Spring 1-1-2012

A New Decision Model for Flood Control Operations of Dworshak Reservoir

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by

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B.C.E., The Catholic University of America, 2010

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Master of Science

Department of Civil, Environmental, and Architectural Engineering

2012

This thesis entitled:
A New Decision Model For Flood Control Operations of Dworshak Reservoir
written by Evan A. Heisman
has been approved for the Department of Civil, Environmental, and Architectural Engineering

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Date

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

Heisman, Evan A. (M.S., Civil Engineering)

A New Decision Model For Flood Control Operations of Dworshak Reservoir

Thesis directed by Prof. Balaji Rajagopalan

Dworshak Reservoir in Idaho is on the snowmelt dominated Clearwater River and provides flood control and conservation for the Snake River and Columbia River basins. During dry years in which the spring inflow forecast is decreasing, problems have occurred with trapped storage and minimum outflow requirements. To mitigate these impacts, and to provide a spring freshet for fish, an modification to the flood control curve may be used, known as the shift policy. In years that end up being wetter than forecast, the resulting operation may cause the reservoir to violate environmental and flood control limits. An improved forecast for pre-season planning is needed to better predict which years the shift is appropriate.

A linked decision support system and statistical forecast is used to try to predict the decision variable of whether or not the shift policy should be implemented. The decision support system analyzes the difference in impacts of the shift policy compared with the default policy. From the output, a binary sequence of the preferred policy for each year is created and predicted by a logistic regression model, with climate and hydrologic variables as predictors. The operational model then uses this forecast to see the impacts of the forecast on the operational policy and the resulting risks.

For seasonal planning, the forecast for years in which the shift is allowed by any rule is shown to be more skillful than a baseline model in January, with a Brier Skill Score of 0.11. For particular reservoir constraints, the model performance varies, with less skill for those which are rarely violated by shifting, and significant skill for more frequent violations by a shift policy, such as environmental flow limits. Using the forecast to inform the fraction of the shift does not result in the shift achieving it's objectives as effectively, but does result in less violations. The model also has applications for long-term studies of the effectiveness of the shift policy and impacts of non-stationary climate variables on the shift policy.

Dedication

To my family and friends, who all supported me though this academic journey.

Acknowledgements

I am very grateful for Prof. Balaji's input, guidance, and support through my work on this thesis. His instruction in class, insight during our weekly meetings, and patience during the last few weeks has been very much appreciated. Thanks to the experience, statistics are no longer just some strange branch of math that I try to avoid, but a new lens through which to view the world.

Thank you to my committee for volunteering to serve: Prof. Balaji, Prof. Zagona and Dr. Subhrendu Gangopadhyay. In addition, Prof. Zagona and CADSWES were very helpful in providing a license of RiverWare for me to use for this project, support when I ran into problems, and a location for my defense.

I would also like to thank the Hydrology branch of the U.S. Army Corps of Engineers, Walla Walla District for their suggestion to work on the problem of the Dworshak shift policy. Particularly, Steve Hall, who helped me understand the problem at hand and the history behind it, and Jeremy Giovando, who offered his time to review this thesis. I hope both find the results useful for reservoir operations. The Army Corps selection of me for the SMART Scholarship program made this work possible financially.

To all my friends in Boulder who helped make this possible: The last couple of years has been awesome, and I'm glad that I got to meet you all.

Finally, I'd like to acknowledge the infinite support from my family, especially my dad, who is always willing to listen to my problems, and help me think out the technical ones by trying to explain them.

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Chapter 1

Introduction

1.1 Basin Description

Dworshak Reservoir is located on the North Fork of the Clearwater River in Idaho, a tributary of the Snake River, itself feeding into the Columbia River. The reservoir is impounded behind Dworshak Dam, completed in 1973, and operated by the U.S. Army Corps of Engineers (USACE), Walla Walla District, for several uses included flood control, power production, recreation, and providing environmental flows. It has a usable storage capacity of 2,016 thousand acre-feet (KAF).(U.S. Army Corps of Engineers, 1986)

Figure 1.1 shows the location of Dworshak Reservoir with respect to other major reservoirs in the Columbia River system, while Figure 1.2 details the area around and immediately downstream from the reservoir to the confluence of the Snake River and the Clearwater River.

The drainage area for the reservoir is 2,440 square miles, and is largely forest (57%), with some agricultural (24%), and bare land (18%) (U.S. Army Corps of Engineers, 1986). This area contributes 11% the average annual runoff for the Snake River basin measured at the Lower Granite Dam. The basin is largely fed by snowmelt, with the March through July streamflow making up 74% of the annual streamflow on average (1927-1985), as shown in Figure 1.3 (U.S. Army Corps of Engineers, 1986). The median annual inflow from 1927 to 2011 was 3,983 KAF.

Streamflow gauges used for the reservoir operations are near the towns of Orofino, Peck, and Spalding, Idaho. The gauge at Orofino is located on the Main Fork of the Clearwater River immediately upstream from the confluence with the North Fork, which is controlled by the reservoir.

Figure 1.1: Major reservoirs in the Columbia River Basin.

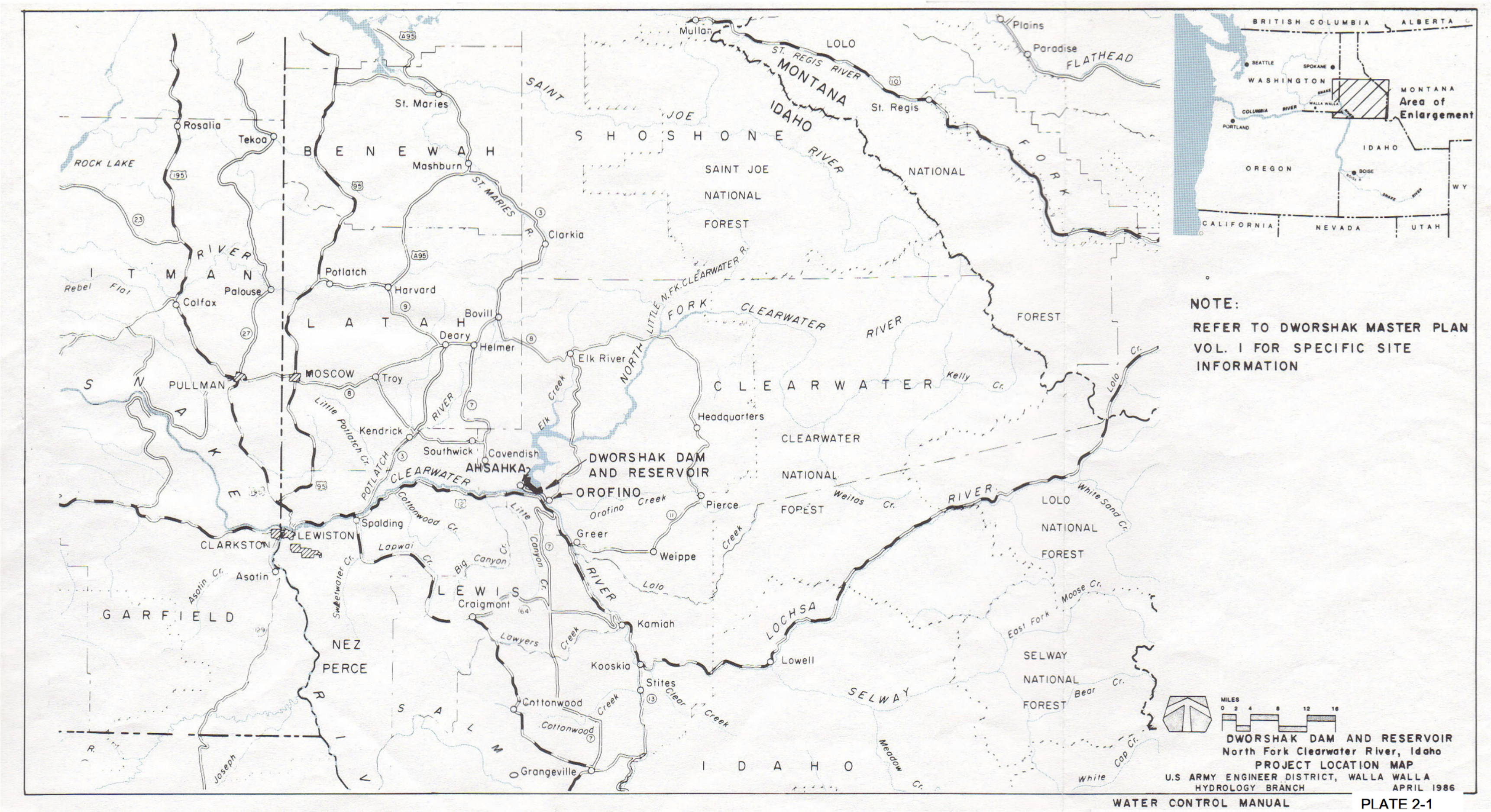

Figure 1.2: Region around and downstream of Dworshak Dam, from the Water Control Manual for Dworshak Reservoir.

Both the flow into the reservoir and the flow at Orofino are natural flows. The outflow from the reservoir combined with the flow at Orofino and intervening flows is then measured at Peck, 5 miles downstream from the dam, and Spalding, located 26 miles downstream from the dam. The average travel time to these locations from the dam is estimated at 1 hour and 6 hours respectively (U.S. Army Corps of Engineers, 1986).

1.2 Dworshak Flood Control Operations

Dworshak Reservoir uses a winter flood control curve that is varies depending on the water supply forecast for April through July. Prior to January 1st, the rule curves are identical for any given year, while after January 1st, each rule curves is determined by the water supply forecast for April through July inflow. This forecast is a regression-based model using the Southern Oscillation Index, late fall and early winter (October and November) precipitation, and the snow-water equivalent (SWE) measurement from several SNOTEL sites in and around the basin. The normal operation is to draft the reservoir to follow the rule curve with the maximum requirement through the winter and spring months until May 1st, when the reservoir is refilled, with a target of being full for the first weekend in July. The refill portion of the curve is based on inflow forecasts from USACE as well as NOAA's Northwest River Forecast Center and constraints laid out in the Dworshak Water Control Manual.

The refill operation is controlled by a number of factors. Inflows are passed until the gauge Spalding, Idaho reaches the limit of 105,000 kcfs, at which point the reservoir's outflow is limited to prevent flooding at both Spalding and downstream at Lewiston, Idaho. Prior to April 1st, the reservoir is required to keep a minimum of 700,000 acre-feet of storage, whereas after this date, the reservoir is limited by the percent snow-covered area (SCA), with full refill only allowed after less than 10% of the basin remains covered.

The operations described here and modeled are from the Water Control Manual for Dworshak Dam and Reservoir, supplemented by verbal and email communication with the head of Reservoir Regulation at the Walla Walla District, Stephen Hall (Hall, 2012).

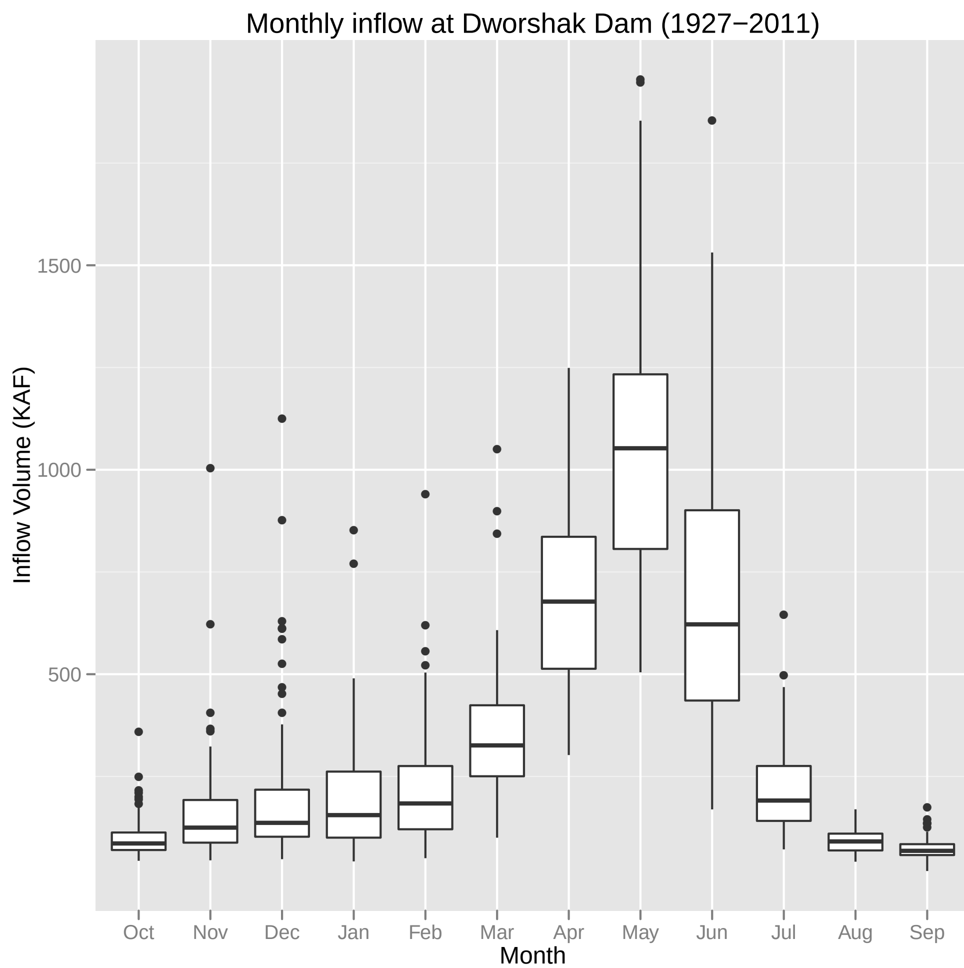

Figure 1.3: Boxplot of monthly inflow to Dworshak Reservoir showing the high variability due to snowmelt runoff.

1.2.1 Dworshak-Grand Coulee Flood Control Shift

Shifting of flood control space for the Columbia River system from Dworshak Reservoir to Lake Roosevelt behind Grand Coulee Dam is an operation used by the system operators to help ensure refill of the reservoir during low flow years and to provide a spring freshet for fish downstream from the dam. The operation consists of taking the additional system flood control storage requirement in Dworshak and allowing it to be reserved behind the Grand Coulee project. This reduction in flood control space is allowed to continue until April 30th, at which point both reservoirs must be back to an unshifted condition.

The shift was first implemented to provide a pulse of water as a spring freshet to help juvenile salmon on the Clearwater River. The other goal of this operation is to protect against years in which the water supply forecast is decreasing with each month. When the monthly water supply forecasts for April through July are decreasing, the reservoir ends up holding back water to meet a higher flood control elevation, thus reducing streamflows, and may not always meet the goal of refilling the reservoir at the end of the season, a condition known as trapped storage. Trapped storage at Dworshak can be a problem when the water is needed for other purposes during the summer, including environmental flows, thermal regulation of the Snake River, and to supplement downstream flows for navigation. If possible, the shift is preferred when it will not result in other problems in the system.

Currently, the allowable shift is computed from the `CRBFC_NWD.xls` spreadsheet used by the USACE Northwest Division offices to coordinate flood control operations for the Columbia River Basin. The allowable shift is the minimum of the difference between Dworshak's system and local flood control space requirements and Grand Coulee's capacity to accept the shifted storage. The amount of storage that can be shifted can range between zero and the maximum allowable shift. First, the volume to shift is decided by the Walla Walla District, then Grand Coulee's operators, the Bureau of Reclamation, decides whether or not to accept the shift and how much to accept. The Walla Walla District has no official procedure exists for the decision to shift, or the volume that should be shifted, but an informal process used is to look at historic years with similar inflows to those observed so far and then examine behavior during April.

1.2.2 Known Issues With Shift Policy

During years where the water supply forecast increases, the shift can result in several conditions which are problematic for the reservoir. If the March 1st forecast is less than the April 1st forecast, the reservoir will need to be further drafted during April to meet the new requirements in addition to the requirement to return to the normal rule curve by the end of April. This can be complicated by increasing inflows through April, sometimes resulting in more inflow than the reservoir can output due to either the total dissolved gas limit of 14kcfs, limits on flooding at Spalding, Idaho, or the maximum physical capacity of the system. This increasing forecast problem can occur at Grand Coulee as well as Dworshak. In this case, Dworshak may be following a shifted rule curve and then need to return to the normal policy earlier than April 30th because Grand Coulee can no longer accept the shifted storage. This problem can be compounded when both reservoirs must draft to meet an increasing flood control requirement.

As there are known potential problems in following the shifted flood control curve, and benefits when it can be used, the Walla Walla District needs a method of predicting when to allow the shift, and what volume to shift. A skillful forecast available in January or February would help avoid operational constraints and therefore provide more flexibility during the spring flood control season.

1.3 Proposed Methodology

In Chapter 2, an operational model will be built to simulate the result of following the shift policy and the normal policy for each historic year. From the output of this model, Chapter 3 presents a statistical model driven by climate variables to predict the years in which the shift can occur. Chapter 4 will show the forecast as input for the operational model to evaluate the usefulness of the forecast and to provide a decision support system (DSS).

Chapter 2

Decision Model for Flood Control Operations of Dworshak Reservoir

2.1 Decision Support Systems

Decision support systems as a tool in water resources planning and management have a long history from more specialized tools developed for a particular basin to more general programs designed to model various basins. Decision support systems offer several advantages the main being, representation of the system visually and the operating rules of all the components in a transparent manner. This enables evaluation of policy options under various input scenarios for short term and long term planning.

Decision support systems have been developed for many water resources systems. On the Colorado River, where planning is often done looking multiple years into the future, these systems are particularly helpful for envisioning possible scenarios and combining stochastic inputs with a deterministic process to better understand the uncertainty in the outcomes (Regonda, 2006). In a study for the Yakima River, a tributary of the Columbia, Stapleton (2004) examined the impacts of water usage on salmon population during drought years using streamflow forecasts and a decision support system. On the Gunnison River basin, in Colorado, a series of similar studies was conducted to model reservoir operations using both direct forecasting of streamflows and categorical forecasts of stream flow (Regonda et al., 2006, 2011). Another useful ability of decision support systems is their ability to be joined with an optimization system, such as was done for Columbia River flood control curves by Lee et al. (2009).

