.45	2.46	2.51	2.58	2.77
		125	2.99	3.01	3.06	3.10	3.28

Objective Function	X Intercept (TAF/yr)	Y Intercept ($/AF)	Discount rate 0%	1%	3%	5%	10%
Irrigation+0.75*Hydropower	Average Applied	50	2.00	2.00	2.01	2.03	2.16
		75	1.56	1.57	1.57	1.59	1.69
		100	1.40	1.41	1.41	1.42	1.49
		125	1.37	1.36	1.34	1.35	1.41
	1.2*Average Applied	50	1.45	1.49	1.58	1.67	1.86
		75	***1.26***	***1.29***	***1.35***	1.43	1.58
		100	1.31	1.34	1.40	1.45	1.60
		125	1.44	1.47	1.51	1.55	1.68
	1.4*Average Applied	50	1.51	1.56	1.68	1.77	1.98
		75	1.84	1.89	1.96	2.02	2.22
		100	2.42	2.44	2.48	2.55	2.74
		125	2.97	2.98	3.02	3.08	3.26
Irrigation+Hydropower	Average Applied	50	1.99	1.99	2.01	2.05	2.20
		75	1.54	1.54	1.56	1.58	1.71
		100	1.36	1.36	1.38	1.40	1.50
		125	1.29	1.30	1.30	1.31	1.40
	1.2*Average Applied	50	1.43	1.46	1.54	1.63	1.87
		75	***1.21***	***1.25***	***1.33***	1.39	1.58
		100	1.30	1.32	1.37	1.44	1.59
		125	1.41	1.44	1.49	1.53	1.68
	1.4*Average Applied	50	1.46	1.52	1.63	1.74	1.99
		75	1.79	1.84	1.94	2.01	2.20
		100	2.39	2.42	2.49	2.54	2.73
		125	2.95	2.99	3.01	3.07	3.25
Pure Hydropower	Average Applied	50	5.37	5.26	5.12	5.18	5.63
		75	6.21	6.11	5.94	5.98	6.51
		100	6.88	6.79	6.60	6.63	7.22
		125	7.39	7.30	7.10	7.11	7.75
	1.2*Average Applied	50	6.10	5.99	5.83	5.87	6.37
		75	7.75	7.65	7.46	7.46	8.09
		100	9.02	8.93	8.72	8.68	9.41
		125	10.01	9.91	9.67	9.60	10.41
	1.4*Average Applied	50	7.14	7.03	6.86	6.87	7.42
		75	9.86	9.75	9.53	9.46	10.20
		100	11.92	11.81	11.68	11.52	12.15
		125	12.93	12.76	12.66	12.42	13.01

* Average Applied corresponds to average amount of water used in the region (based on C2VSIM simulations)

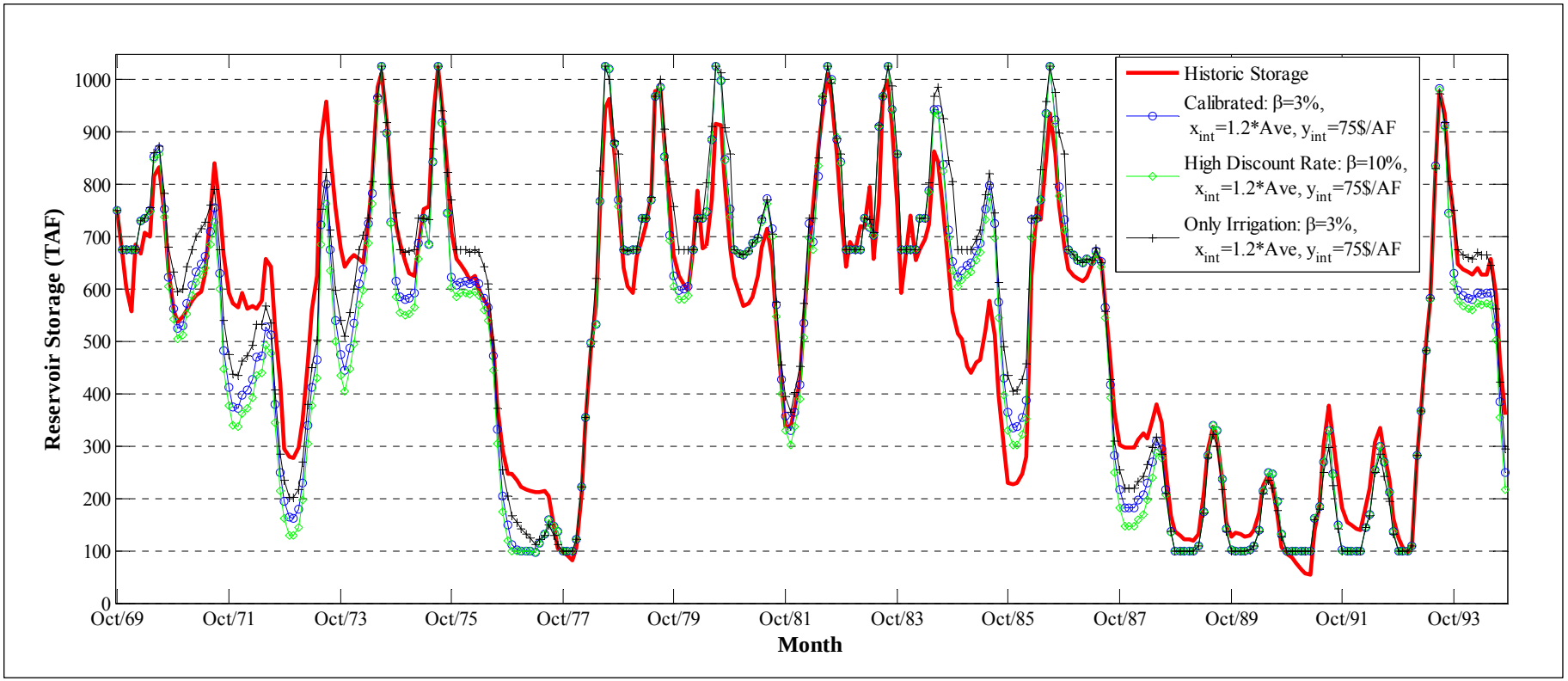

Figure C.1. Comparison of simulated (using optimized operating rules) and historic reservoir storage in Lake McClure