There are several limitations to using only the historic data from Dworshak operations in trying to understand the shift policy, such as a limited amount of data, and an inconsistent record of historic decisions in making the shift. With those considerations in mind, a decision support system (DSS) may be helpful in modeling the reservoir's operations. For this study, RiverWare was selected as a general decision support tool and hydrologic model as it allowed for rule based simulations and the ability to easily modify the rules governing a model run Zagona et al. (2001). The object oriented interface presents an easy to understand schematic of the system and how the components of a system interact. Object types such as reservoirs and river reaches account for common hydrologic equations such as storage curves, hydrologic routing, and computation of the maximum outflow given a particular pool elevation. Another advantage of using RiverWare is its ability to interface with a number of data storage systems, including the Army Corps of Engineers' HEC-DSS formatted files and Microsoft Excel.

2.2 Operational Model for Dworshak Reservoir

The system schematic for the operational model for Dworshak Reservoir implemented in RiverWare is in Figure 2.1. The model contains the reservoir and dam as the object for which rules are written. The hydropower aspects of the dam are ignored, so a storage reservoir object is used. The model also contains objects for the portions of the Clearwater River downstream from Orofino and the dam through the gauge at Spalding, Idaho. As the reservoirs local operations are determined by this gauge and the one at Peck, Idaho, these are included in the model. The two data objects for the variables that govern the operation of the dam and for exporting the rule statuses for analysis.

Running two operational models, one for the non-modified, normal policy and one where the shift always occurs allows the study of the difference between the normal policy and the shift policy. By running historic data through a standardized model, the impact of the shift with current policy and forecasting procedures can be studied across all years on record and, future changes to the operational policies can be implemented and studied with the same model, an example of which will be done in Chapter 4.

The model was implemented on a daily time-step from January 1st through July 1st for each year. These dates were chosen as on January 1st the flood control curves begin to change depending on the forecast, and the reservoir is supposed to refill by the beginning of July. The model was run for the years of 1976 to 2011, for which daily inflow data is available at the reservoir and the other gauge locations. A batch file loops through through each year, setting the timeframe for the run, loading the input data, running the model, and exporting the output data for each year.

The operational model made several simplifications with respect to the actual planning process. The most significant is ignoring the operations of the Grand Coulee project, as this can limit the size of the potential shift, and in some years can prevent the shift from occurring. For the model where the shift is performed in ever year, it is further assumed that the entire difference between the system and local flood control curves is shifted. Also, no routing equations for the rivers were used as the model was run with daily time steps and this was larger than the 6-hour travel time between the dam and Spalding, Idaho (U.S. Army Corps of Engineers, 1986).

2.3 Rules Implemented

A rule set, which is detailed under Table 2.1, is used in both the normal and shift policy models. The flood control rule curve computed in a expression series slot that implements the shift policy depending on variable set prior to the model run. The outflow and reservoir storage data for both models are compared to the observed data to ensure that the rules are properly implemented. Results for this process are shown in Section 2.5.

During January through March, the reservoir is operated to maintain a minimum of 700,000 acre-feet (700 KAF), and any additional required by the flood control curves. During April through July, safe flood control levels must be provided while trying to follow a rule curve that provides a 95% probability of reaching the full pool elevation at 1600 feet. Table 2.1 shows the rules used in this model as detailed in Chapter 7 of the Dworshak Water Control Manual (U.S. Army Corps of Engineers, 1986). The level column translates into priorities for each group of the rules. While several rules are listed at the same level, the generally apply to different time periods and together

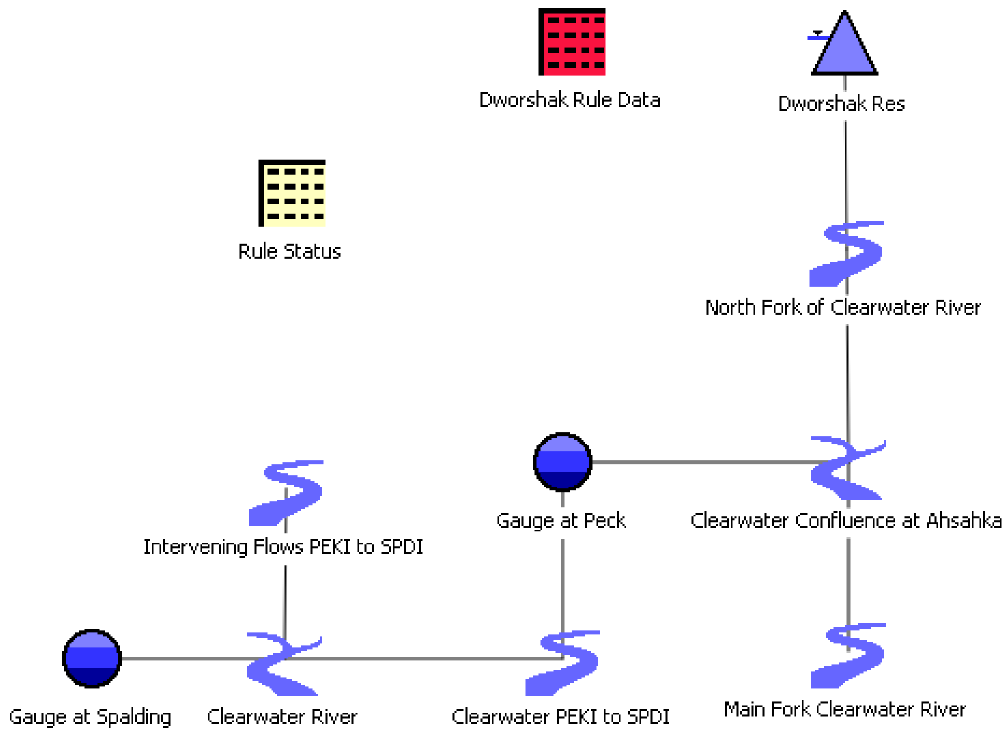

Figure 2.1: Schematic of Dworshak Reservoir System as implemented in RiverWare, showing the objects that make up the model.

work towards the same goal. The rules not applicable to the January through June timeframe of the model are ignored, as are the environmental constraints for goose nesting and limiting river fluctuation during the spring steelhead season, for both of which no data was available. Not specifically implemented in the RiverWare policy set, but monitored for violations are the maximum flow to limit total dissolved gas and flows at Spalding over 80,000 cfs where flooding damage starts to occur.

The rules as implemented in the RiverWare Policy Language can be found in Appendix A. The snow-covered area rules and normal evacuation, refill policy, and snow-covered area explained below:

The flood control curve as followed by the reservoir is determined by interpolation on a set of charts with a line for various inflow forecasts. The curves for several forecasts are shown in Figure 2.2 as an example. The rule as implemented in the model follows a single rule curve, which is computed from separate system and local flood control requirements that are input to the model. These requirements are created from a water supply forecast and reevaluated on the first of each month. Depending on the value of a slot set by the batch file controlling the model, either the shift policy or normal policy will be followed in combining the two requirements for the flood control curve. When the shift policy is used, the local flood control curve is followed, until April when the operations should transition to bring it back to the maximum of the system and local curves by the end of April. For the normal policy, only the maximum of the two curves is followed.

The flow at Spalding is used to trigger the refill operation. If the flow exceeds the 105,000 cfs threshold the reservoir's outflow is reduced to hold flows at the threshold. After the flow at Spalding starts to recede, the reservoir is allowed to fill to within 140,000 AF of full, holding there until the reservoir inflow goes below 30,000 cfs.

For the snow-covered area rule, a series slot is set from input data, and the value at the current time-step is looked up and interpolated from a table, obtained in Chapter 7 of the water control manual, to compute the storage requirement. Similarly, the limit on the rate of change in release is determined by the stage at Peck, with the rule implemented from a similar table detailing the maximum change in flow depending on the flow at Peck.

2.4 Model Input Data

The inputs used by the model are streamflow at several key locations, the rule curve computed for each year from the spring inflow volume forecast, and a time series of the percent snow covered area for the basin. All input data was stored in a Hydrologic Engineering Center Data Storage System (HEC-DSS) database which is accessed by the RiverWare program. The HEC-DSS database was chosen for its ability to store time series data, and its interoperability with current USACE systems as well as RiverWare's Data Management Interface (DMI) (U.S. Army Corps of Engineers - Hydrologic Engineering Center, 2009; Zagona et al., 2001). The output data was exported to two separate HEC-DSS databases. The first contains the flow at Spalding and the reservoir's discharge, storage, and pool elevation. The second database is used to store the sequence of rules that constrained reservoir operations.

The flow data was taken from USGS gauge data and from the USACE DataQuery database. The historic flow at Spalding, ID, Peck, ID, and Orofino, ID are all from gauges, while the historic inflow to the reservoir is computed from the discharge and change in storage. Intervening flows downstream of the dam, between Peck and Spalding, are computed as the differences in the two gauges. The USGS gauges and corresponding RiverWare objects are shown in Table 2.2.

The rule curve was computed for each year outside of the RiverWare model by taking the forecasted inflows from the Walla Walla District's 2011Z forecast[1] , a regression based method using snow-water equivalent (SWE) at several SNOTEL sites, the southern oscillation index (SOI), and inflows from previous months as predictors. The older NWD2005 forecast was also considered, but input data is available for fewer years, and as the 2011Z forecast is used in the current operations procedure, it was considered more representative of current policy.

For each year, given rule curve points are interpolated from the forecast for each month, and

[1] This forecast is implemented in a spreadsheet that was obtained from the USACE Walla Walla District. The spreadsheet can be used to compute both the estimate for the current year and has cross-validated forecasts for all previous years.

Level	Degree of Constraint	Operational Items
1	Not to be violated except during extreme emergencies.	(1) 1000-cfs minimum flow. (2) 700,000 acre-feet minimum winter flood control (15 December - 1 April). (3) Snow-covered area versus flood control space. (4) Evacuate surcharge space.
2	Can be violated with the requirements of: • Consideration of all other alternatives to avoid violation. • Consultation with District Engineer to explain necessity and alternatives. • Notification of other interested agencies, organizations, and officials or individuals as soon as possible.	(1) Rate of change in release. (2) Evacuation below ability to refill to elevation 1570 by 1 July with 95 percent certainty.
	Normal operations:	(1) Refill at 4,000-cfs once inflows drop below 30,000-cfs. (2) Maintain pool elevation below 700,000 acre-feet while inflows are greater than 30,000-cfs. (3) Reduce outflow to limit flow at Spalding below 105,000-cfs. (4) Pass outflow and follow spring flood control curve.

Table 2.1: Rules modeled in RiverWare policy set

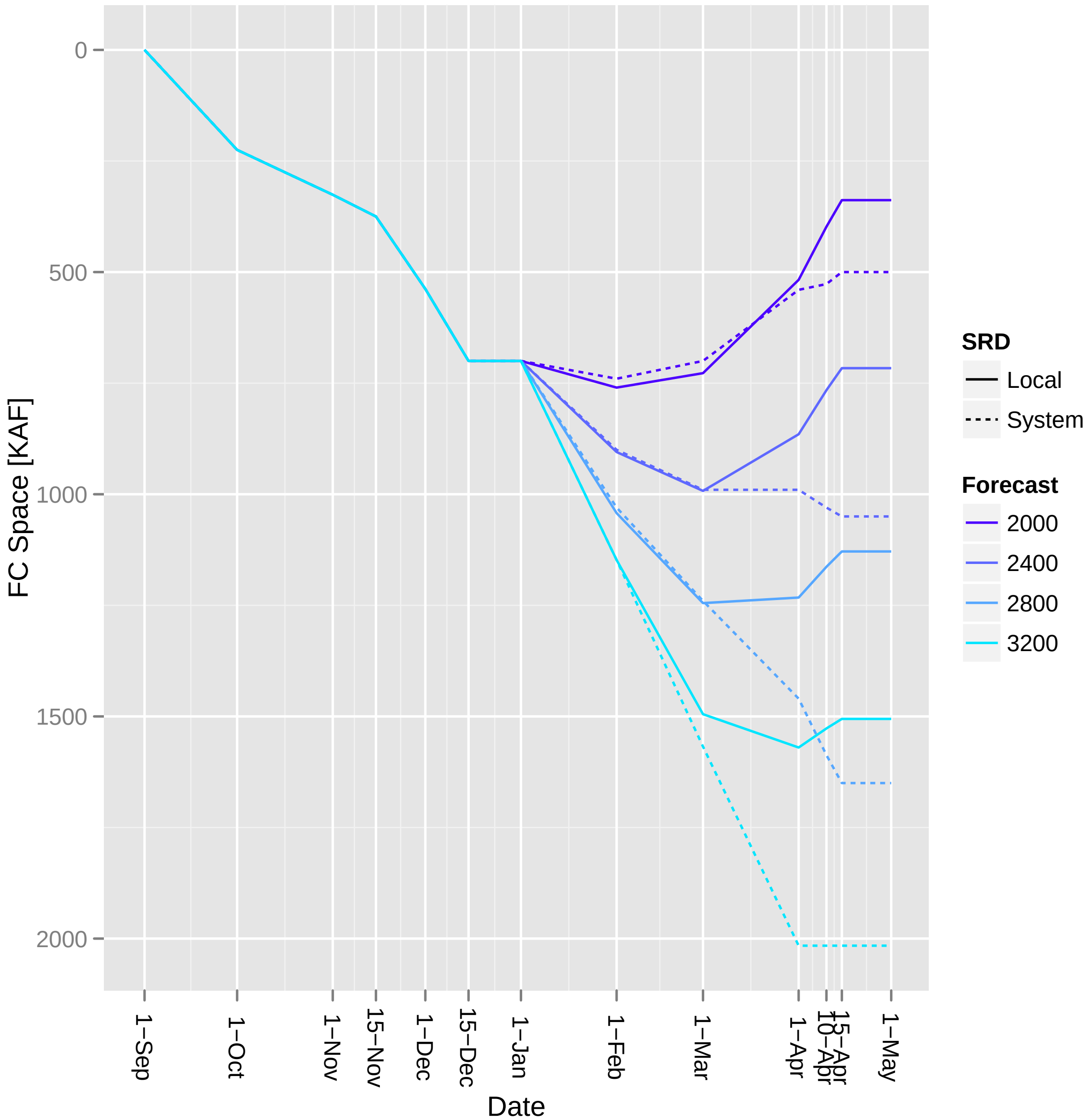

Figure 2.2: Storage reservation diagrams (SRD) showing the system and local flood control requirements interpolated to four example forecasts. The SRDs are translated into the rule curve for a given year by interpolating between them using the forecast of spring inflows.

USGS-ID	Gauge Name	RiverWare Model Name
13342500	Clearwater River at Spalding, ID	Gauge at Spalding
13341050	Clearwater River near Peck, ID	Gauge at Peck
13340950	Dworshak Reservoir near Ahsahka, ID	Dworshak Res
13340000	Clearwater River at Orofino, ID	Main Fork Clearwater River

Table 2.2: Water gauges used with USGS-ID number and name in RiverWare model, listed from downstream to upstream.

at the first of each month, the latest forecast is used, and a new rule curve is used going forward. This is done for both the local and system curves using a script written in the R programming language (R Development Core Team, 2012). The resulting values are output to a text file and read into the input HEC-DSS database.

The data for the percent snow covered area was derived by two means. For the water years 2004 to 2011, the percent snow covered area is computed from the SNODAS dataset (National Operational Hydrologic Remote Sensing Center, 2004) with each point in the dataset considered snow covered if more than 100mm of snow depth is reported. For years prior to 2004, the Northern Hemisphere EASE-Grid Weekly Snow Cover and Sea Ice Extent Version 3 dataset is used (Armstrong and Brodzik, 2007). Because the data presented is created from a very coarse dataset, it effectively has two pixels that fall within the basin. This results in only four possible values of snow covered extent, 0%, two complementary values of about 6% and 93%, and 100%. The two middle values fall outside of the range where the storage requirements vary, simplifying it further to two possible operational states, allowed to refill and a 700,000 acre-feet requirement. To help solve the problems this creates, and because the dataset is presented on a weekly timescale, a moving average of 31 days was applied to smooth the daily time-series of snow covered area.

2.5 Operational Model Output and Validation

After taking the input data and running it through the operational model outlined above, two sets of output are generated: the resulting decision variables of reservoir outflow and storage, which were used to ensure the calibration of the model, and series of which rules were violated or a limiting factor in operating the reservoir on each day. These series will be converted into binary sequences of which years the shift is preferred, based on criteria outlined below.

The Nash-Sutcliffe model efficiency coefficient (N-S coefficient) was computed for both the normal and shifted policies to see how well they matched the observed data. As both of these policies are making an assumption, either that the shift never occurs, or always occurs, it is expected that neither will fit perfectly. The Nash-Sutcliffe coefficient (Equation 2.1) is based on ratio between the index of disagreement for the model to the observed data, F_m^2 and the the index of disagreement for the mean of the observed data, F_o^2 (Nash and Sutcliffe, 1970). The index of disagreement is the sum of squared differences between a model and the observed data, $F^2 = \sum(\vec{x}_{\text{model}} - \vec{x}_{\text{observed}})^2$. The coefficient varies from $-\infty$ to 1, with a positive coefficient (0 to 1) indicating a model that is more useful than taking the mean value. A model with a higher coefficient fits the observed data better.

$$E = 1 - \frac{F_m^2}{F_o^2} \tag{2.1}$$

Over the entire modeled sequence, the normal policy, the N-S coefficient was found to be 0.67 and for the shifted policy, 0.77. For just the last ten years, 2002 to 2011, the normal and shifted policies had coefficients of 0.69 and 0.92 respectively.

The model output was visually validated by comparing the reservoir's storage and outflow to the historical operations. Figure 2.3 through Figure 2.6 show the modeled storage for both policies, in blue for the normal policy, red for the shift policy, and the storage from the actual operations in green. For most years, these line up closely, with either one of the modeled policies following the curve. When a partial shift was performed, neither matches well, but will be above and below the actual operations. A common error is being above the actual operations, a result of an operational preference to stay below and not exactly on the flood control curve (Hall, 2012). Larger errors may be a result of the model failing to replicate the actual operations, most likely due to a different water supply forecast being used or the the water supply forecast being significantly different than the actual inflows. Several years are significantly off, with difficult to explain behavior in the actual operations, an example of which is 1996. With 1996 it would appear that the forecast used in the model (2011Z), greatly under-predicted the volume compared to the historical operations, and tried to refill rather than follow the fluctuations seen historically.

A notable feature in both the observed data and the models is the reservoir holding 2,768,000 acre-feet, or 700,000 acre-feet below full, as required by either the minimum flood control space prior to April 1st, or when the snow covered area limit is in place with more than 80% snow covered area. This is seen as a small bump near that storage level can be seen on a number of the plots. In the modeled runs, this limit is sharper than it is in the historical operations. Another common difference, seen in 1978, 1987, 1992, and 1994, is a sudden decrease in storage in either the historical or the modeled data. This results in a failure to refill the reservoir. One possibility for these differences is the use of the modeled snow-covered area data varying from the data used by the historical operations.

Figure 2.7 through Figure 2.10 show the total outflow from the reservoir for the normal and shift policy, as well as the historically observed outflow. These do not line up quite as well as the storage curves, but do match up with when peaks should occur. The modeled discharge is not as smooth as the observed discharge. The sharpness may be the result of the model responding to sudden changes in inflow and making changes in the required flood control space at a much longer timescale, once a month for January through March, and three times in April. Another note is that the maximum discharge peaks at 30,000 cfs, a result of a maximum outflow limitation in the model. Examining the historic outflow data found that the discharge never exceeded 25,000 cfs, and while the dam has a much larger outflow capacity, it was capped at 30,000 cfs to prevent computational errors in solving the storage equation.

From the output of the shift and non-shifted models, the total number of days where various rules were the deciding factor was computed, and for years where the shift policy had an equal or smaller number of violations, or as computed by the model, it was considered to be a year in which the shift was allowed. This was repeated for each rule, as well as the total number of violations.

From the individual rule sequences, a sequence of years in which none of the rules would be violated by the shift was created, referred to as the "Policy Difference" rule sequence. The policy difference rule sequence is useful in showing when any rule will be violated more frequently by the shift policy, but does not highlight which rule was violated. These binary sequence of allowable shift years was then fed into the logistic model developed in Chapter 3, but the primary one of interest was the policy difference. The resulting sequences can be found in Table 2.3.

2.6 Summary

An operational model for the Dworshak Reservoir was developed and used to simulate the alternatives of using the entire allowable shift each year or none of the allowable shift. Using on historic inflow hydrograph and basin conditions with the current forecast and policies, model inputs are run through the physical system and reservoir operations to develop a scenario of potential outcomes. The difference between the shift policy and the normal policy are then examined and used to develop a sequence of which years the shift is preferred by each rule, and the policy difference sequence, consisting of years in which the shift is allowed by all the rules is created.

As was previously discussed in Section 2.1, developing a model for this reservoir in a decision model such as RiverWare opens new possibilities for management. By modeling the rules as understood by the reservoir regulators and other stakeholders, the model can show how the reservoir would react when those rules are followed. This will also help fill in the understanding of the operations by showing some of the inconsistencies between the modeled results and the historic operations of the reservoir that could be the result of the rules not being interpreted the same as in this model. Additional rules could be implemented to include operational policy not reflected in official documents, such as holding the reservoir slightly below the actual rule curve, or the operations that result from visual observations of snow-covered area during snow flights.

The model as presented could serve as the start of a seasonal planning model, which will be done in Chapter 4. Other uses for this model may be for operations to respond to weather events, and for long term planning to such as understand the impact of changing forecasting components.

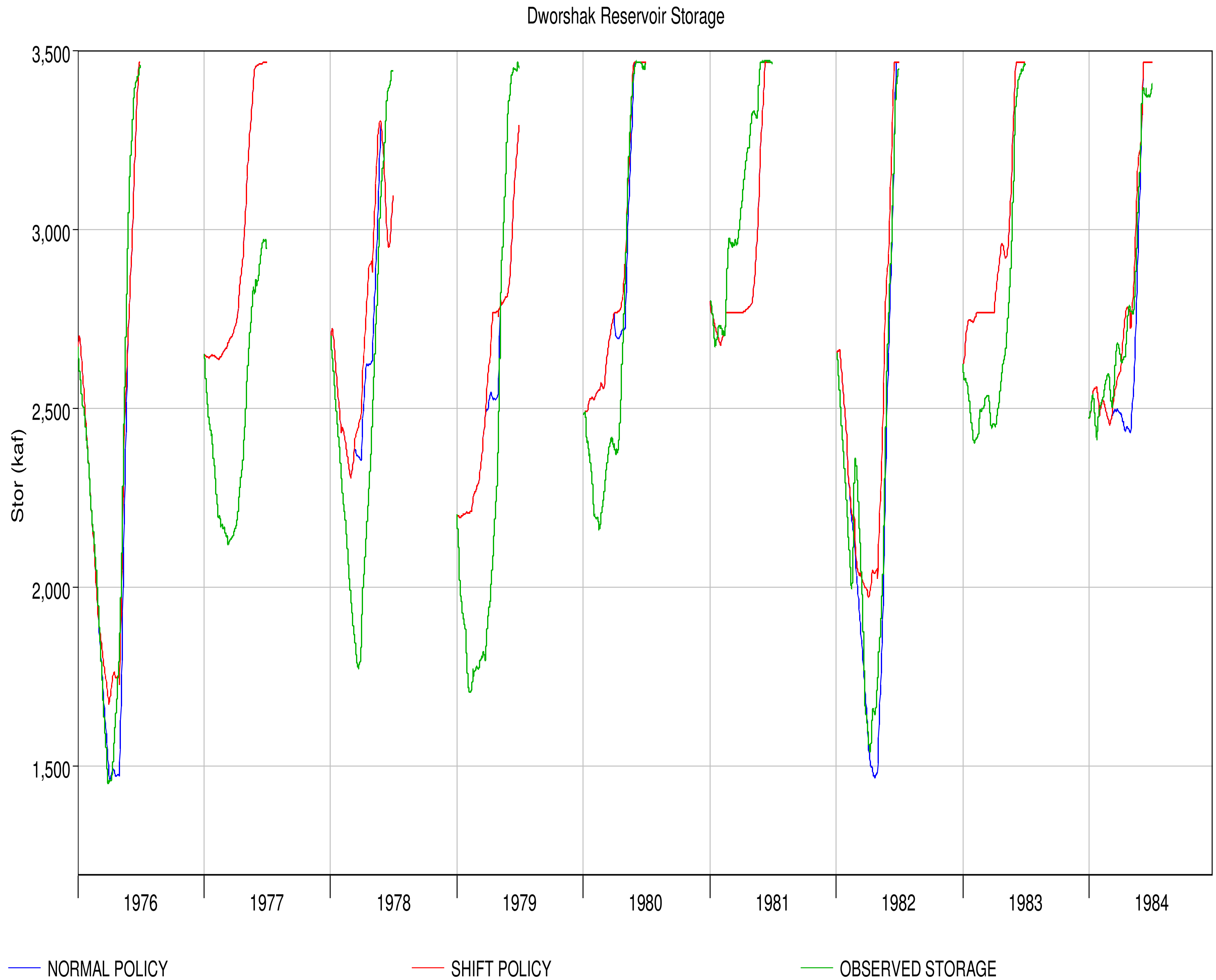

Figure 2.3: Modeled storage at Dworshak Reservoir, 1976 to 1984.

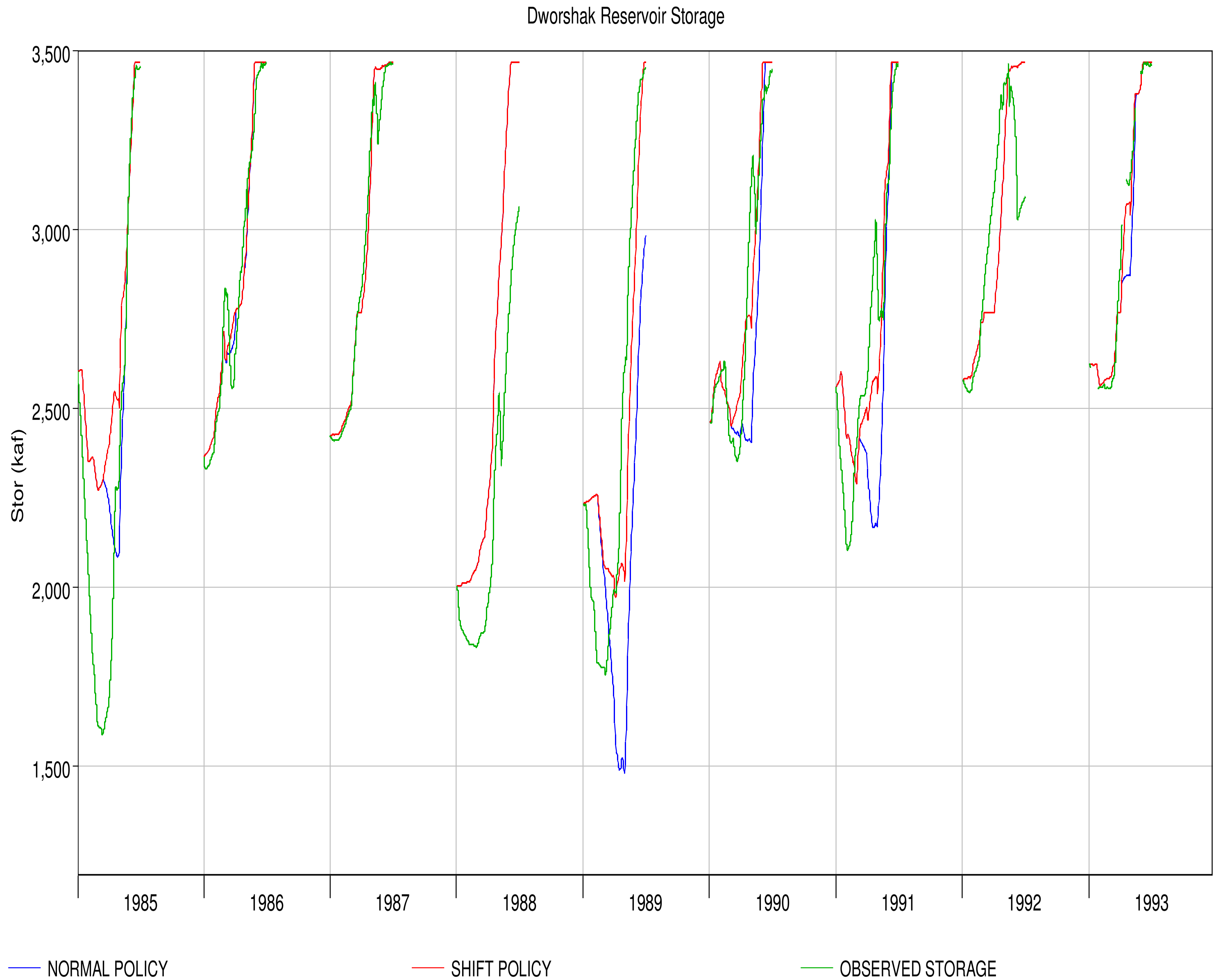

Figure 2.4: Modeled storage at Dworshak Reservoir, 1985 to 1993.

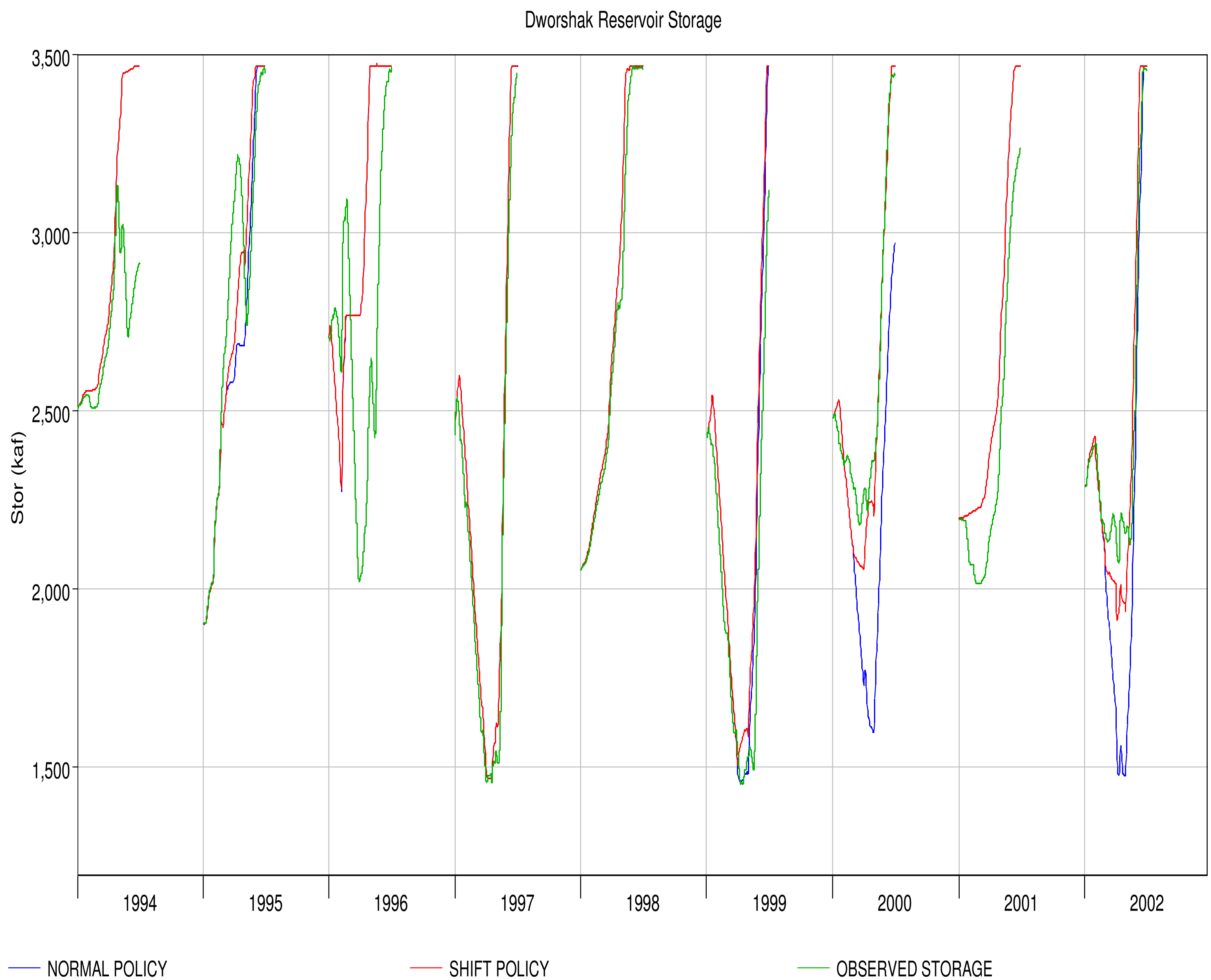

Figure 2.5: Modeled storage at Dworshak Reservoir, 1994 to 2002.

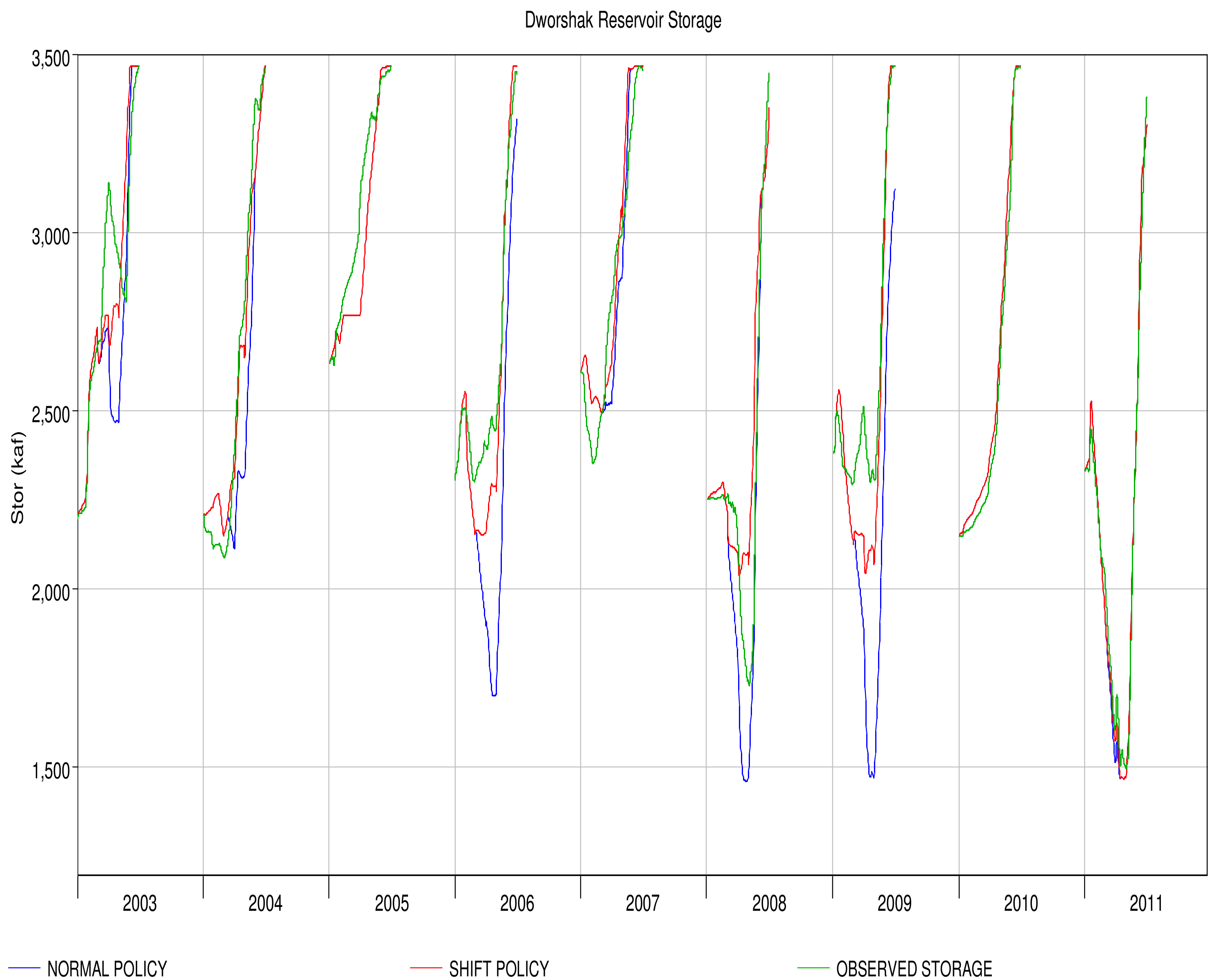

Figure 2.6: Modeled storage at Dworshak Reservoir, 2003 to 2011.