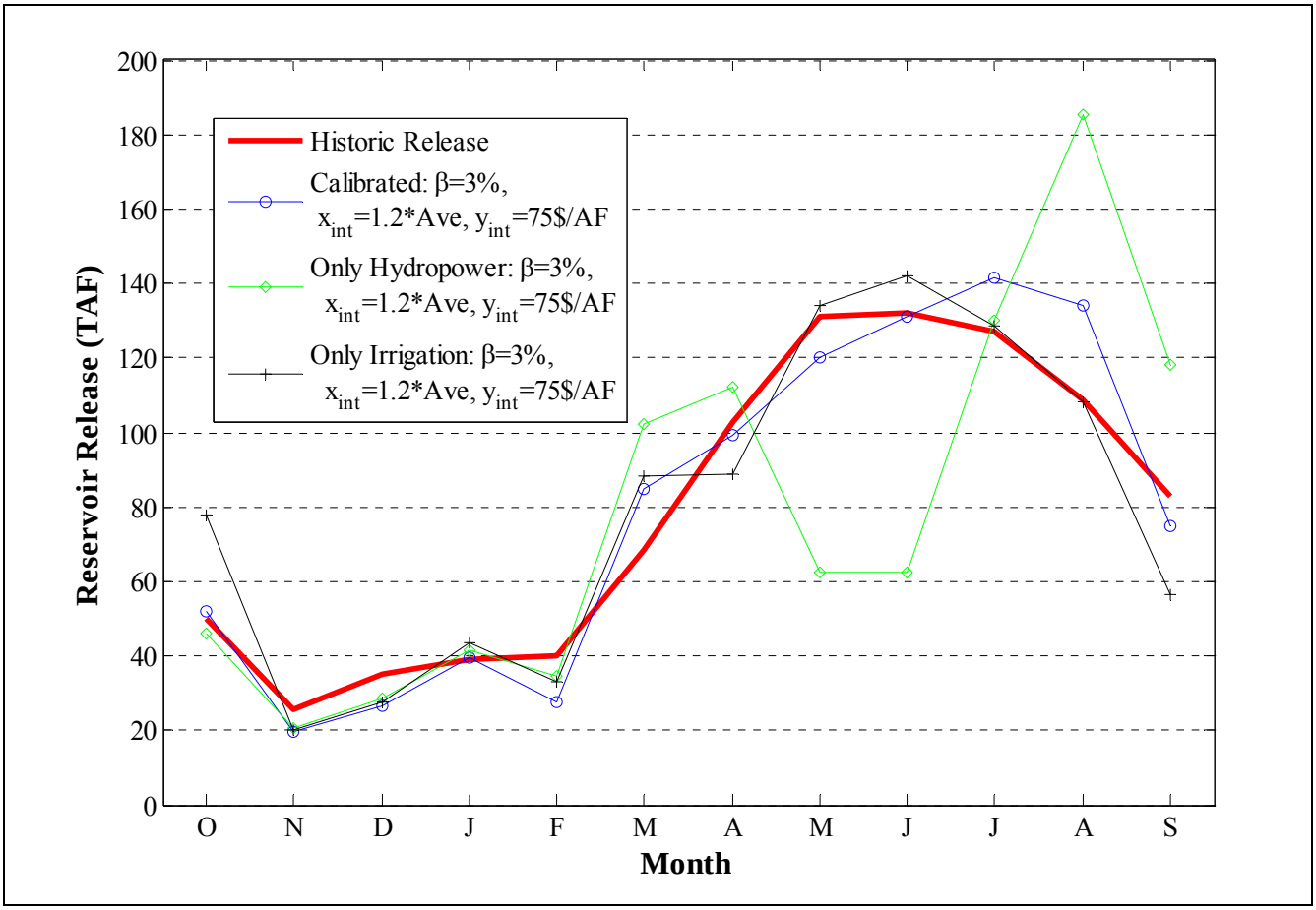

Figure C.2.A. Comparison of simulated (using optimized operating rules) and historic average reservoir releases

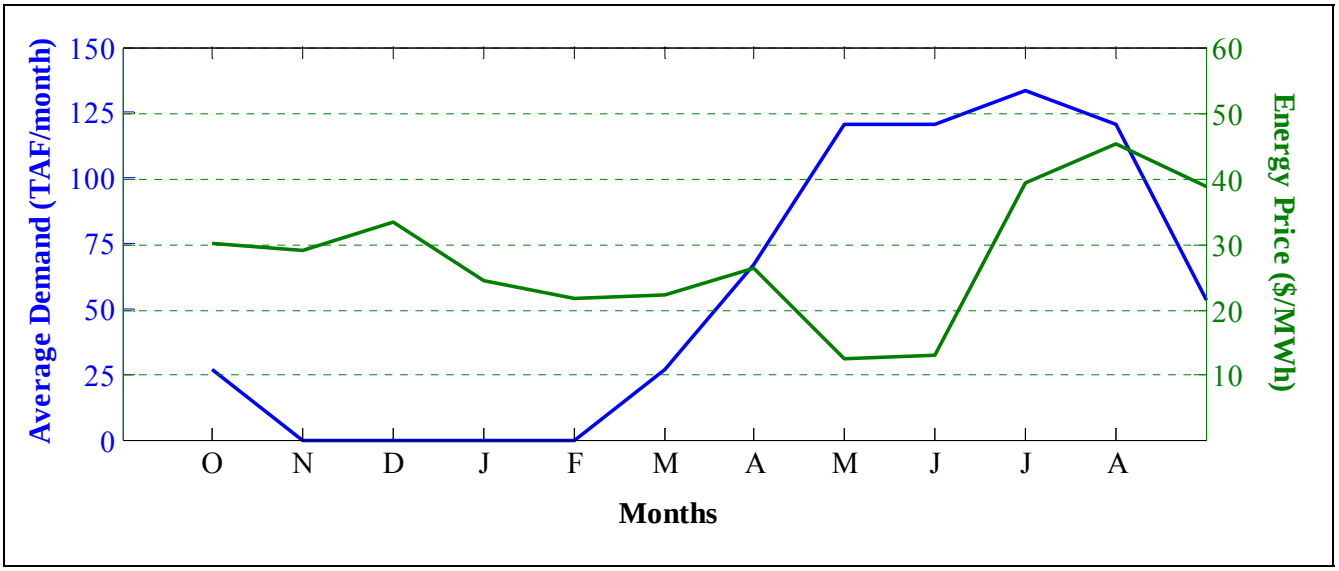

Figure C.2.B. Monthly pattern of energy prices and average demand

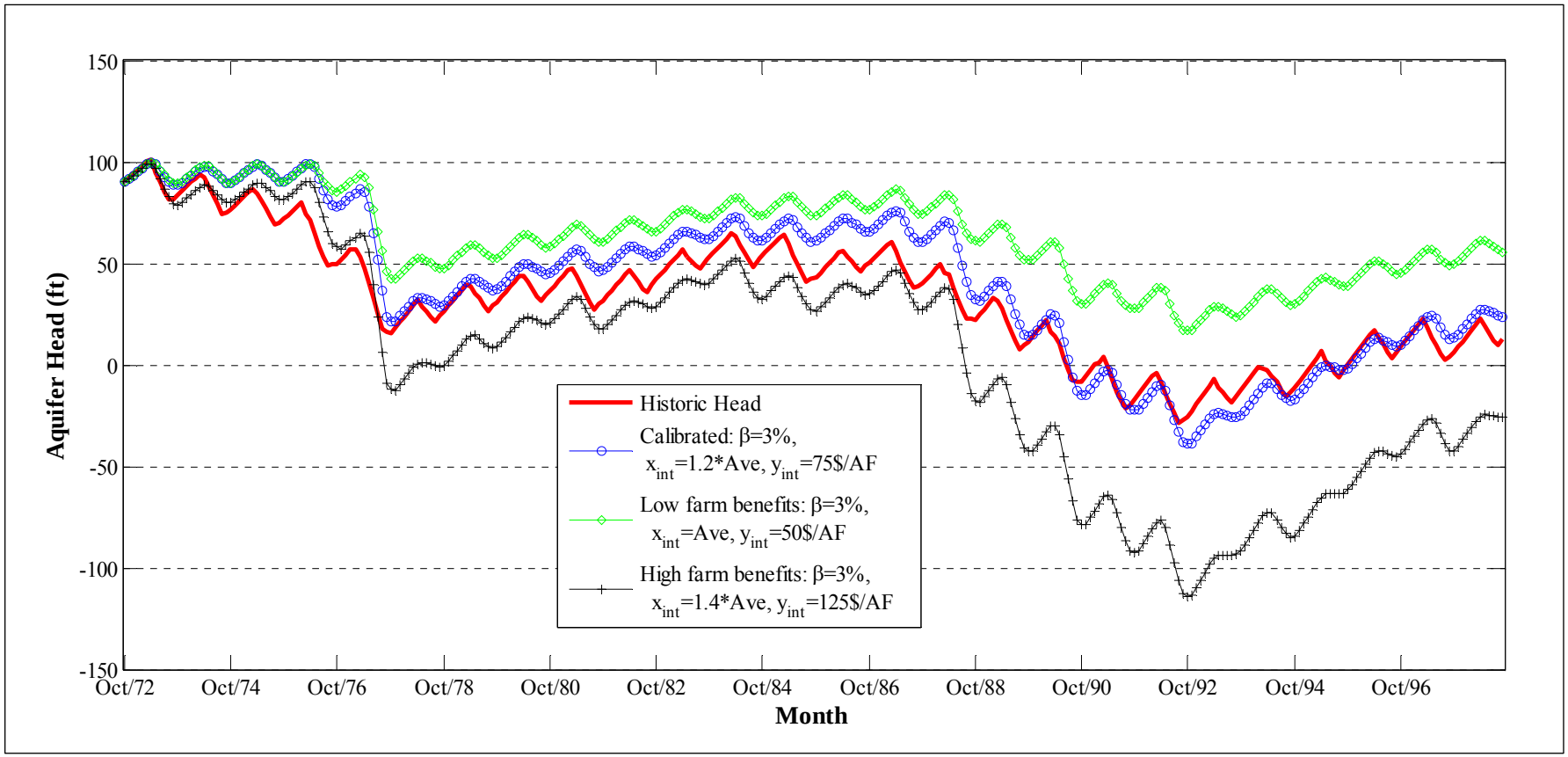

Figure C.3. Comparison of simulated (using optimized operating rules) and historic (as simulated by reduced groundwater model) head in second layer of Merced Basin aquifer

The demand function parameters and discount rate chosen are the set of parameters that best describe historic operations in the Merced River Basin when used in a SDP/NLP optimization model to obtain operating rules to actually simulate historic conditions. This said it's important to mention then that the calibration process is limited by how accurate overall the optimization model is able to reproduce operations in the basin. There are several points were the authors think the model could not be doing a perfect job in this sense. For example, it is assumed that the total amount of land area devoted for agriculture does not changing over time. This is a fair assumption for the period of time considered in the analysis (1970-1998), but is not necessary true. The authors also assumed no changes in the farming costs nor energy prices throughout this period. The authors also estimated the amount of water demand as a function of overall wetness in the basin not based on the physical underpinning of that process based on the relationship between soil moisture available in the soil, precipitation and evapotranspiration but on a statistical analysis of results derived from a hydrologic model used to simulate condition in this basin (C2VSIM).