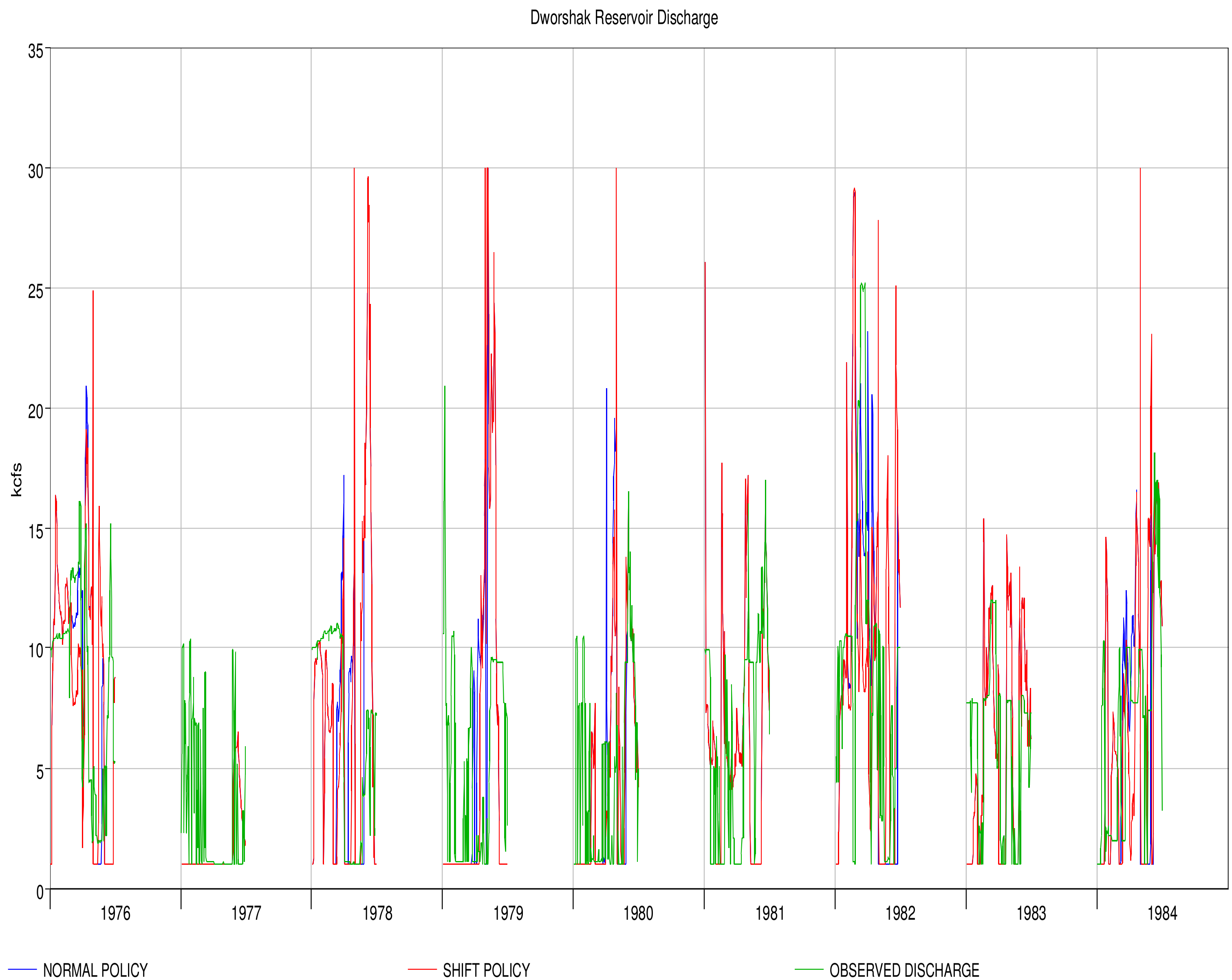

Figure 2.7: Modeled discharge at Dworshak Reservoir, 1976 to 1984.

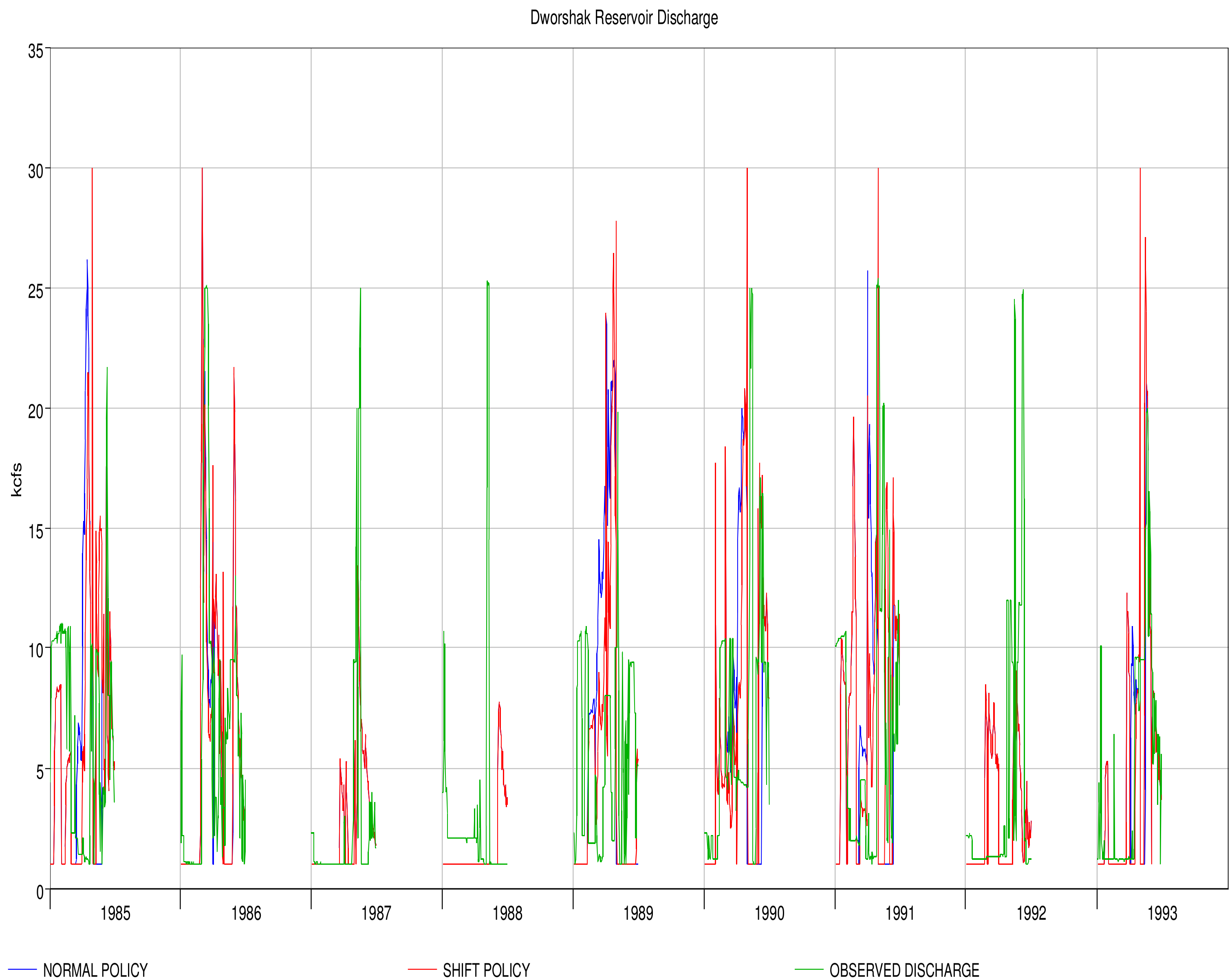

Figure 2.8: Modeled discharge at Dworshak Reservoir, 1985 to 1993.

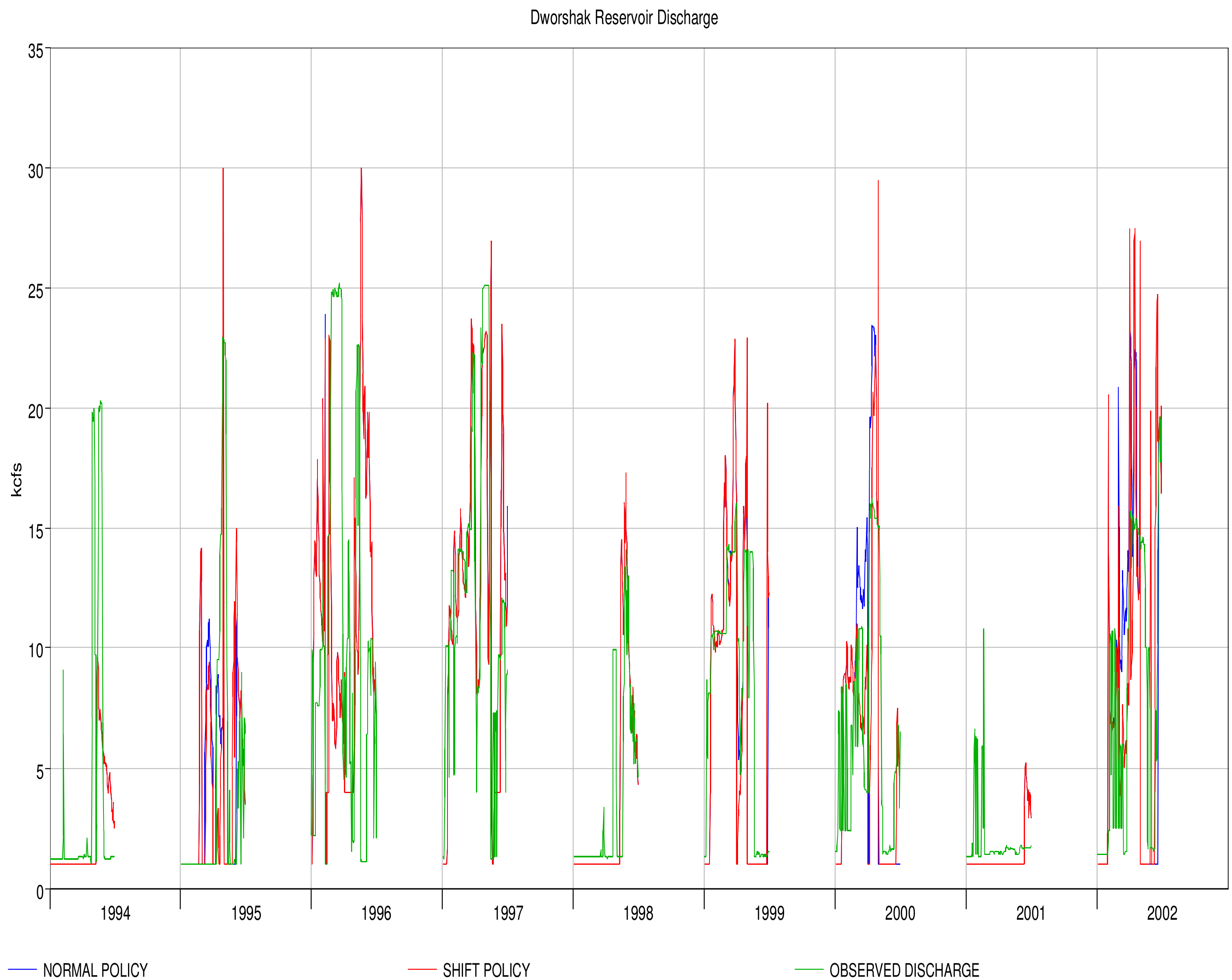

Figure 2.9: Modeled discharge at Dworshak Reservoir, 1994 to 2002.

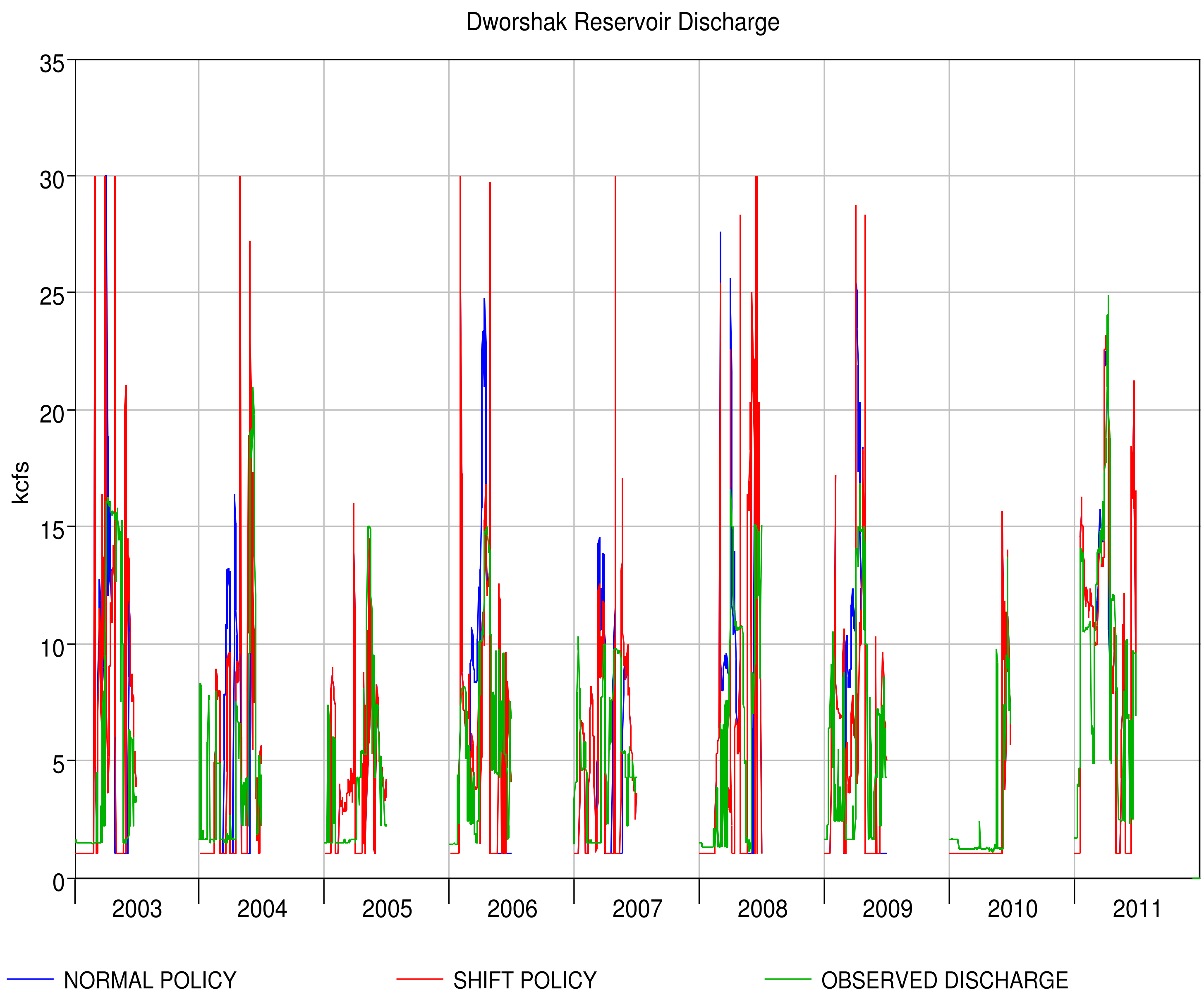

Figure 2.10: Modeled discharge at Dworshak Reservoir, 2003 to 2011.

As a subset of the operational policy is implemented here, other policies will need to be included for such studies. Ignoring the impact of operations at Grand Coulee on the ability to use the shift policy at Dworshak is a significant assumption in this model, and adding that component could result in further improvements.

Year	Spalding > 80kcfs	SCA Limit	FC Space Requirement	TDG Limit	Rate of ΔOutflow	Policy Difference
1976	X	X	X		X	
1977	X	X	X	X	X	X
1978	X		X			
1979	X		X			
1980	X		X	X		
1981	X	X	X	X	X	X
1982			X	X		
1983	X	X	X	X	X	X
1984	X	X	X			
1985	X		X	X		
1986	X			X	X	
1987	X	X	X	X	X	X
1988	X	X	X	X	X	X
1989	X		X	X		
1990	X		X	X		
1991	X		X	X		
1992	X	X	X	X	X	X
1993			X			
1994	X	X	X	X	X	X
1995	X		X			
1996	X	X	X	X	X	X
1997	X	X	X	X	X	X
1998	X	X	X	X	X	X
1999	X		X		X	
2000	X		X	X		
2001	X	X	X	X	X	X
2002	X		X	X		
2003				X		
2004	X		X			
2005	X	X	X	X	X	X
2006	X		X	X		
2007	X		X			
2008			X			
2009	X		X	X		
2010	X	X	X	X	X	X
2011	X	X	X	X	X	X
Sum	32	16	34	26	17	14

Table 2.3: Years in which shift is allowed, separated by rules and combined under the Policy Difference column. (X = yes)

Chapter 3

Statistical Model for Forecasting Shift Policy

3.1 Hydrologic Forecasts in Western US

Seasonal streamflow forecasts from regression models is an often applied in water resources planning and management. It's use with hydrologic variables as predictors, and the more recent inclusion of climate variables, has been shown to be effective across the western US (Garen, 1992; Pagano et al., 2004; Hamlet and Lettenmaier, 1999). The expanded knowledge of climate systems and their teleconnections to hydrology is a newer development that has increased skill in forecast at long lead times, allowing planning to take place much earlier and decrease risk (Regonda et al., 2006; Salas et al., 2011). While many climate indices exist, any particular index may not have a strong correlation with the hydrologic time series time series of interest (Grantz et al., 2005). The use of a regression models to predict categorical variables of streamflow, rather than streamflow forecasts has been shown to be comparable in skill and useful for operations which may depend on a threshold value (Regonda et al., 2006).

As the issues that have been encountered with the shift policy result from uncertainty in the spring inflow forecast, an alternative presented here is to forecast the appropriate policy decision directly. This should reduce possible errors introduced by using sequential models, and provide insight to a problem that results from the inherent error in the current forecast. The spring inflow forecasts for Dworshak are generally regression based model (Wortman, 2005; U.S. Army Corps of Engineers, 1986), typically taking into account snowpack, precipitation, and previous month's streamflow, with climate added recently through the use of the Southern Oscillation Index. The previously used predictors for the Dworshak spring inflow forecast, as well as additional climate indices, will be used to develop a more skillful model than the current climatology.

3.2 Methodology

3.2.1 Logistic Regression

Generalized linear models (GLM) allows extending linear regression techniques from predicting a normally distributed variable to one with any distribution in the exponential family through the use of a link function (McCullagh and Nelder, 1989). The link function, $G(\nu)$ is applied to the predictand, such that it can be modeled as a normal variable. When used with the logit link function (Equation 3.2), GLM is known as logistic regression and predicts the probability of a binary sequence being equal to 1. In the GLM model 3.1, $\bar{Y}$ is the binary sequence being predicted, X is the vector of predictors, β_i are the model coefficients, and β_0 is the intercept. The parameters β, the coefficients and intercept, are determined by maximizing the likelihood function.

The set of predictors used are detailed later, and selected by a two part processes. First, the top ten predictors by strongest correlation are chosen and used as an initial set of predictors. Next, using the Akiake Information Criterion, the best set of predictors was chosen (Venables and Ripley, 2002). The AIC is defined as $2k - \log(L)$, where k is the number of predictors and L is the maximized likelihood function from an iterative weighted least squares method. Minimizing this criteria by maximizing the likelihood while reducing the number of parameters will help prevent over-fitting the model and associated errors. The **MASS** library within the **R** programming language offers an algorithm known as **StepAIC** to search for the best set of predictors by selectively adding or removing the parameter that minimizes the AIC.

$$G(E(Y)) = \beta_0 + \sum \beta_i X_i \tag{3.1}$$

$$G(\bar{Y}) = \log\left(\frac{\bar{Y}}{1-\bar{Y}}\right) \tag{3.2}$$

3.2.2 Categorical Forecast Evaluation

The Brier Skill Score (Equation 3.3) is used to evaluate the a categorical forecast's ability compared to using the climatological mean or against an alternative forecast method (Wilks, 1995). It is based on the Brier Skill which indicates a model's ability to replicated the observed probabilities. The equation for the Brier Skill can be found in Equation 3.4, where N is the number of points, p_i is the modeled probabilities, either from a forecast or the climatological average, and o_i is the observation at each point. The Brier Skill Score ranges from negative infinity to 1, and indicates that the model is more skillful than the alternative if it is greater than zero. The BSS is computed for to the logistic regression model fitted to the entire data set, as well as to the mean probability for each year from an ensemble of cross-validated models.

$$\text{BSS} = 1 - \frac{\text{BS}_{\text{forecast}}}{\text{BS}_{\text{alternative}}} \tag{3.3}$$

$$\text{BS} = \frac{\sum_{i=1}^{N}(p_i - o_i)^2}{N} \tag{3.4}$$

Cross-validation stresses the model, by dropping a certain number of points and predicting the dropped points by predicting them with the remaining data, providing a more accurate evaluation of a model's forecasting ability. The cross-validation technique used in this model was to drop each year and an additional random sample of 10% of the remaining points. This was repeated fifty times, with a cross-validated mean and standard-error computed from the values produced for each year. This cross-validated mean was used for computing a BSS and as input for the model presented in Chapter 4.

Also of interest to operations is the number of years in which the model predicts that the shift can occur when the observed data suggests that it should not, or the number of false positives. To use this metric, a threshold value that the probability must exceed is needed, and for simplicity, the mean probability of a shift is used. This is an arbitrary threshold, but was selected as a simple metric to show the model's ability to distinguish between good and bad years to shift. Using this threshold, a shift is allowed when the model gives it a probability greater than the mean probability of a shift. This threshold should be adjusted for each model, other values may reduce the number of false positive without reducing the number of actual shift years.

Finally, the maximum coefficient P-value is given for each model, as an indicator of the quality of that model's fit by giving the highest probability of a coefficient not taking the value it is given. For a well fit model this value will be closer to 0.

3.3 Model Application

The logistic regression was used with the rule sequences created in Chapter 2 as the predictand; thus the output would give a probability of a shift being allowed in a given year. The model is fitted for available predictors for the first of the months January through April. Each rule sequence as well as the policy difference sequence were modeled.

For the Brier Skill Score assessment, the alternative forecast used was a prediction of the shift probability based on the quartile of spring inflow in which the forecasted inflow falls. If it is within the bottom quartile, a 75% probability of shift is use. For the middle two quartiles, 50% is used, and for the top quartile, a 25% chance of shifting is assumed. This quartile model is meant to replicate the current process where the forecasted inflow is compared with historic to estimate a probability of shifting used for operational planning.

The predictors considered for this model include predictors used for the current streamflow forecast as well as additional climate variables. The current streamflow forecast uses several hydrologic variables such as accumulated snowpack, fall precipitation, and winter streamflows, as well as the Southern Oscillation Index (SOI), just one estimate of the activity of the El Nino - Southern Oscillation (ENSO). The additional climate variables were selected based on an examination of the correlation of the policy difference sequence with with spring sea surface temperatures from the NCEP/NCAR reanalysis dataset, a map of which can be found in Figure 3.1 (Kalney et al., 1996). The map shows strong correlations with the temperatures in the tropical Pacific, where the ENSO pattern is dominant as well as the northern Pacific, suggests several patterns to look for, including the Southern Oscillation Index, Northern Oscillation Index, focused on the northeast Pacific, the Multivariate ENSO Index, and the Pacific-North American pattern, which indicates the teleconnection between the Pacific ocean and regions of North America (Trenberth and Shea, 1987; Schwing et al., 2002; Wolter and Timlin, 1993, 1998; Wallace and Gutzler, 1981). Once the full set of predictors was created, they were pre-selected to simplify the modeling process by only taking those with the ten strongest correlations to the rule sequence being modeled.

3.4 Results

Table 3.2 shows the best predictors for the model of the policy difference sequence at each lead time. Table 3.3 through Table 3.8 list the model evaluation metrics for each rule modeled at each lead time, with the table for the policy difference rule table in Table 3.8. The first five columns show error statistics with respect to the mean probability of shift threshold. The first column shows the number of years that exceeded the threshold, while the second shows the number of actual shift years. The third column reports the total that were on the wrong side of the threshold, either too high for a year in which a shift should not occur, and or too low when a shift could have occurred. The fourth and fifth columns show the false positive and false negative error rates. False positives are the years in which the model predicted a value greater than the threshold but a shift should not occur. The false positive error rate is the number of false positives over the number of years predicted to be greater than the threshold. The false negative error rate is similar for years in which a shift could have occurred but the model assigned too low of a probability.

The last three columns show the cross-validated BSS, the fitted BSS, and the maximum coefficient p-value. The BSS columns give an idea of the model's effectiveness, with the cross-validated BSS representing a mean of the predictive ability and the fitted BSS showing the upper bound for the predictive ability. The maximum coefficient p-value shows how well the model was fit.

For the policy difference rule results, shown in Table 3.8, the cross-validated BSS says the model performs better than climatology early in January, and about on par with climatology for

Dataset	Months	Station	Source
Monthly Inflow	October - Prev. Month	Dworshak Dam	dataquery [a]
Observed Total Spring Inflow	Sum of April to July	Dworshak Dam	dataquery
Total Precipitation	Sum of October and November	Elk River, ID and Headquarters, ID	dataquery
First of month snow-water equivalent (SWE)	January through current month	Six stations in and near basin, first principle component only. Stations: Elk Butte, Idaho - **16C20S** [b] , Hemlock Butte, Idaho - **15C06S**, Hoodoo Basin, Montana - **15C10S**, Pierce Ranger Station, Idaho - **15C05S**, Lost Lake, Idaho - **15B14S**, Shanghi Summit, Idaho - **15C04S**	NRCS
Southern Oscillation Index (SOI)	October - Prev. Month		Trenberth and Shea (1987)
Northern Oscillation Index (NOI)	October - Prev. Month		Schwing et al. (2002)
Multivariate ENSO Index (MEI)	October - Prev. Month		Wolter and Timlin (1993, 1998)
Pacific-North American Pattern (PNA)	October - Prev. Month		Wallace and Gutzler (1981)

Table 3.1: Predictors considered in modeling process.

[a] U.S. Army Corps of Engineers - Northwestern Division (U.S. Army Corps of Engineers - Northwestern Division)
[b] NRCS SNOTEL station number

the other three months. The fitted BSS shows a better performance, with the lowest performance being the March model. The model is wrong about a third of the time that it predicts a shift based on the threshold value. The models for limiting Spalding flooding Table 3.3, and the minimum flood control space rule Table 3.5, and are both poorly fit, as shown in the P-value column, but match the original data very well, with a fitted BSS of 1, and getting none of the years wrong. The SCA limit model (Table 3.4) is not as well fit as the policy shift, but has similar performance, getting fewer false positives as the season progresses. The total dissolved gas (TDG) model (Table 3.6) performs a bit better, but has a very high number of false negatives. The model for the limit on change in release (Table 3.7) has a good fit, with fitted BSS of greater than 0.26, but does poorly at prediction, with a minimum cross-validated BSS of 0.07. For the rules where there is less of a link between inflows and the shift being allowed, the logistic regression model performs better than the quartile model.

Visual results are shown in Figure 3.2 through Figure 3.7 shows the March 1st model output for each of the rule sequences. The years are arranged on the x-axis from lowest spring inflow year (1977) to highest (1997). Black cicles represent the preferred policy for that year, located at 0 for a no shift year and at 1 for a shift year, with a colored dot in between showing the probability predicted by the model. A blue dot is on the correct side of the threshold from, while red dots show false positives, and green dots show false negatives. The threshold used is the historic probability of a shift, shown by the horizontal grey line. A black error bar shows the $\pm 2\sigma$ error from the cross-validated standard error for that year. Vertical grey lines link the model's predicted probability with the preferred result for each year. The black squares show the predicted shift value from the quartile model used to simulate the current process.

The policy difference model shown in Figure 3.2 shows a variety of results, but a trend towards lower flow years having a preference for a shift, and the model results reflecting that. The TDG model, Figure 3.4 shows better discrimination based on the threshold value, but all of the probabilities are quite high. The TDG model also shows how increasing the threshold could possibly reduce the number of false positives, as they both fall near the historic mean. The change in release model, Figure 3.5, shows a number of false positives that are in the same range as years in which the shift should have occurred, but could possibly be distinguished by being above a certain flow threshold. As was seen in the evaluation metrics, the minimum flood control space model, Figure 3.6, and the Spalding flooding model, Figure 3.7, both capture the historic shift sequence quite well, but the metrics indicate possible problems with using these model.

Date	Jan SWE PC 1	Feb SWE PC 1	Dec NOI	Jan PNA	Mar SOI
January 1st	x		x		
February 1st	x			x	
March 1st		x		x	
April 1st	x			x	x

Table 3.2: Predictors used in the model for the policy difference sequence

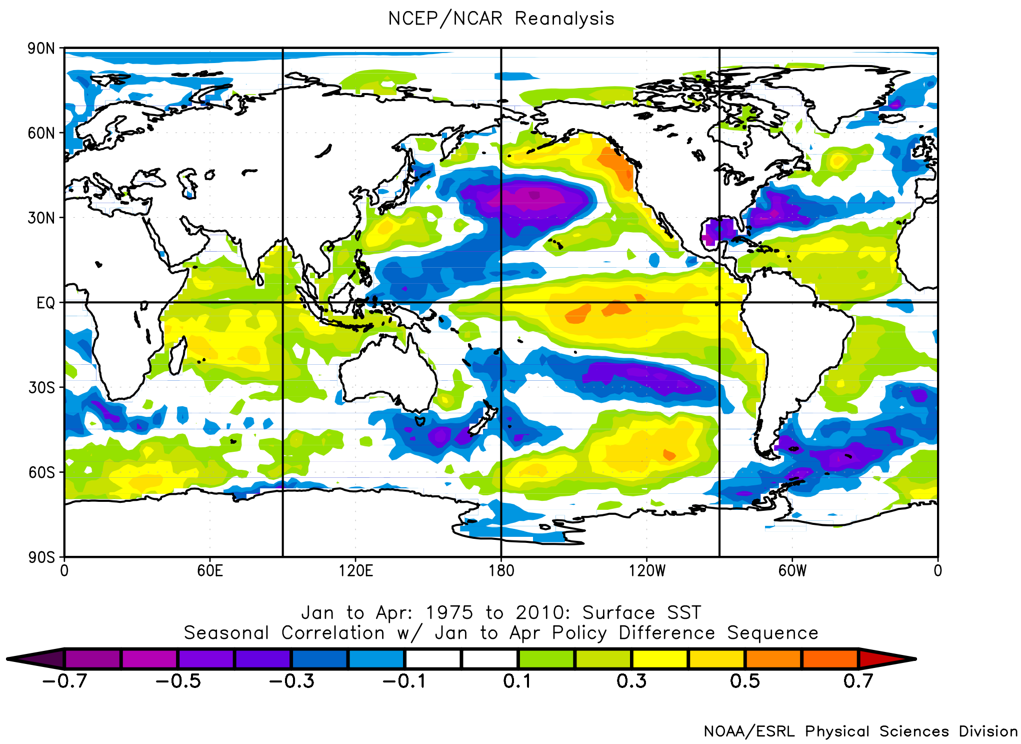

Figure 3.1: Correlation between the policy difference sequence and January through April sea surface temperatures from the NCAR reanalysis dataset. Image provided by the NOAA/ESRL Physical Sciences Division, Boulder Colorado from their Web site at http://www.esrl.noaa.gov/psd/

	Predicted Years	Actual Years	Total Wrong	% False +	% False −	C.V. BSS	Fitted BSS	Max. Coeff. P-Value
Jan	32	32	0	0.00	0.00	0.69	1.00	0.99
Feb	32	32	0	0.00	0.00	0.81	1.00	1.00
Mar	32	32	0	0.00	0.00	0.78	1.00	1.00
Apr	32	32	0	0.00	0.00	0.79	1.00	1.00

Table 3.3: Spalding Flow over 80,000 cfs

	Predicted Years	Actual Years	Total Wrong	% False +	% False −	C.V. BSS	Fitted BSS	Max. Coeff. P-Value
Jan	20	16	10	35.00	18.80	0.09	0.23	0.18
Feb	17	16	7	23.50	15.80	0.00	0.33	0.19
Mar	17	16	7	23.50	15.80	0.05	0.38	0.48
Apr	14	16	4	7.10	13.60	0.06	0.25	0.10

Table 3.4: Rule: SCA Limit

	Predicted Years	Actual Years	Total Wrong	% False +	% False −	C.V. BSS	Fitted BSS	Max. Coeff. P-Value
Jan	34	34	0	0.00	0.00	0.82	1.00	1.00
Feb	34	34	0	0.00	0.00	0.83	1.00	1.00
Mar	34	34	0	0.00	0.00	0.65	1.00	0.97
Apr	34	34	0	0.00	0.00	0.91	1.00	1.00

Table 3.5: Rule: Minimum FC Space

	Predicted Years	Actual Years	Total Wrong	% False +	% False −	C.V. BSS	Fitted BSS	Max. Coeff. P-Value
Jan	22	26	10	13.60	50.00	0.18	0.40	0.11
Feb	23	26	11	17.40	53.80	0.18	0.51	0.11
Mar	19	26	11	10.50	52.90	0.12	0.24	0.06
Apr	21	26	7	4.80	40.00	0.19	0.54	0.16

Table 3.6: Total Dissolved Gas Limit (DWR Outflow over 14,000 cfs)

	Predicted Years	Actual Years	Total Wrong	% False +	% False −	C.V. BSS	Fitted BSS	Max. Coeff. P-Value
Jan	15	17	10	26.70	28.60	0.13	0.31	0.96
Feb	18	17	5	16.70	11.10	0.05	0.37	0.40
Mar	20	17	7	25.00	12.50	0.07	0.29	0.09
Apr	16	17	9	25.00	25.00	-0.08	0.26	0.46

Table 3.7: Rule: Maximum change in release

	Predicted Years	Actual Years	Total Wrong	% False +	% False −	C.V. BSS	Fitted BSS	Max. Coeff. P-Value
Jan	19	14	7	31.60	5.90	0.12	0.25	0.09
Feb	18	14	8	33.30	11.10	0.04	0.21	0.07
Mar	18	14	8	33.30	11.10	-0.03	0.15	0.05
Apr	14	14	8	28.60	18.20	-0.02	0.20	0.15

Table 3.8: Policy Difference

3.5 Summary and Discussion

First examining the policy difference sequence in Table 3.8: The predictive ability in January is better than the current forecast, with a cross-validated BSS of 0.12, and on par with the current forecast for the later months. This decrease in perceived skill is likely a result of the streamflow forecast getting more accurate in later months. The best fit model, as measured by the maximum coefficient P-value is for February, while the best fit by cross-validated standard error is the model for March. Looking at the visual plot for this model shows a few things. First, it confirms the relationship between the shift is allowed during low flow years, and problematic during high flow years. However, it is interesting to see that the two highest flow years on record, 1997 and 2011 would have allowed the shift, and the policy difference model predicts a low probability to each. Across each of the logistic regression models, there is a tendency to have higher Brier Skill Scores in the early season than in the late season. This does not appear to be a result of the model declining in performance, but of the quantile model improving.

Figure 3.3 and Figure 3.5, showing the SCA limit model and the maximum change in flow model, are reasonably well fit, and show that the years with a moderate amount of flow are those where the shift is most likely to fail. This may be a result of the streamflow forecast having a lot of fluctuations for these years. This is also where the logistic models are most likely to fail, with most of their false positives in the middle range of flows.

From the model evaluation tables, it is clear that the Spalding Flow limit and the Minimum FC space both are poorly fit, however predict the shift perfectly. These models have very few years where the shift is not allowed, 4 and 2 respectively, and very poorly fit, as evidenced by their maximum P-value seen Tables 3.3 and 3.5.