Finally and more importantly the model is not well suited to represent conditions that happen at timescales smaller than a month. This is critical to get good estimates of effects of floods on spills and reservoir operations for example. The model having a monthly timescale is underestimating the amount of reservoir release that could be happening due to the effect of short time events such as storms. This is the main reason why the authors believe that historic releases in winter time are greater in average than those simulated by the model. Another problem related is that fact that the monthly NLP model is deterministic in terms of inflow foresight throughout a year. Clearly this is an overestimation of the capabilities of a reservoir operator to manage the timing of inflows throughout a year. This overestimation is more critical, in a snow-melt dominated basin such as the Merced River, in the fall, winter and early spring months because for the rest of the water year reservoir operators have a decent forecast of future inflows based in essence in the amount of water stored as snowpack in the Sierra Nevada Mountains. Based on this, the authors decided to cut the water year in two segments. In the first segment running from October to February, there is no optimization happening but rather a simulation of conditions based on a series of simple rules (see below). From March to September the authors represent conditions as through a perfect foresight optimization NLP model with initial border conditions dictated by the simulation model of the first half of the water year. The full set of equations representing this hybrid of a simulation and optimization model is presented below. Basically what the authors modify is the structure of $\mathbf{B}_t^a(\mathbf{k},\mathbf{l},Q_h^t)$ (as shown in *Eq 8* and detailed in Appendix A). Originally the authors had that:

$$\mathbf{B}_t^a(\mathbf{k},\mathbf{l},Q_h^t) = \underset{\mathbf{U}_1,\mathbf{U}_2..\mathbf{U}_{12}}{Max}\left(\sum_{m=1}^{m=12}\left(\mathbf{B}_m(\mathbf{X}_m,\mathbf{U}_m)\right)\right)$$

$$\begin{aligned}
&st: \\
&\quad \mathbf{X}_{m+1} = \mathbf{T}(\mathbf{X}_m,\mathbf{U}_m,Q_m^h) \\
&\quad Q_m^h = f(Q_h^t) \\
&\quad \mathbf{X}_m \in \Theta_m;\ \mathbf{U}_m \in \Pi_m \\
&\quad \mathbf{X}_1 \in \mathbf{k};\ \mathbf{X}_{12} \in \mathbf{l}
\end{aligned} \tag{C.3}$$

Now the authors consider the following case:

$$\mathbf{B}_t^a(\mathbf{k},\mathbf{l},Q_h^t) = \sum_{m=1}^{m=5}\left(\mathbf{B}_m(\mathbf{X}_m^s,\mathbf{U}_m^s)\right) + \underset{\mathbf{U}_6,\mathbf{U}_7..\mathbf{U}_{12}}{Max}\left(\sum_{m=6}^{m=12}\left(\mathbf{B}_m(\mathbf{X}_m,\mathbf{U}_m)\right)\right) \tag{C.4}$$

$$\begin{aligned}
&st. \\
&\quad \mathbf{X}_{m+1} = \mathbf{T}(\mathbf{X}_m,\mathbf{U}_m,Q_m^h) \\
&\quad \mathbf{X}_{m+1}^s = \mathbf{T}(\mathbf{X}_m^s,\mathbf{U}_m^s,Q_m^h) \\
&\quad \mathbf{U}_m^s = \mathrm{Rule}(\mathbf{X}_m^s,Q_m^h) \\
&\quad Q_m^h = f(Q_h^t) \\
&\quad \mathbf{X}_m^s \in \Theta_m;\ \mathbf{U}_m^s \in \Pi_m \\
&\quad \mathbf{X}_m \in \Theta_m;\ \mathbf{U}_m \in \Pi_m \\
&\quad \mathbf{X}_1 \in \mathbf{k};\ \mathbf{X}_{12} \in \mathbf{l} \\
&\quad \mathbf{X}_5 = \mathbf{X}_5^s
\end{aligned}$$

where new notation includes:

$\mathbf{X}_m^s$	=	State vector in “simulation” months (October-February)
$\mathbf{U}_m^s$	=	Control vector in “simulation” months (October -February)
$\mathrm{Rule}(\mathbf{X}_m^s,Q_m^h)$	=	Rule of operation during simulation months.

The rule of operation during the winter months decides water released through turbines, spills and river diversions (R_m^t, R_m^s and D_m^{ag}) based on the amount of water stored in the reservoir and monthly inflow (S_m^R and Q_m^h) through the following statements:

First the maximum and minimum water release $(R_m^{\max}, R_m^{\min})$ are calculated based on monthly inflow (Q_m^h), current storage (S_m^R) and maximum and minimum storage capacities $(S_{\min}^R, S_{m,\max}^R)$. If water is available and water demand for irrigation is greater than 0, there will be a release in excess of minimum streamflow requirement up to the maximum water release. If there is no irrigation demand release is equal to the minimum release. Every time there is release, spills will happen if these exceed turbine capacity. With these rules, reservoir level in March (before the optimization routine takes place) will be at maximum level based on availability of water.

Appendix D

Additional figures

Appendix D.

Additional figures

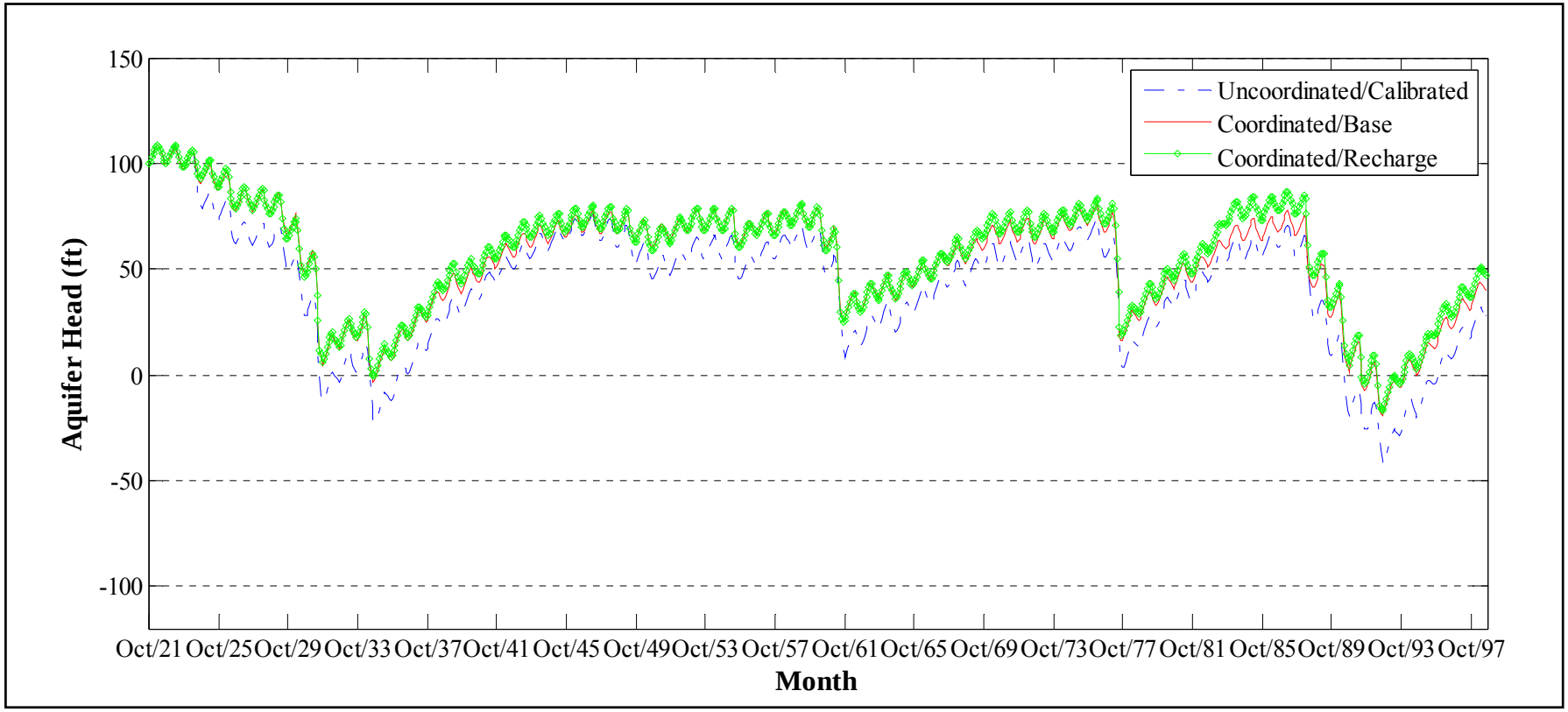

Figure D.1. Comparison of aquifer head levels for different scenarios: Recharge option