The predictors chosen for the model (Table 3.2) are interest, especially the choice of timing for the SWE variables. With the exception of the March model, the January SWE variable was chosen for each model. Something to be investigated further is the choice of predictors for the February model, where the **StepAIC** algorithm did not select the predictors chosen for the March

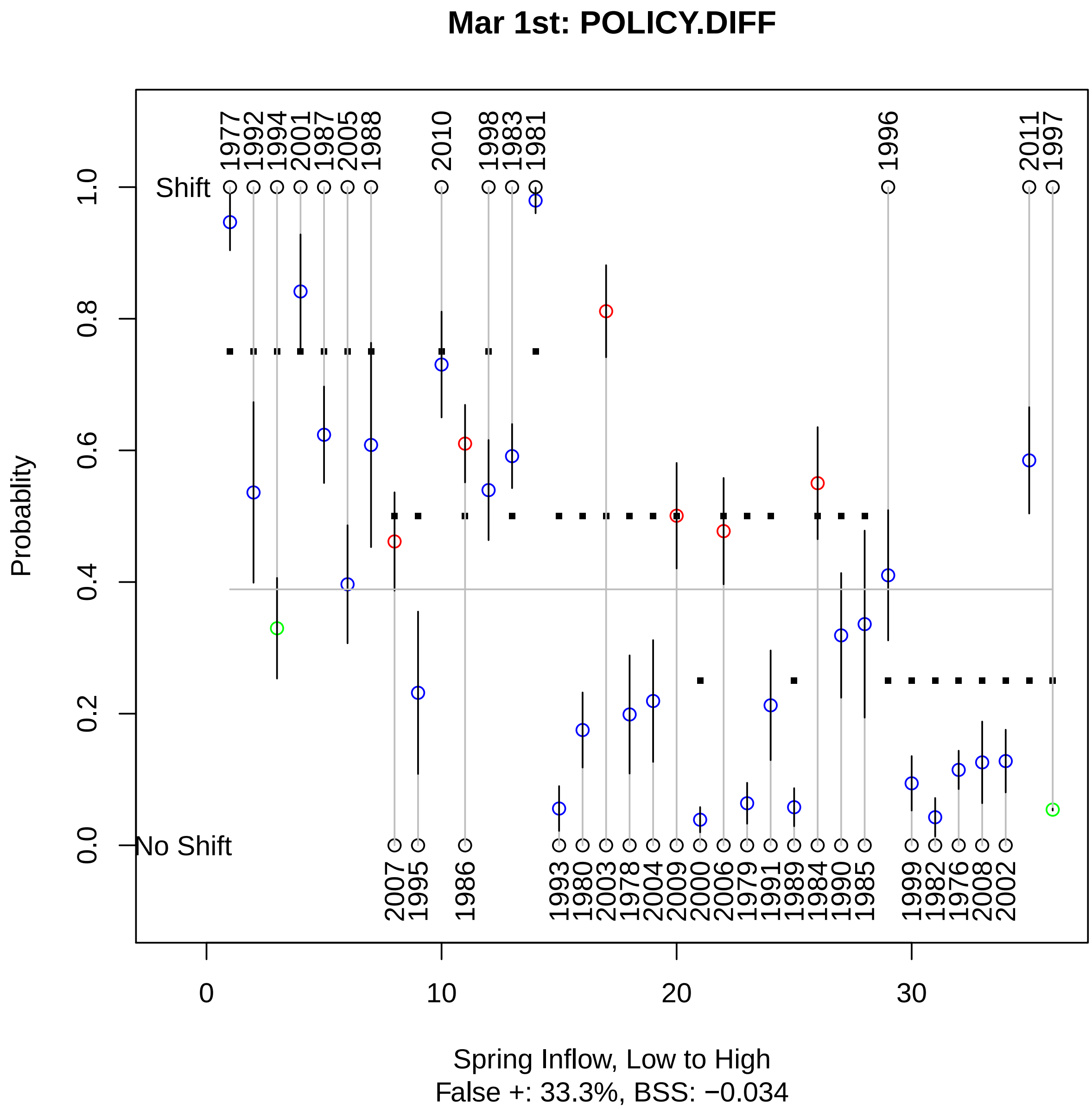

Figure 3.2: Plot of model for policy difference sequence for March 1st. The x-axis is sorted from lowest spring inflow to highest spring inflow. The black circles show the preferred policy for each year, at one when a shift is allowed, and zero when it is not. The colored dot in between shows the predicted probability, with a blue dot if the model is on the correct side of the historic mean. A red dot shows when a false positive occurs, and a green dot shows a false negative. The threshold is shown by the horizontal grey line. The black squares show the probability from the quartile rule used for the Brier Skill Score comparison.

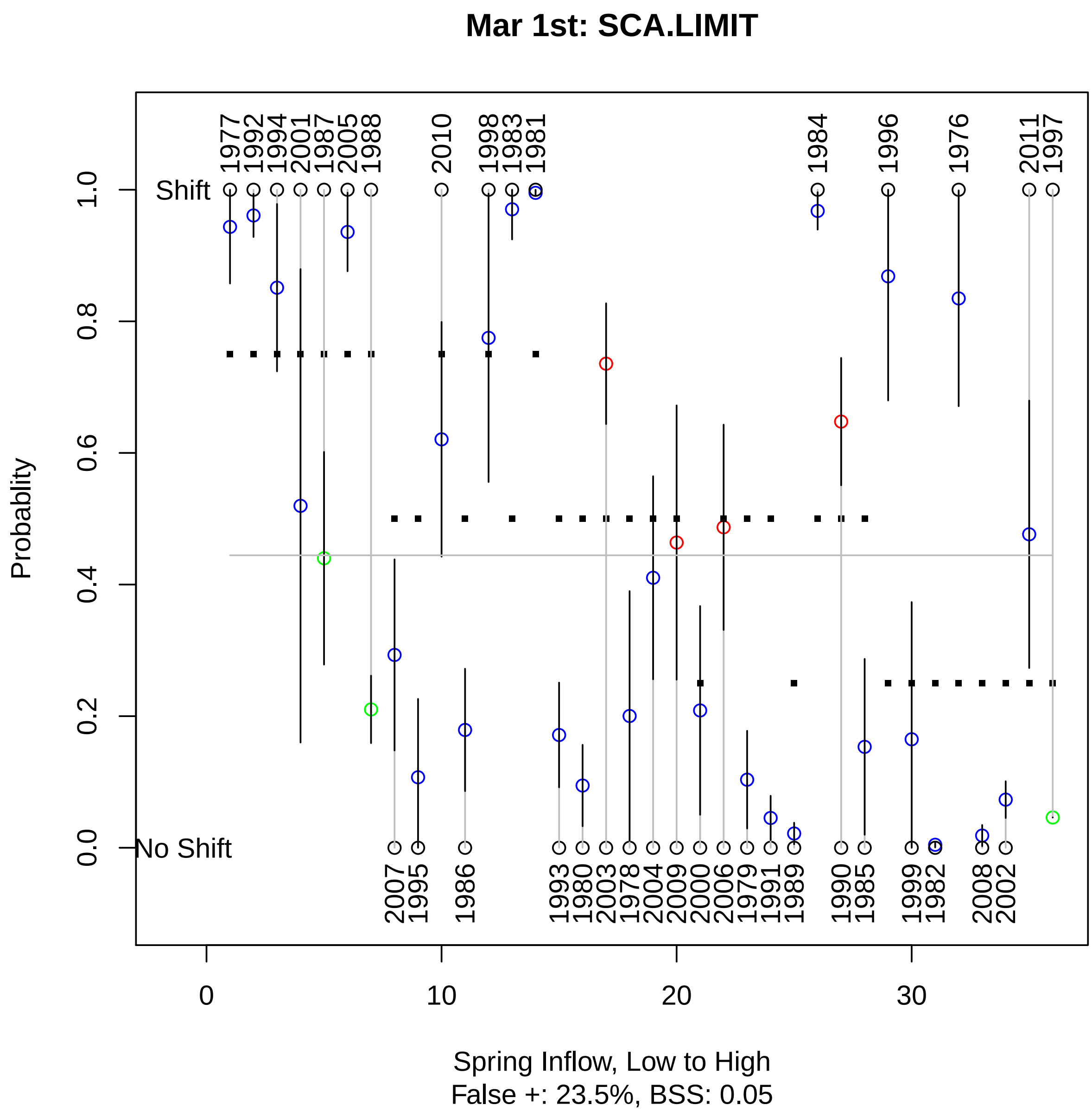

Figure 3.3: Plot of model for the SCA limit sequence for March 1st. See Figure 3.2 for a description.

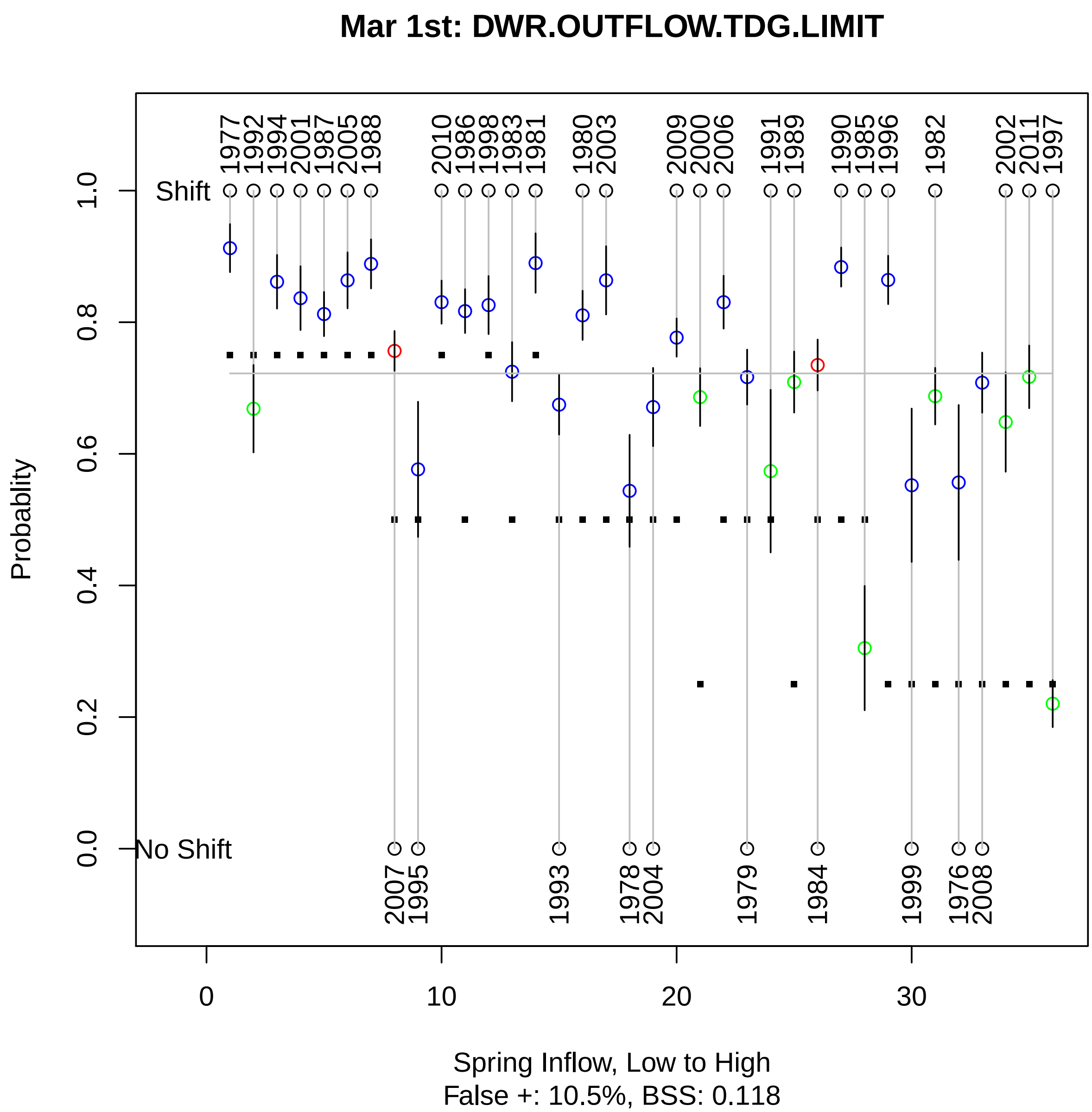

Figure 3.4: Plot of model for total dissolved gas limit sequence for March 1st. See Figure 3.2 for a description.

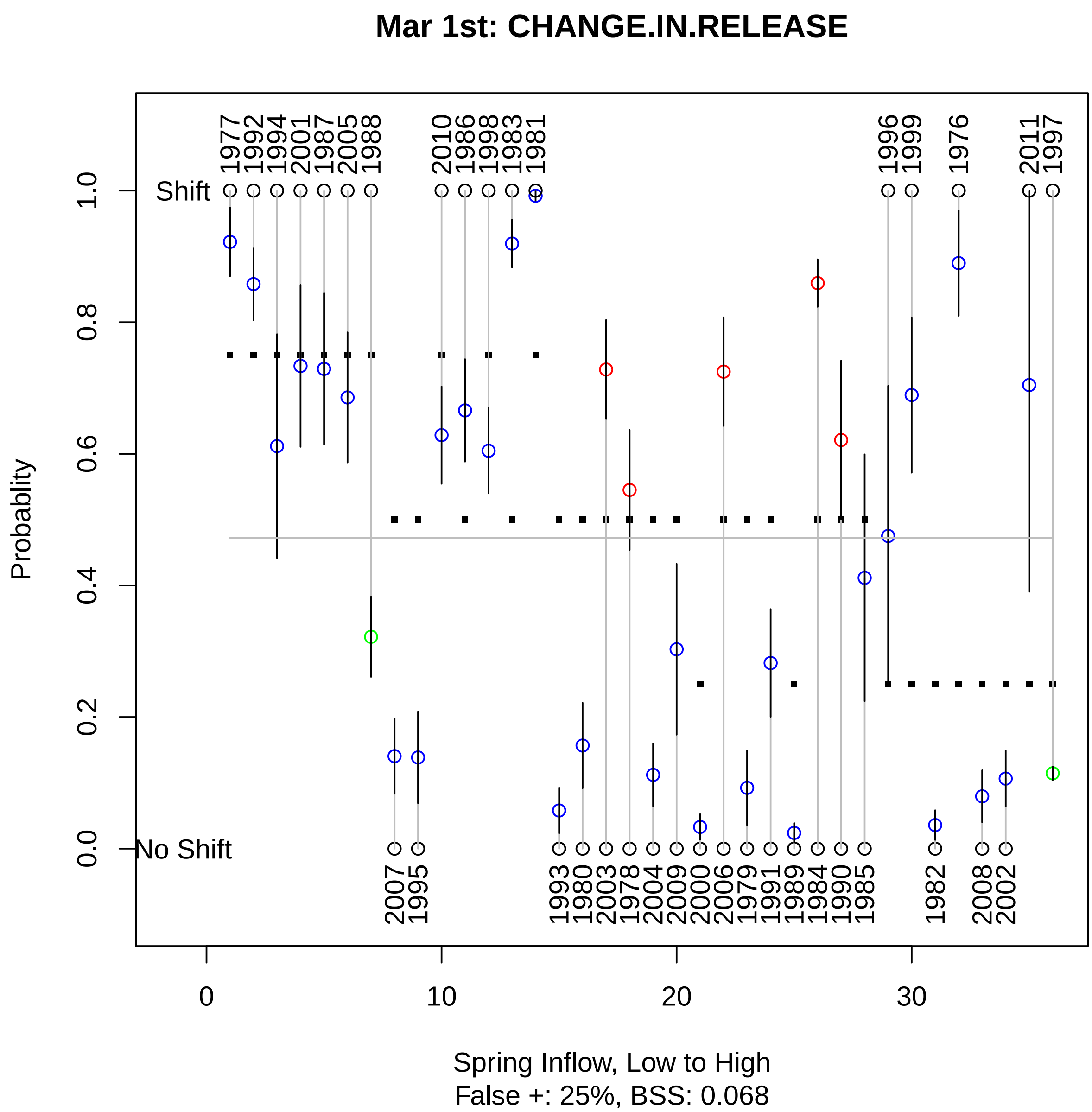

Figure 3.5: Plot of model for rate of change in outflow sequence for March 1st. See Figure 3.2 for a description.

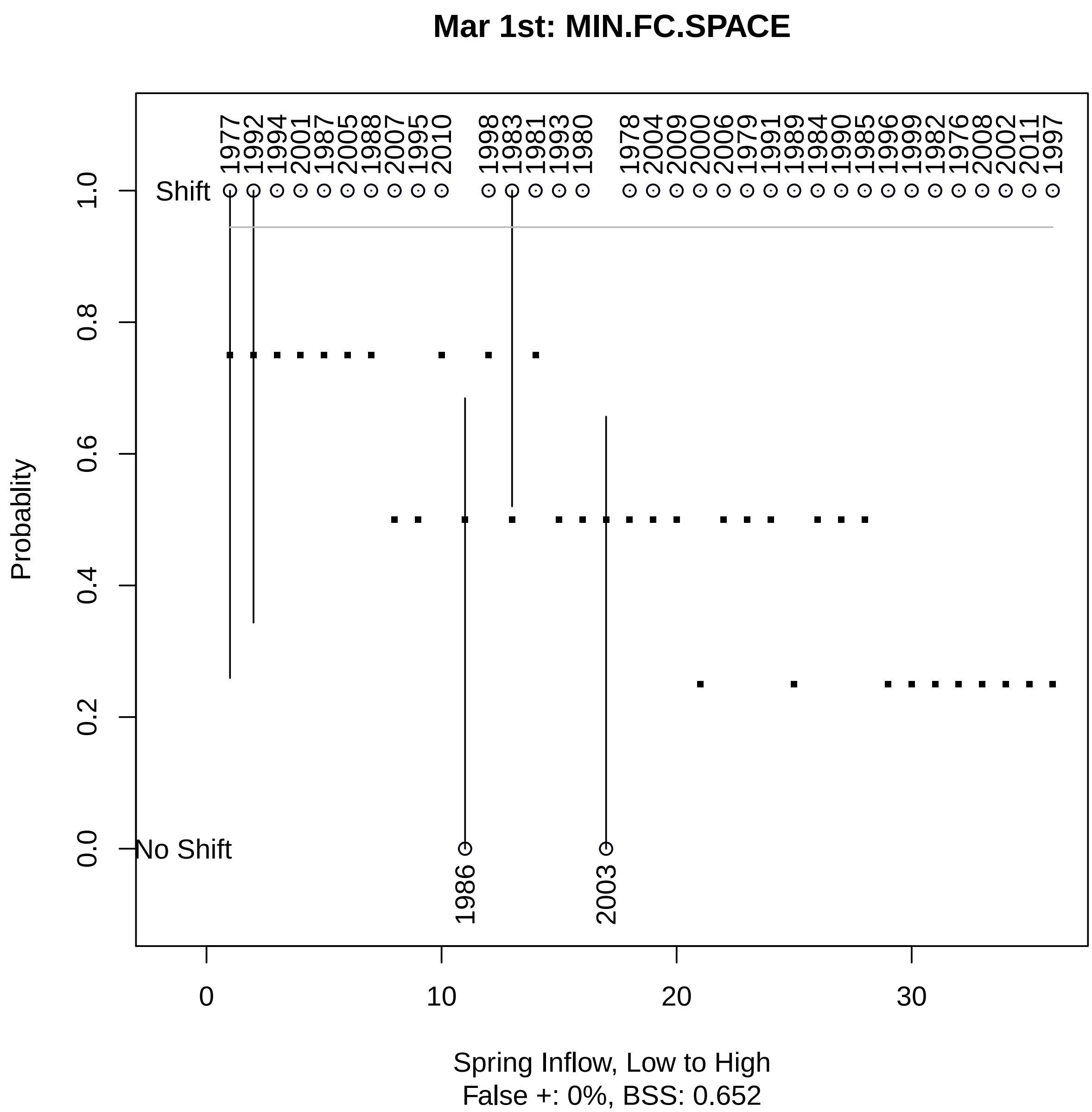

Figure 3.6: Plot of model for required flood control of at least 700 KAF sequence for March 1st. See Figure 3.2 for a description.

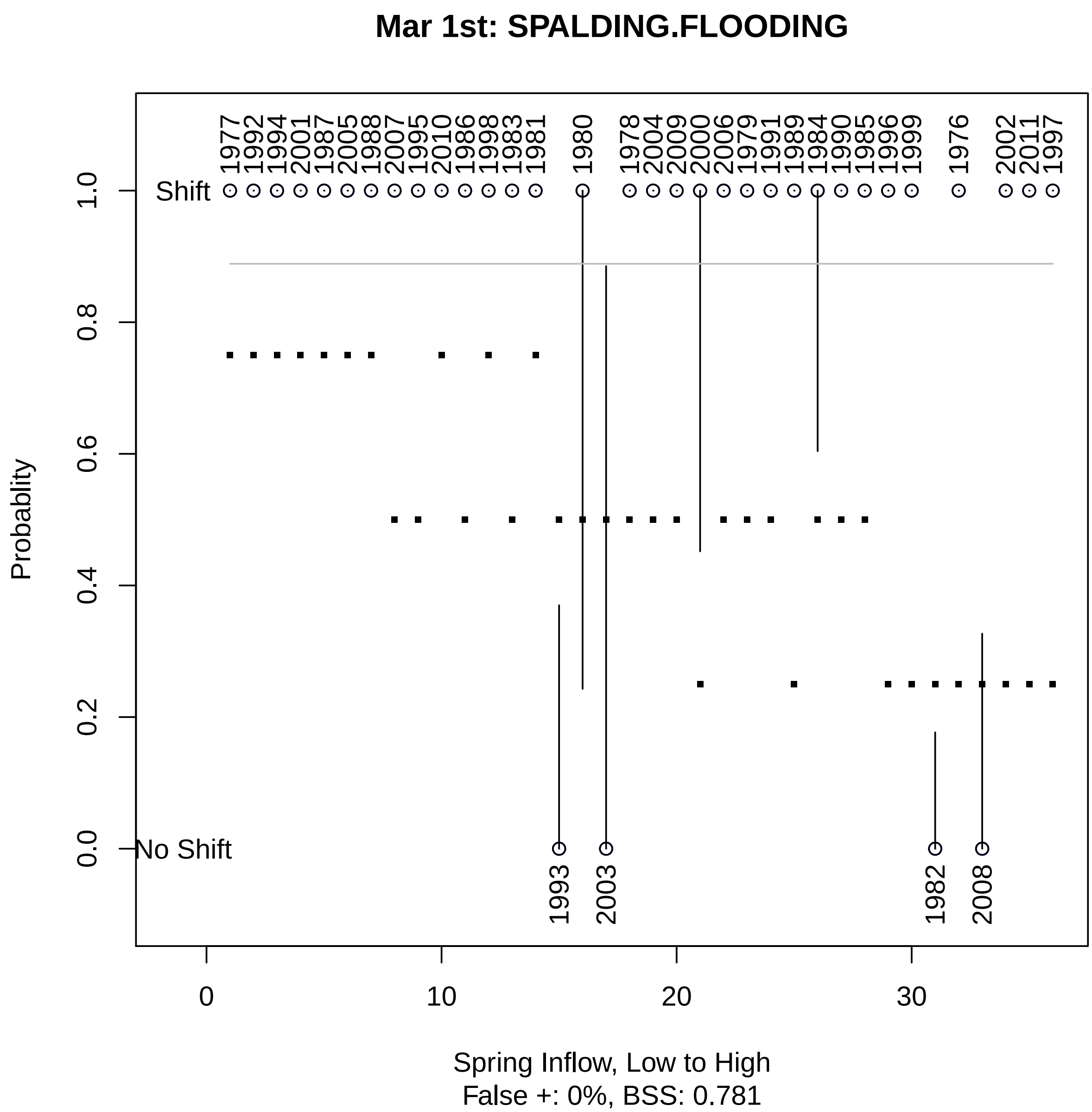

Figure 3.7: Plot of model for the Spalding flow greater than 80,000 cfs sequence for March 1st. See Figure 3.2 for a description.

model, even though they were available at that point. This is notable in that the model for March could be used in February. One explanation for this is the algorithm does not perform an exhaustive search but selectively removes predictors from the given set, which differs between the two models, and selects based on AIC.

The results shown above show that with some degree of skill, a logistic regression based forecast can predict the right policy at an early lead time. The model is more useful for modeling particular rules, rather than modeling the aggregate response to the shift. Similar models could be useful where the factors that influence the acceptability of an operation are uncertain or complex to model. Several approaches not explored in this study could provide further improvements and improve the forecast model's skill over the current model, especially for the aggregate policy difference. The use of non-parametric methods such as local polynomial regression, or classification and regression trees could provide improved discrimination between years in which the shift should be allowed or not. Regression trees however may artificially inflate the Other climate indices or a custom climate variable created from the NCEP/NCAR reanalysis data, could provide an improved predictive skill.

Chapter 4

Integrating policy shift forecast with the decision model

4.1 Introduction

In Chapter 2, an operations model was developed for Dworshak reservoir and used to model the difference between the normal policy and a policy in which the full allowable shift was used. In Chapter 3, a forecast was developed based on a logistic regression. This forecast gives an estimated probability of the shift being successful from hydrologic and climate variables. Forecasts at several lead times, the first of the month for January through April are developed, thus giving a useful information for both pre-shift planning and during the shift. This forecast was shown to have some skill in estimating which years the shift should be allowed. In this chapter, the integration of the forecast with a decision model will be shown, with impact of using the forecast to predict the fraction of the shift to be made.

4.2 Proposed Approach

One possible approach is to use the probability from the forecast as the fraction of shift to make. For example, a 30% probability of shifting would lead to 30% of the allowable shift to be shifted. This follows with the current shift procedure: years in which the operators are less certain about the need to shift, they may operate with only a partial or small shift, using more or less necessary. In this combined model, a similar approach will be taken, where the probability of a shift being allowed is used as the portion of shift to use. This hedging strategy attempts to take advantage of the shift when possible.

To accomplish this, first the forecast for the policy difference sequence is run at each lead time. The resulting set of probabilities is fed into a HEC-DSS database as a monthly time series. The operational model, modified to use a portion of the allowed shift when computing the flood control curves, is run for each year of the simulation. The allowed shift was computed from both the logistic regression model, as well as the previous shift estimated method. The fraction of the allowed shift for each method in Table 4.1. The values in the Forecast column show the probability of shift as determined by the logistic regression model, which is used as the fraction to shift for this model. The Quartile columns show the probability from the quartile rule to be used as the fraction of shift. The probabilities used in the forecast model are taken from the cross-validated values, using the cross-validation technique described in Chapter 3. All other input data is the same as was outlined for the models in Chapter 2.

The results using the forecasted probability as the amount to shift will be with using the probability from the informal estimate used for comparison in Chapter 3. The estimate, called the "quartile" method below, assigns a 75% probability of a shift when the forecasted inflow in the bottom quartile, 25% probability of a shift when the forecasted when it is in the top quartile, and a 50% probability for the two middle quartiles.

4.3 Results

Plots of the resulting storage in the reservoir are used, similar to those from Chapter 2, for model validation. The years in which either method allowed the shift to occur are shown in Table 4.2. A partial shift's ability to achieve the goals of the shift policy will be shown in a series of tables next to the results from the full shift as a point of comparison. To assess the ability to meet goal of the shift is to prevent the reservoir from having trapped storage, the final pool elevation on July 1st is examined for at for each year. In addition, the size of the spring freshet, measured as the maximum difference in outflow between the normal policy and the partial shift policy will be examined. The change in timing of the peak flow will be shown as well.

The plots of storage from the resulting operations are in Figure 4.1 through Figure 4.4. The normal, non-shifted policy is shown in blue, with the partial shift by the quartile method in red, and the forecast method in green. The observed flows are shown in light grey. In many years the partial shift policies made very little difference from the normal policy, especially for high inflow volume years, where the probability was low.

The difference in the rule violations is shown in Table 4.2, showing the years in which the partial shift is allowed, highlighting those added by the partial shift operation with the symbol **P**. For the policy difference sequence, four additional years are allowed by the partial shift, however looking at their probabilities and the storage curves, these are years in which the partial shift is very close to the normal policy. The partial shift reduces the number of violations of the flooding condition at Spalding from four violations to one. In only the year 2011 did the full shift policy perform better than the partial shift policy, specifically for the total dissolved gas limit.

Table 4.3 shows the final pool elevations for years in which the reservoir did not reach the minimum elevation of 1595 feet at which the refill is considered to be successful. For years in which the partial shift made a difference in the refill level, the difference is shown in the fourth column. The last two columns show years in which the rules would allow a partial shift by the quartile method or the forecast method.

Table 4.4 shows the resulting changes in reservoir peak discharge flow and peak discharge timing for years in which it makes a difference. The difference in flow from the non-shifted policy is computed, as is the change in timing. The last two columns show which years the the shift policy by each method is allowed.

4.4 Implications

4.4.1 Shift Volatility

The probability of the shift being allowed, and thus the fraction of shift used in this model is shown in Table 4.2. With the forecast method, the probability of shift never varied from March to April by more than 0.29 in either direction, and for change in probability from March to April,

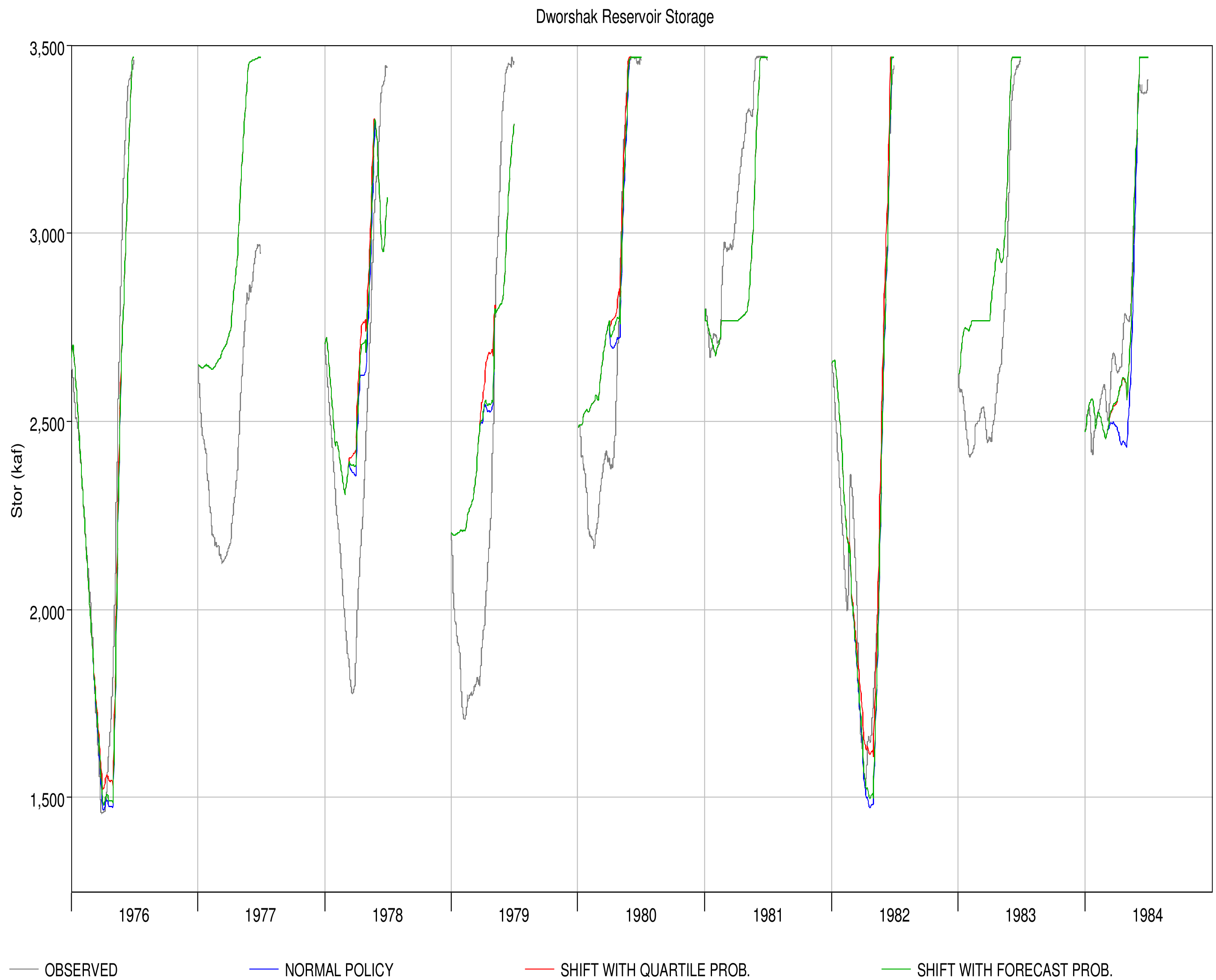

Figure 4.1: Modeled storage at Dworshak Reservoir, 1976 to 1984.

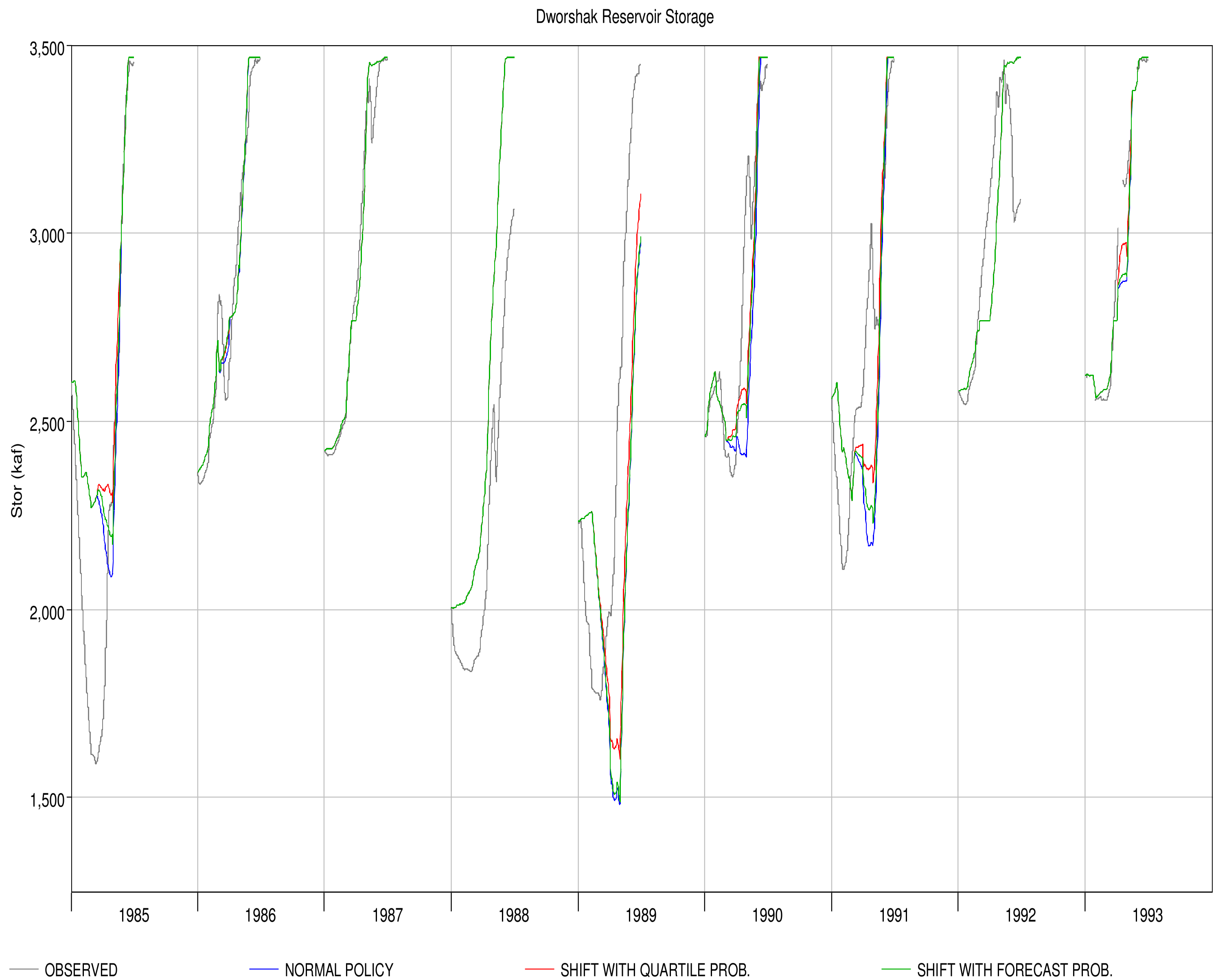

Figure 4.2: Modeled storage at Dworshak Reservoir, 1985 to 1993.