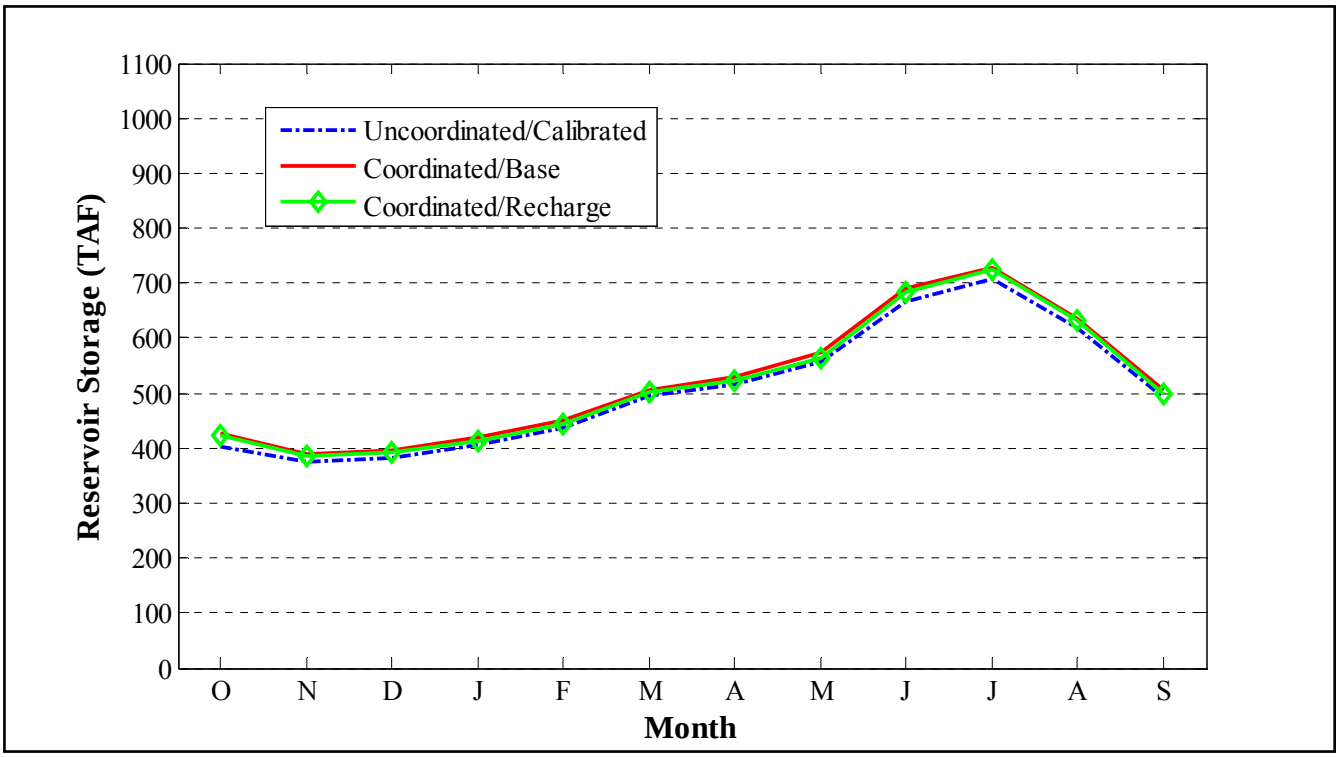

Figure D.2. Comparison of average reservoir storage for different scenarios: recharge option

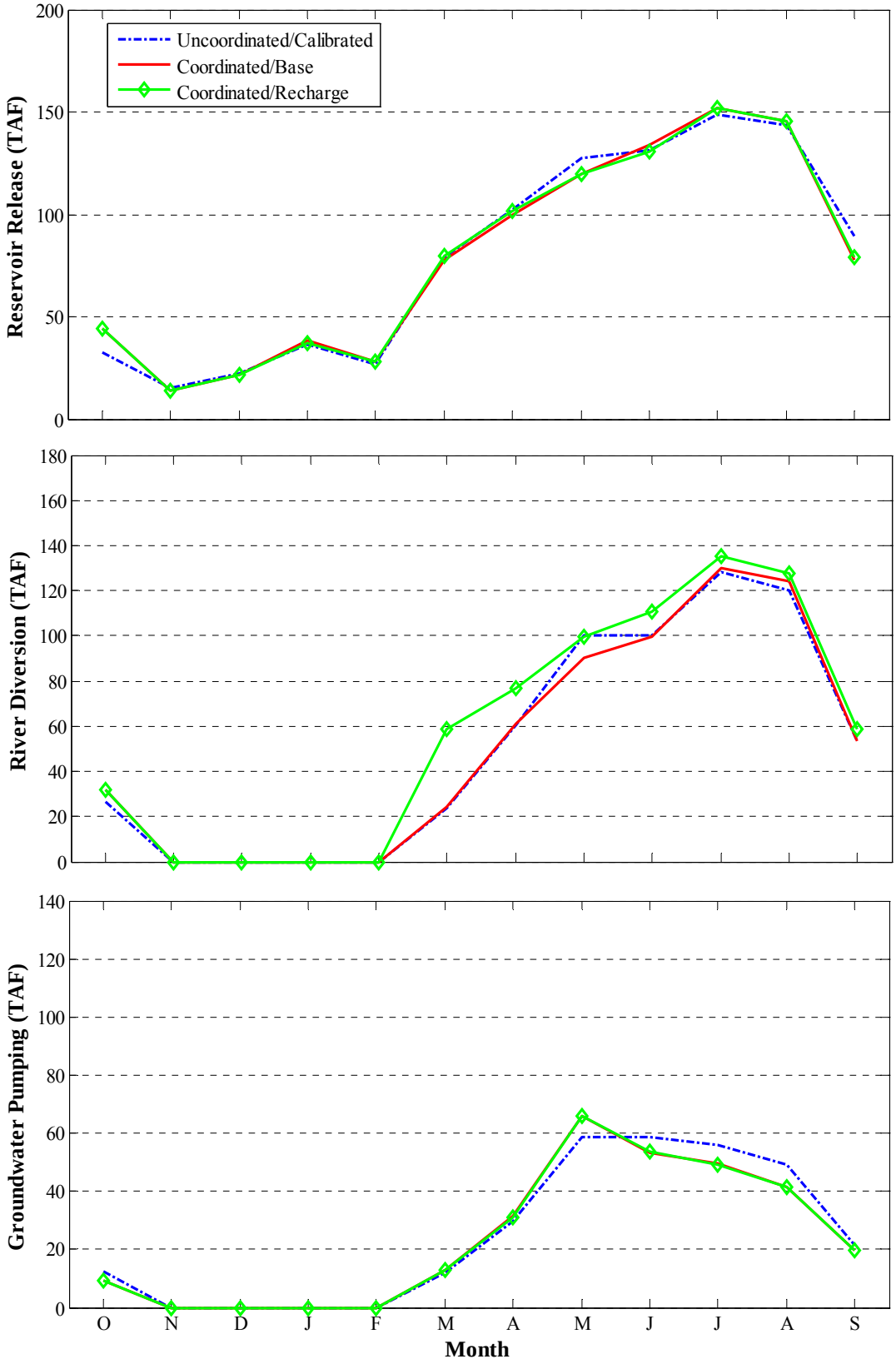

Figure D.3. Comparison of simulated operations, recharge option: A. Releases; B. River Diversion; C. Groundwater

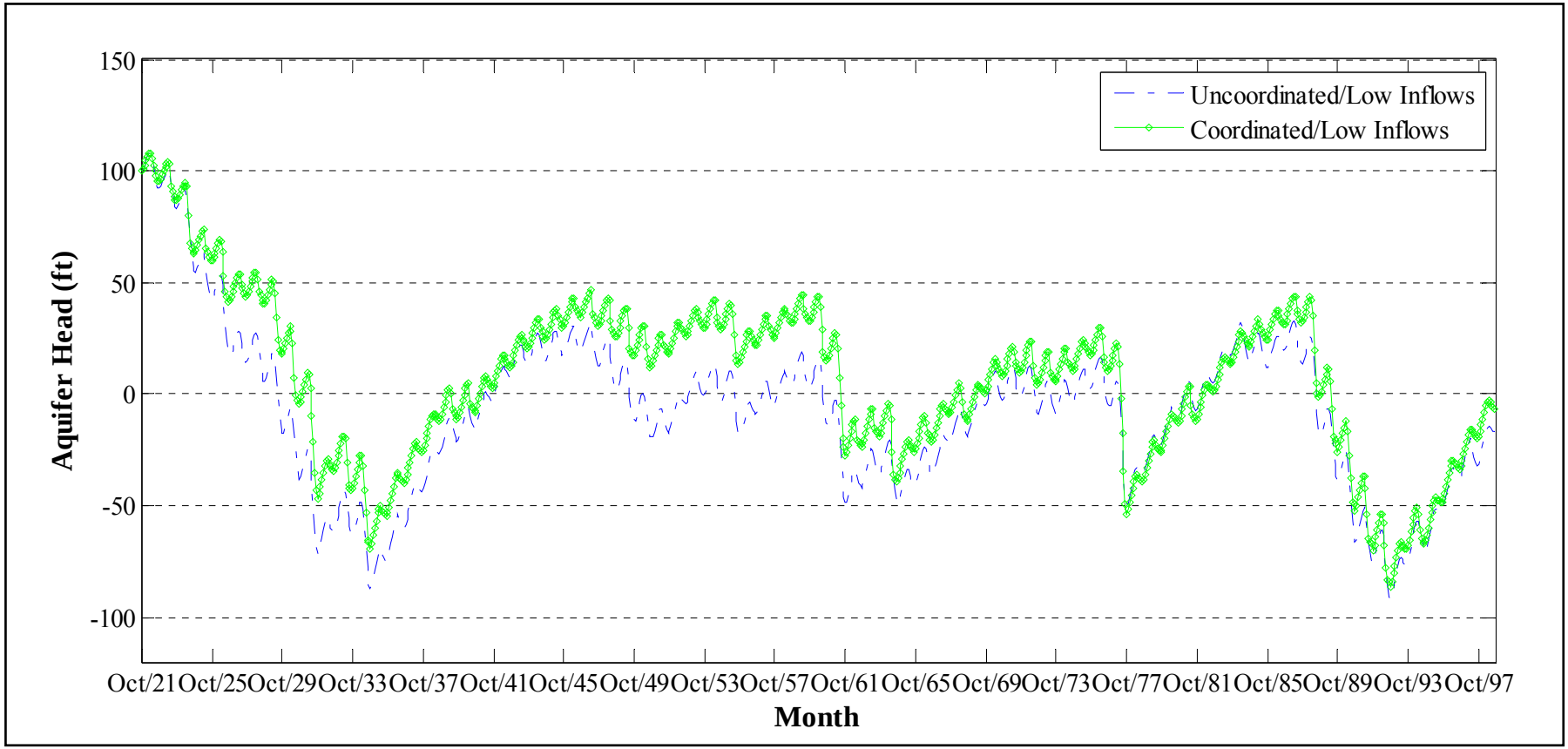

Figure D.4. Comparison of aquifer head levels for different scenarios: Low Inflow option

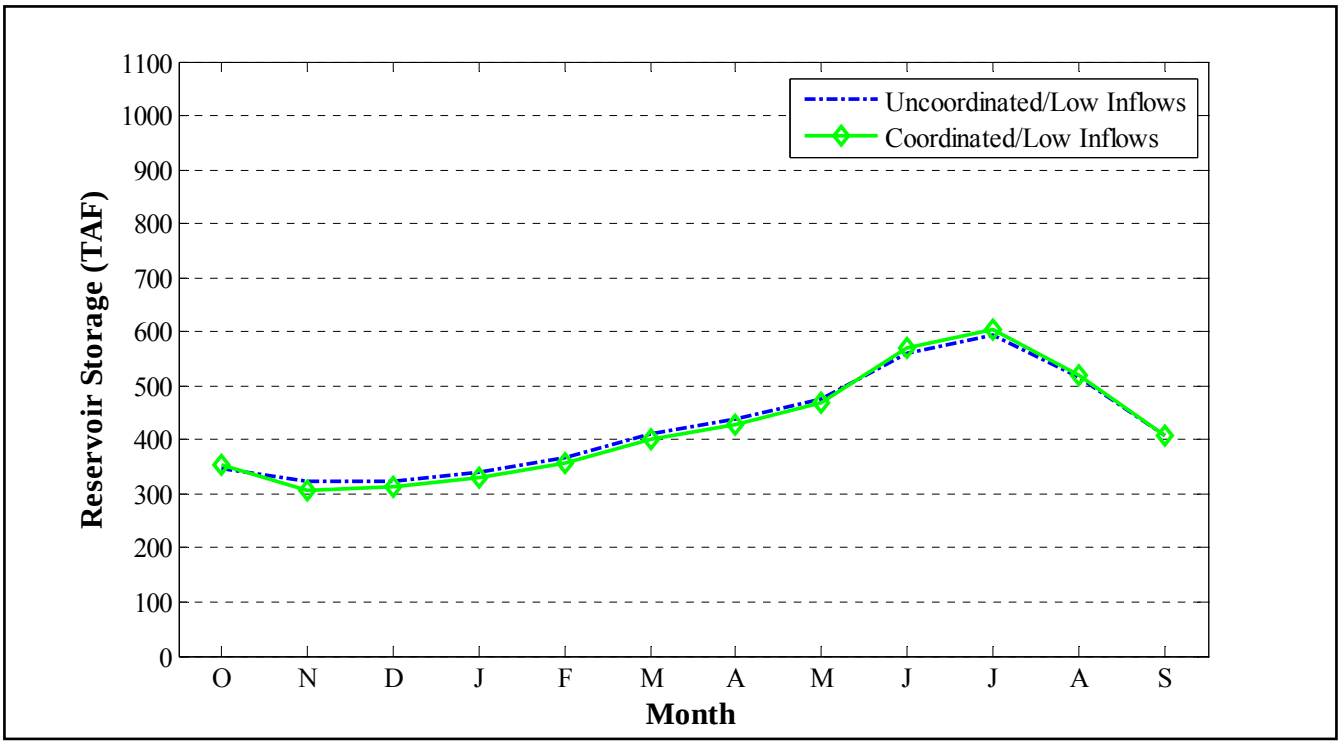

Figure D.5. Comparison of average reservoir storage for different scenarios: Low Inflow option

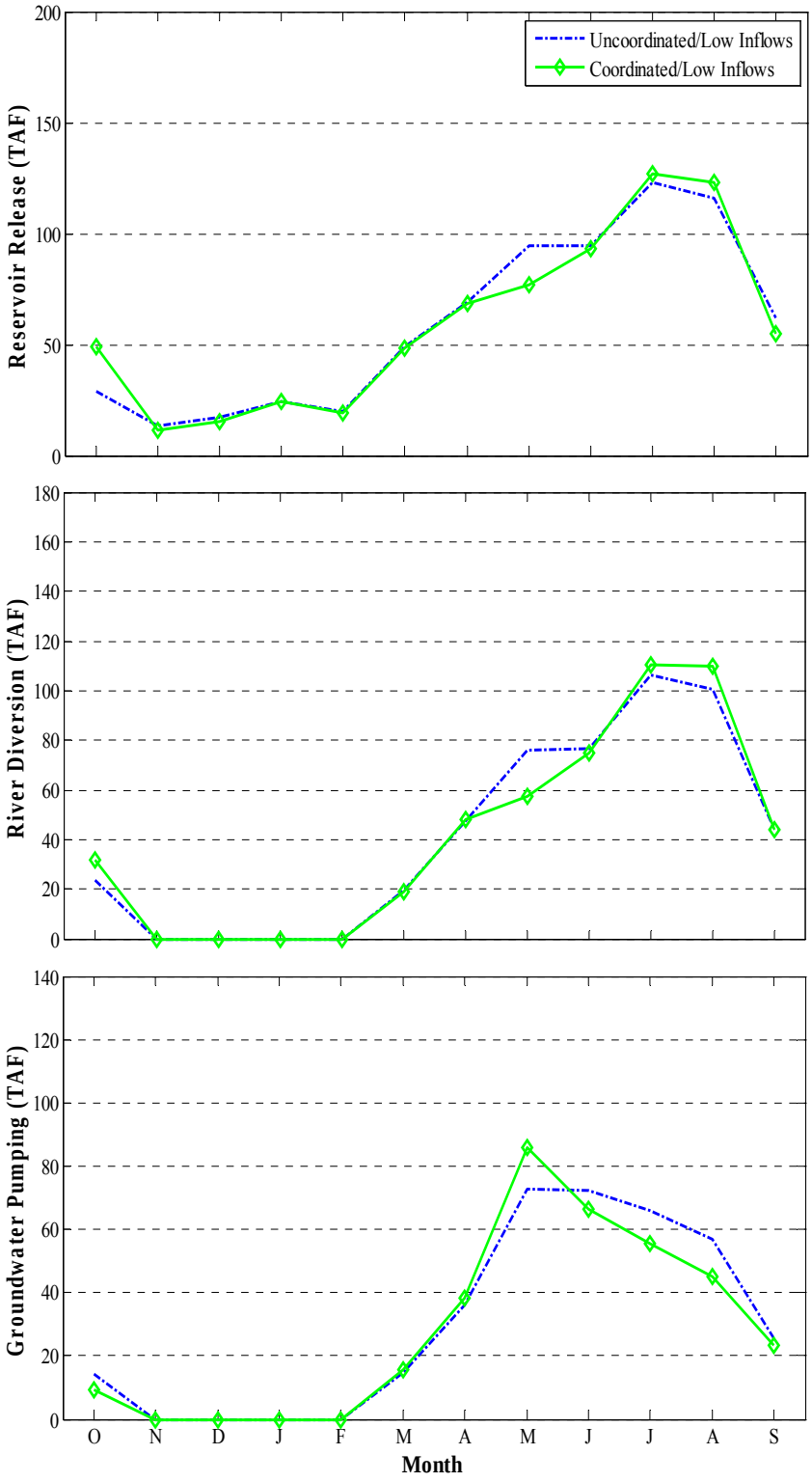

Figure D.6. Comparison of simulated operations, Low Inflow option: A. Releases; B. River Diversion; C. Groundwater Pumping

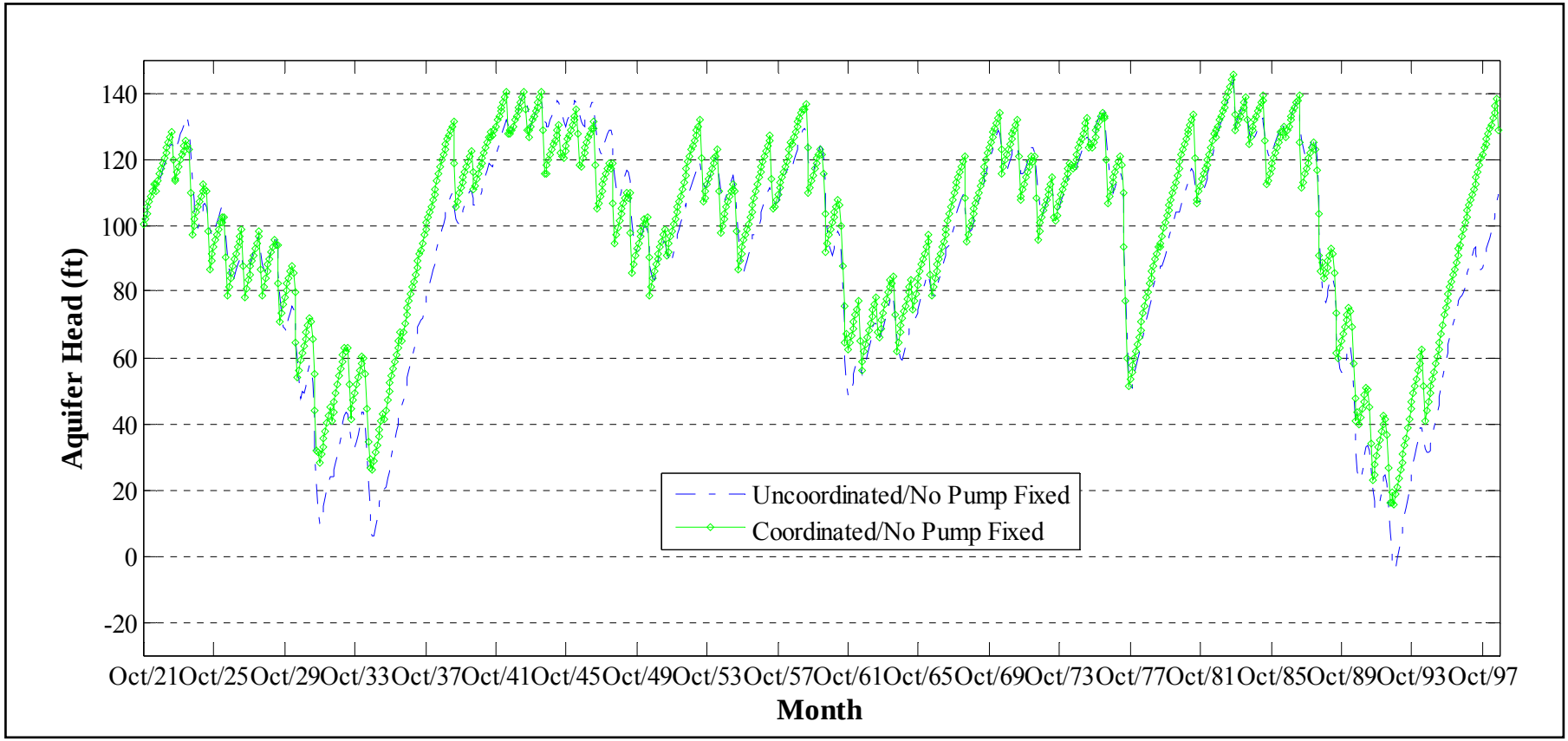

Figure D.7. Comparison of aquifer head levels for different scenarios: No fixed pump option

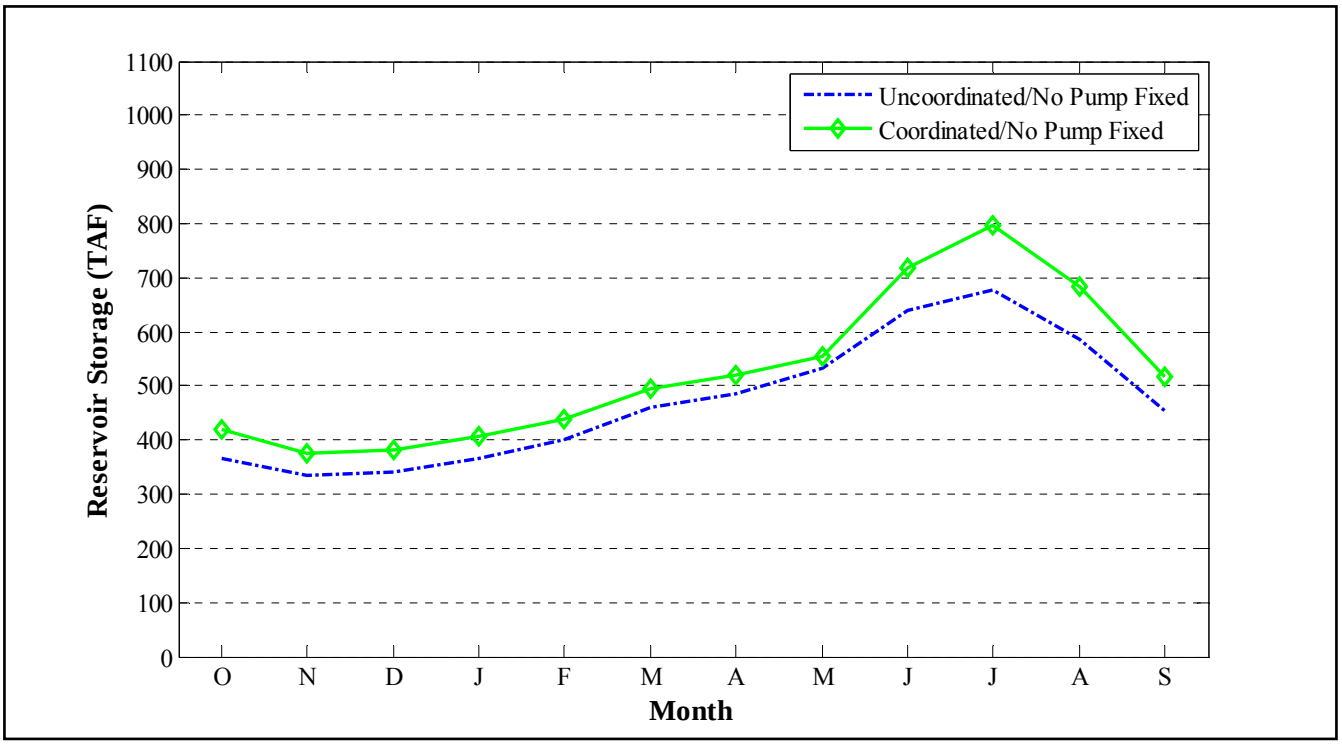

Figure D.8. Comparison of average reservoir storage for different scenarios: No fixed pump option

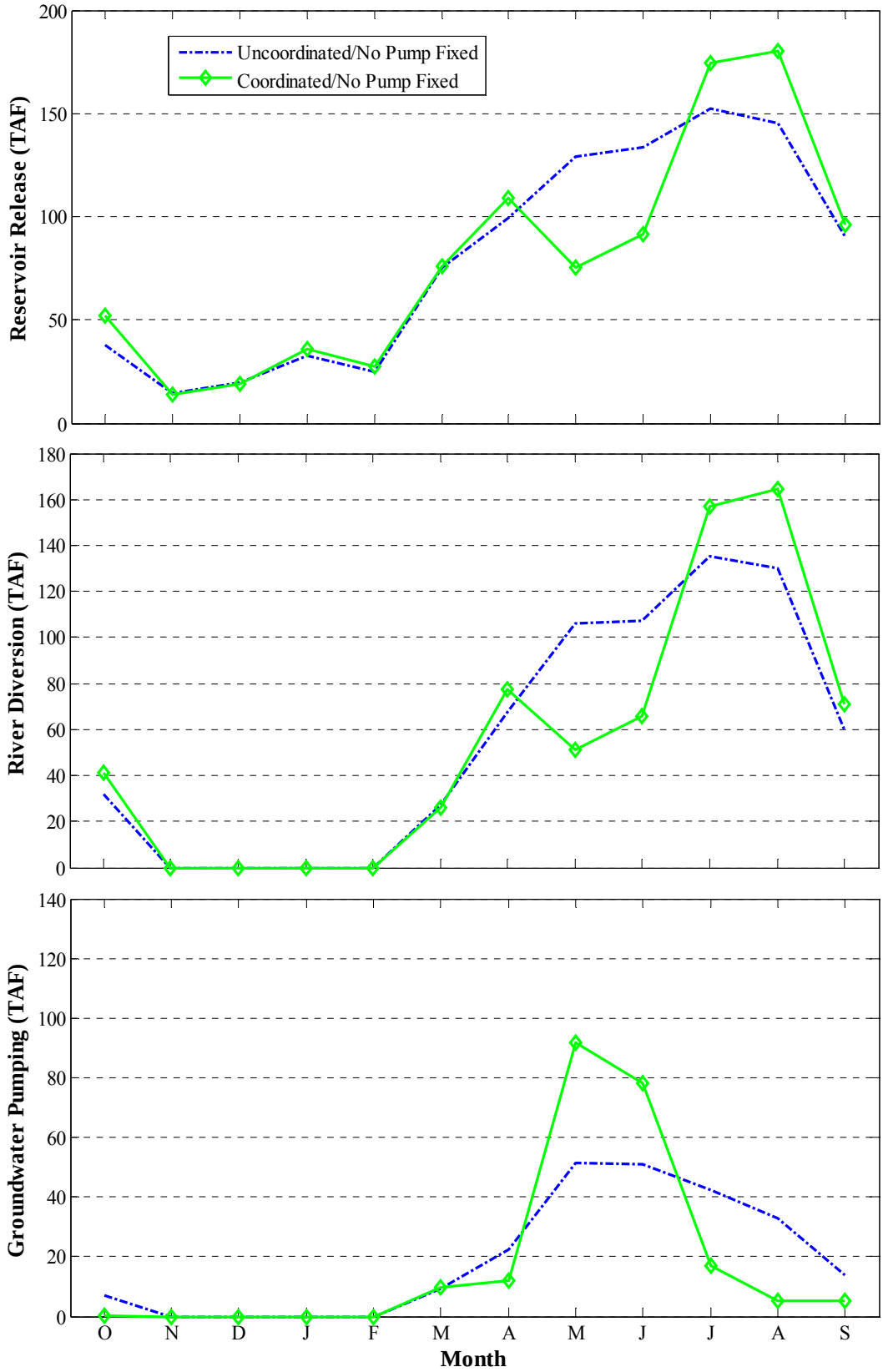

Figure D.9. Comparison of simulated operations, No fixed pumping option: A. Releases; B. River Diversion; C. Groundwater Pumping

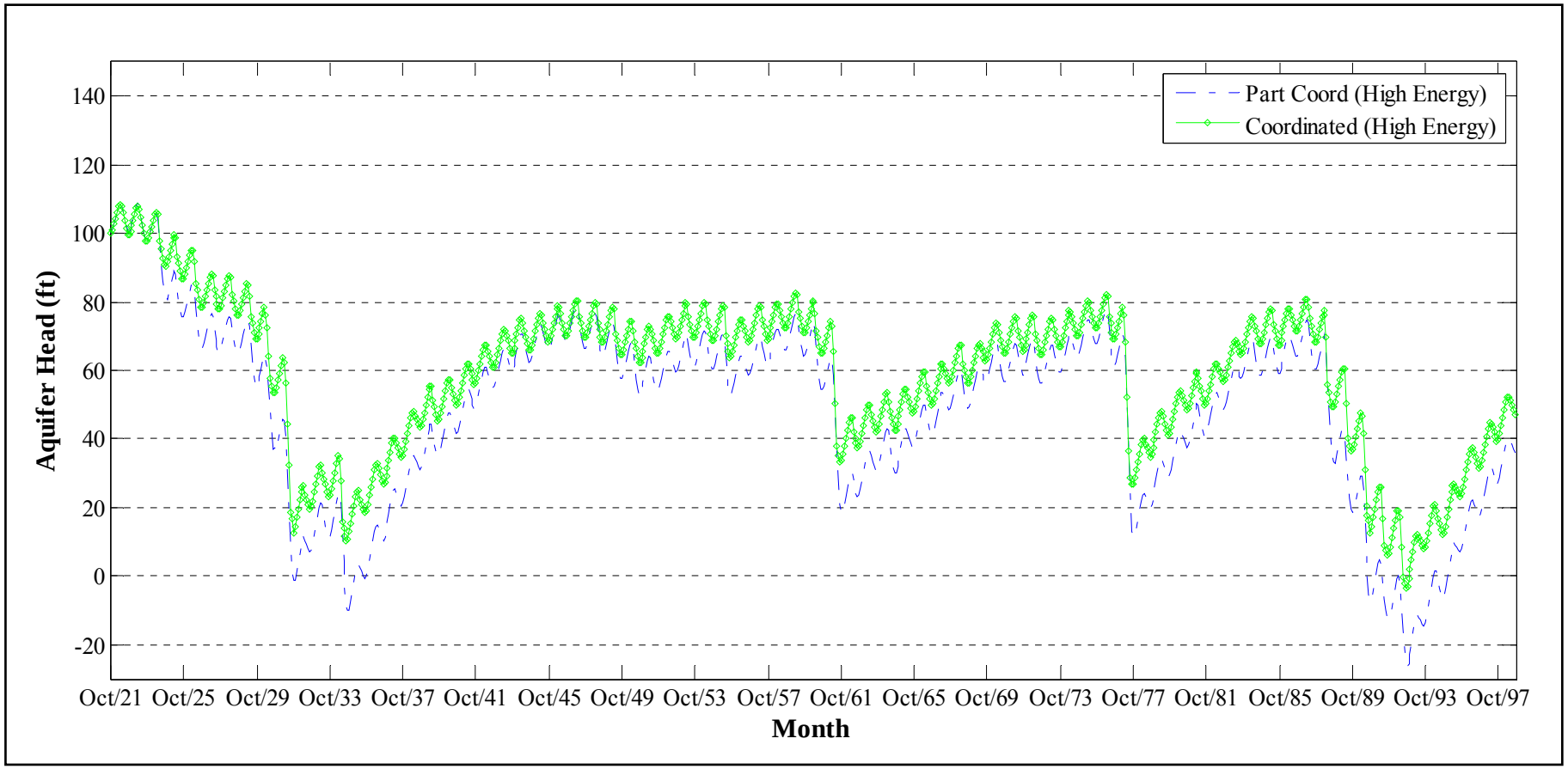

Figure D.10. Comparison of aquifer head levels for different scenarios: High energy option

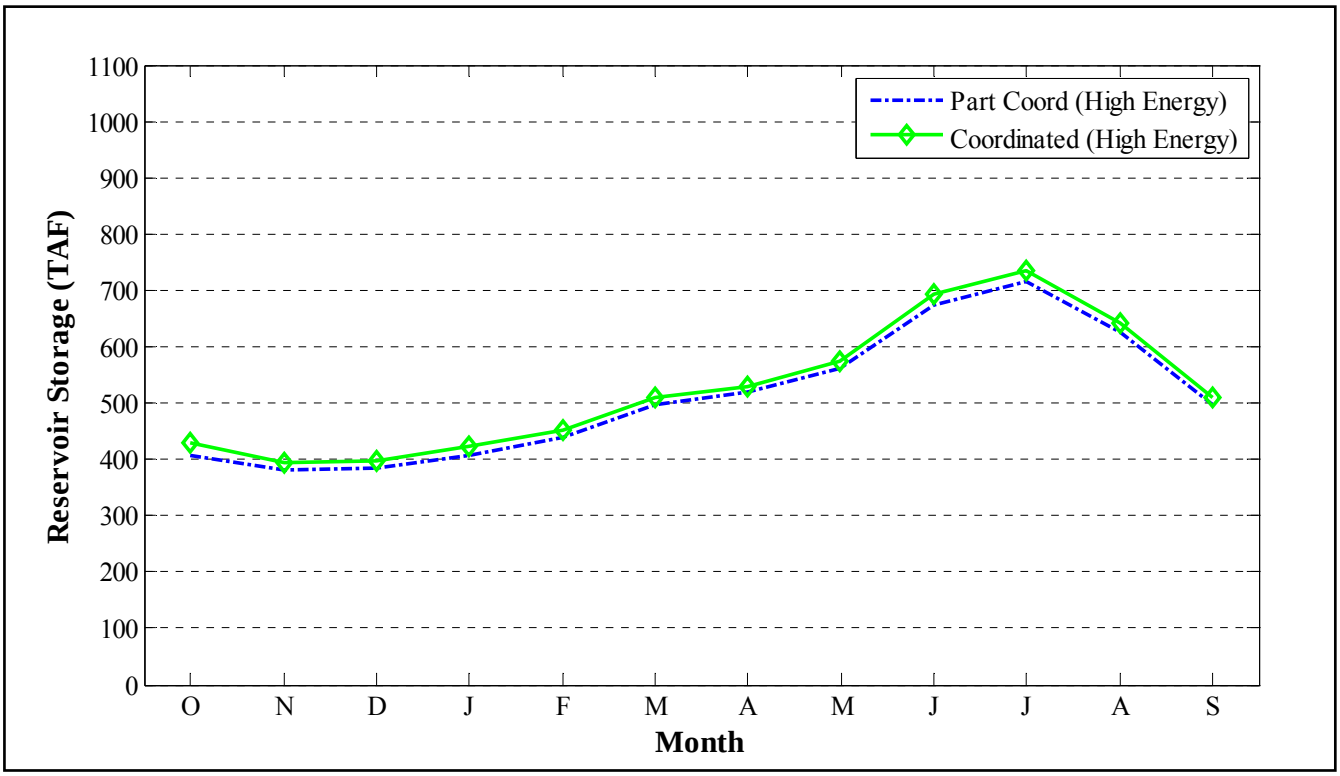

Figure D.11. Comparison of average reservoir storage for different scenarios: High energy option

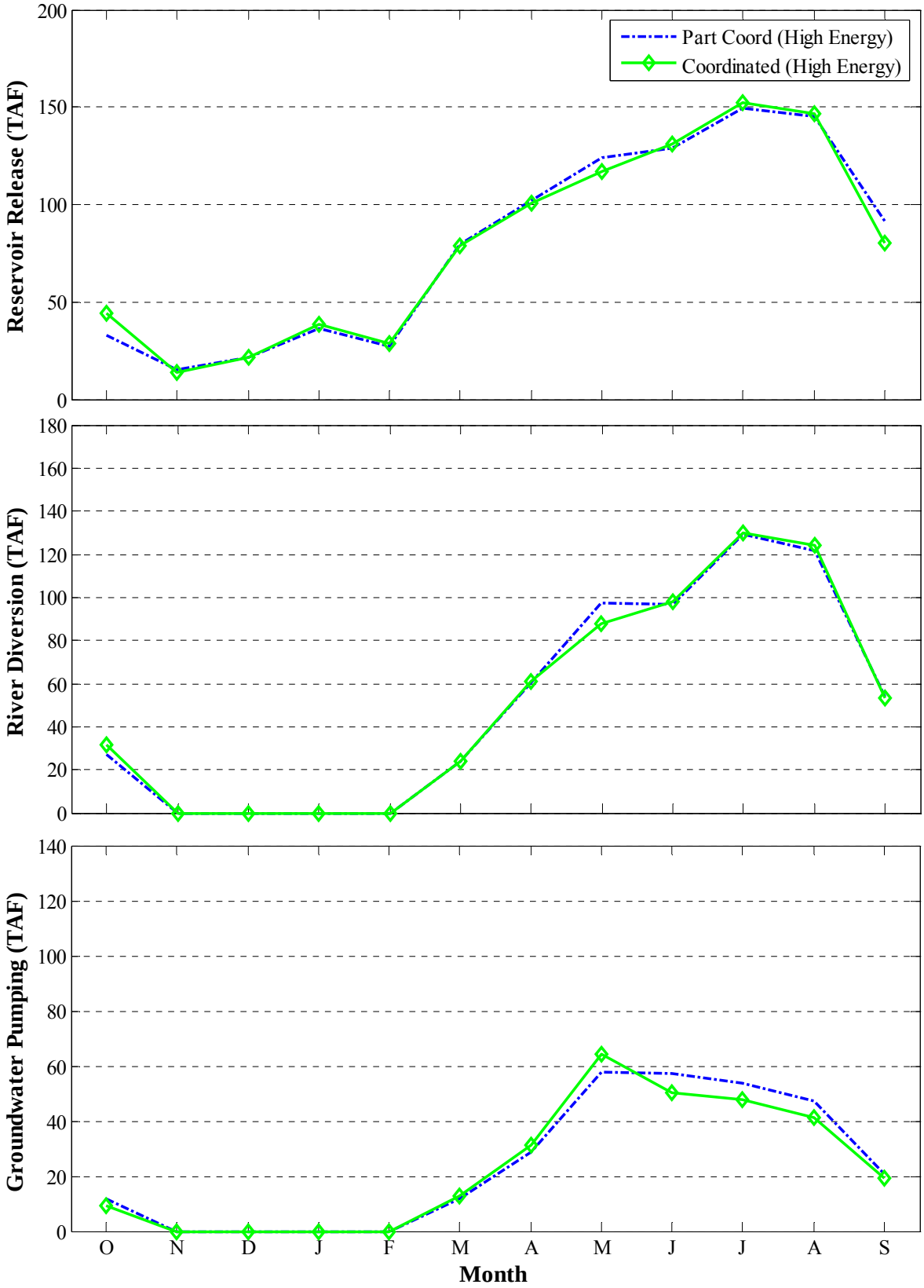

Figure D.12. Comparison of simulated operations, High energy option: A. Releases; B. River Diversion; C. Groundwater Pumping