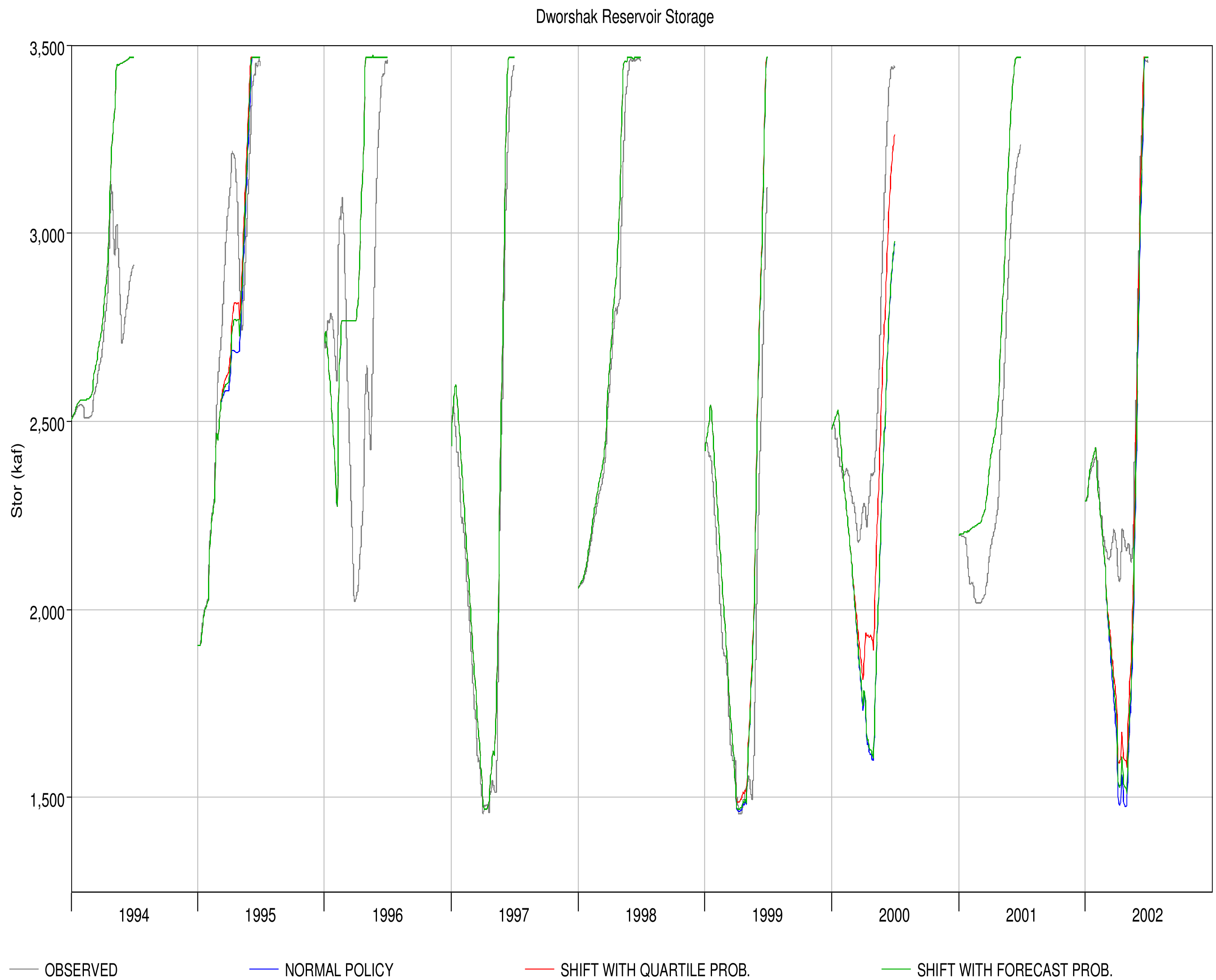

Figure 4.3: Modeled storage at Dworshak Reservoir, 1994 to 2002.

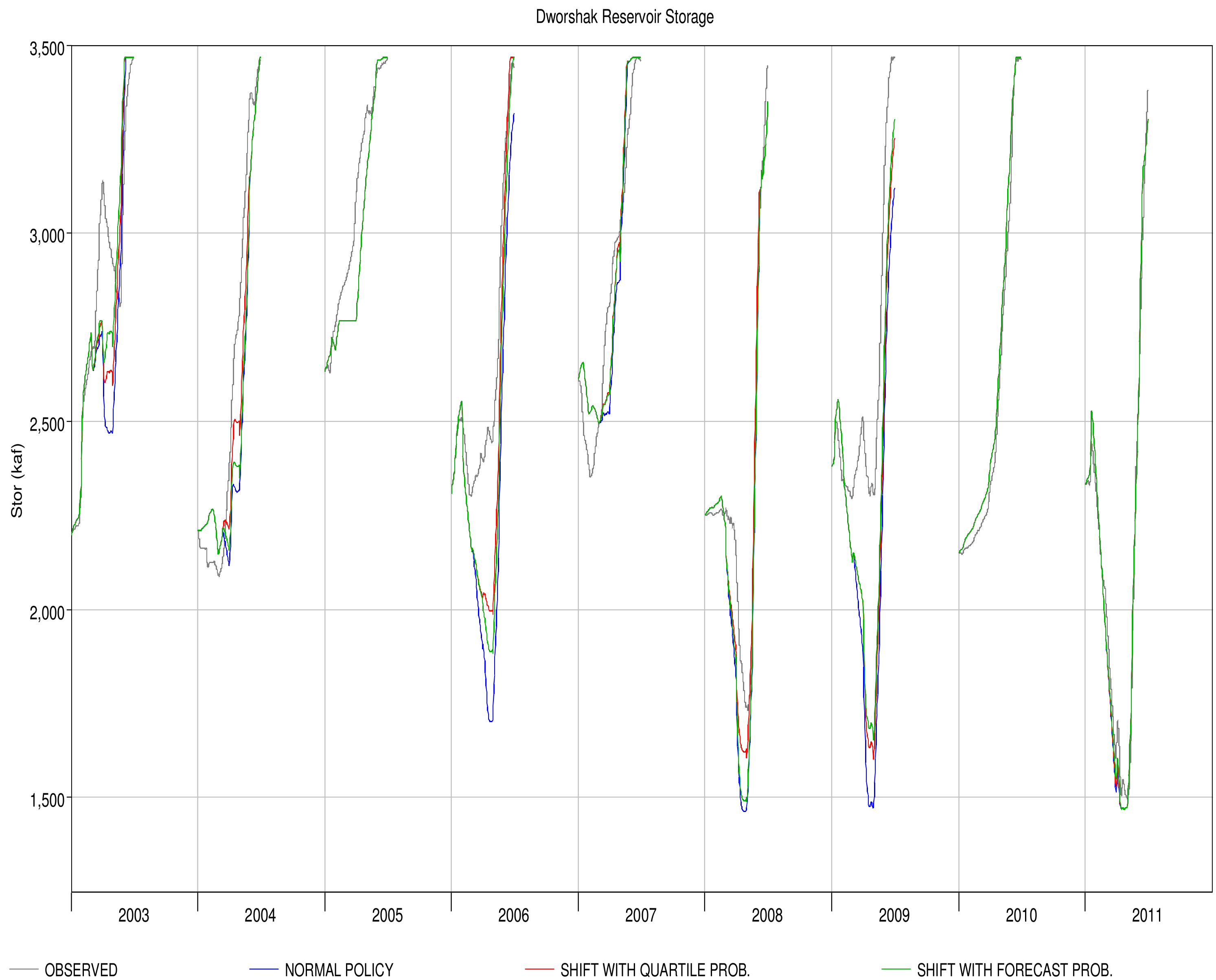

Figure 4.4: Modeled storage at Dworshak Reservoir, 2003 to 2011.

the the 25^{th} and 75^{th} quantiles are -0.05 to 0.05. Thus, half of the time the change in shift amount was never more than 5% of the full shift volume. The forecast appears then to not have much volatility, which is good for using it to predict how much of a shift to make, as a large volatility could potentially lead to additional rule violations from rapidly switching in and out of a shift. The quartile method has less years with a change; only three years where the fraction of shift changed by 0.25, and none with a large change. This method appears to be relatively stable as well.

4.4.2 Impact on Operational Constraints

Using the forecast method increased the number of years in which a shift can be made more significantly than the quartile method. In only one year, for one rule, did the quartile method allow shift that was not allowed using the forecast. For the aggregated policy difference sequence, the forecast method allowed six additional years. The forecast method appears to be more forgiving for operations than the quartile method. This is possibly a result of increased model volatility, with the forecast method changing the amount that can be shifted from March to April.

4.4.3 Refill Impacts

As outlined in the introduction, not refilling the reservoir can produce problems later in the year in which water is demanded for use in supplementing flow, providing environmental flows, and thermal regulation downstream. In years in which the reservoir did not refill under a non-shifted policy, the shift policies only allowed complete refill in one year, 2006, during which the shift was not allowed using either method. In that year, both policies allowed the same amount of refill to the maximum pool elevation of 1600 feet. Of the other three years in which a shift made a difference, the quartile method produced a larger refill on average, with only one year where the forecast method produced a greater refill than the quartile method. Only two years resulted in a refill of larger than 1 with the forecast method, while all of the years in which the quartile increased the final pool elevation, it was greater than 7 feet. The shift from the forecast method was allowed in three of the four years where a shift allowed additional refill, while the shift from the quartile method was only allowed in two of those four years.

The quartile method appears to produced a larger refill, however is allowed in less years than the forecast method. The forecast method created a small difference in two of the years. The forecast method seems to be less effective for achieving the goal of refilling the reservoir.

4.4.4 Flow Impacts

Out of the 36 years simulated, 19 resulted in an increased maximum discharge from using either shift policy. The peak discharge did not change significantly with the forecast method, with the median peak discharge changing from 30 kcfs with the quartile method to 28.75 kcfs with the forecast. Compared to the normal policy, the forecast method produced a smaller change in peak discharge than the quartile method, with an increase of 0.68 kcfs as the median change. The quartile method produced a larger change in discharge, with an increase 3.17 kcfs as the median change. The maximum change was approximately the same, nearly 16 kcfs, while the quartile method having a minimum change of zero, and the forecast method having only one year where it actually decreased the peak discharge. The change of timing in peak discharge had a median value of zero days for both policies, however the quartile method had a large inner-quartile (IQR) range, of 20.5 days. The forecast method had a smaller IQR, 10.5 days, with the median and the 25^{th} percentile being zero, also the median. Both had the same maximum and minimum change in timing for the peak discharge. In years in which the peak flow was modified by the shift, a shift by the forecast method was allowed more frequently than the quartile method.

4.5 Summary

Using the regression model from Chapter 3 to drive the decision support system developed in Chapter 2 shows one example of how it could be used in the operations of the reservoir, although in an imperfect case. The information provided from the forecast model will be useful in the actual operations of the reservoir to help make the operational decision of how much to shift, although as seen in the results, the forecasted probability does not directly translate to a good estimate of how much the reservoir should be shifted. This particular application could be improved with other techniques, such as a categorical forecast of the amount of shift to use, in which the operational model and forecast outlined in this paper would be repeated not just for a full shift but for multiple fractions, with the reservoir operated at the most likely fraction of shift that will not increase rule violations.

Several objectives are examined in this study with respect to the shift and a simplification was made that any increase in violations is enough to make the shift unacceptable in a particular year, a multi-objective decision making process could be useful here. The regression based forecast in providing a probability of a particular rule violation could also be used to estimate risk from taking on a certain operation, which combined with risk estimations from other policies could be used to compute a risk from shifting versus not shifting. Including a sequence in the model based on a benefit of shifting, rather than a cost, would be needed. An example would be to look at the refill criteria and use the logistic regression approach to predict years in which the shift would provide a pool elevation above that from not shifting. This could also applied to look at when certain flow criteria are met by shifting. Combining the probability from these models and the potential benefit of meeting those goals could then be used as the benefit side of a cost-benefit analysis for shifting. This allows the incorporation of trade-offs between otherwise incomparable rules. A benefit to this risk-based approach would be the ability to use the rule sequence models, which have better skill than the policy difference model.

Year	Forecast March	Forecast April	Forecast Change	Quartile March	Quartile April	Quartile Change	Shift Allowed by Policy Diff.
1976	0.95	0.91	-0.04	0.75	0.75		
1977	0.54	0.77	0.24	0.75	0.75		Yes
1978	0.33	0.29	-0.04	0.75	0.75		
1979	0.84	0.69	-0.15	0.75	0.75		
1980	0.62	0.78	0.15	0.75	0.75		
1981	0.40	0.48	0.08	0.75	0.75		Yes
1982	0.61	0.59	-0.02	0.75	0.75		
1983	0.46	0.42	-0.05	0.50	0.50		Yes
1984	0.23	0.33	0.10	0.50	0.50		
1985	0.73	0.82	0.09	0.75	0.75		
1986	0.61	0.53	-0.08	0.50	0.50		
1987	0.54	0.83	0.29	0.75	0.75		Yes
1988	0.59	0.89	0.29	0.50	0.75	0.25	Yes
1989	0.98	0.97	-0.01	0.75	0.75		
1990	0.06	0.10	0.04	0.50	0.50		
1991	0.18	0.21	0.04	0.50	0.50		
1992	0.81	0.82	0.01	0.50	0.50		Yes
1993	0.20	0.30	0.10	0.50	0.50		
1994	0.22	0.18	-0.04	0.50	0.50		Yes
1995	0.50	0.33	-0.17	0.50	0.25	-0.25	
1996	0.04	0.02	-0.02	0.25	0.50	0.25	Yes
1997	0.48	0.32	-0.16	0.50	0.50		Yes
1998	0.06	0.06	-0.01	0.50	0.50		Yes
1999	0.21	0.24	0.03	0.50	0.50		
2000	0.06	0.03	-0.03	0.25	0.25		
2001	0.55	0.51	-0.04	0.50	0.50		Yes
2002	0.32	0.39	0.07	0.50	0.50		
2003	0.34	0.24	-0.09	0.50	0.50		
2004	0.41	0.30	-0.11	0.25	0.25		
2005	0.09	0.05	-0.04	0.25	0.25		Yes
2006	0.04	0.05	0.01	0.25	0.25		
2007	0.11	0.06	-0.06	0.25	0.25		
2008	0.13	0.05	-0.08	0.25	0.25		
2009	0.13	0.10	-0.03	0.25	0.25		
2010	0.58	0.29	-0.29	0.25	0.25		Yes
2011	0.05	0.06	0.01	0.25	0.25		Yes
Min	0.04	0.02	-0.29	0.25	0.25	-0.25	
Median	0.37	0.31	-0.02	0.50	0.50		
Maximum	0.98	0.97	0.29	0.75	0.75	0.25	

Table 4.1: Fractional shift used for each year at each time. The new model is shown in the forecast columns, while the quartile columns show the shift probability from the quartile-based procedure. As the shift only makes a difference after March 1st, only the March and April values are presented. The change column shows the difference in the April probability and March probability. Blank spaces represent years where no change occurred. The shift allowed column shows which years the operational model from Chapter 2 resulted in the shift being allowed.

Year	Spalding > 80kcfs	SCA Limit	FC Space Requirement	TDG Limit	Rate of ΔOutflow	Policy Difference
1976	X	X	X	X	X	X
1977	X	X	X	X	X	X
1978	X		X			
1979	X	**F**	X	**F**	**F**	**F**
1980	X		X	X		
1981	X	X	X	X	X	X
1982	X	**F**	X	X	X	**F**
1983	X	X	X	X	X	X
1984	X	X	X			
1985	X		X	X		
1986	X			X	X	
1987	X	X	X	X	X	X
1988	X	X	X	X	X	X
1989	X	X	X	X	X	X
1990	X		X	X		
1991	X		X	X		
1992	X	X	X	X	X	X
1993	**F**	**F**	X		**F**	
1994	X	X	X	X	X	X
1995	X		X			
1996	X	X	**F**	X	X	**F**
1997	X	X	X	X	X	X
1998	X	X	X	X	X	X
1999	X	**F**	X	X	X	**F**
2000	X	X	X	X	**F**	**F**
2001	X	X	X	X	X	X
2002	X		X	X	X	
2003	**Q**			X		
2004	X	**F**	X			
2005	X	X	X	X	X	X
2006	X		X	X		
2007	X	X	X	X		
2008	X	**F**	X		X	
2009	X	X	X	X	X	X
2010	X	X	X	X	X	X
2011	X	X	X	**F**	X	**F**
Quartile	35	20	33	28	22	15
Forecast	35	26	34	30	25	21
Change	1	6	1	2	3	6

Table 4.2: Years in which a partial shift is allowed, separated by rules and combined under the Policy Difference column. X marks spots where both models partial shifts are allowed, with **F** for years in which only the partial shift from the forecast is allowed, while **Q** shows where the quartile model only results in a partial shift. The final row shows the number of additional years in which a partial shift is allowed over the full shift.

Year	Normal Pool Elev.	Quartile Pool Elev.	Forecast Pool Elev.	Quartile Δ Pool Elev.	Forecast Δ Pool Elev.	Quartile Allowed	Forecast Allowed
1978	1579.10	1579.10	1579.10	-	-		
1979	1590.40	1590.40	1590.40	-	-		Yes
1989	1572.30	1579.70	1572.80	7.40	0.50	Yes	Yes
2000	1571.60	1588.90	1572.00	17.30	0.40		Yes
2006	1591.90	1600.00	1600.00	8.10	8.10		
2008	1593.80	1593.80	1593.80	-	-		
2009	1580.70	1588.30	1591.10	7.60	10.40	Yes	Yes
2011	1591.00	1591.00	1591.00	-	-		Yes

Table 4.3: Final pool elevation for years in which the reservoir did not reach the minimum elevation to be considered refilled, 1595 feet. The first three columns show the pool elevation reached on June 30$^{\text{th}}$, the next two columns show the difference from the normal policy that the two forecast methods made, and the last two columns shows which years in which the model's partial shift is allowed by the "Policy difference" sequence. Dashes are used for years in which the change in elevation from a non-shifted policy was zero.

Year	Peak Discharge Quartile kcfs	Peak Discharge Forecast kcfs	Δ Max. Dis. Quartile kcfs	Δ Max. Dis. Forecast kcfs	Δ Day of Peak Quartile Days	Δ Day of Peak Forecast Days	Quartile Allowed	Forecast Allowed
1976	22.15	20.81	1.24	-0.10	18	-	Yes	Yes
1978	30.00	30.00	0.40	0.40	-38	-38		
1979	30.00	30.00	-	-	-6	-		Yes
1980	30.00	30.00	9.21	9.21	29	29		
1982	28.99	28.94	0.06	0.01	-	-		Yes
1984	30.00	30.00	10.39	10.39	-31	-31		
1985	29.86	29.16	3.70	3.00	15	15		
1989	25.12	24.20	1.26	0.34	-	-	Yes	Yes
1990	30.00	30.00	9.20	9.20	6	6		
1991	30.00	29.64	4.29	3.93	29	29		
1993	30.00	22.04	8.00	0.04	-18	-1		
1995	30.00	28.75	15.87	14.61	63	63		
1999	22.83	22.82	0.02	0.01	-	-		Yes
2000	26.58	23.55	3.17	0.14	17	-		Yes
2002	24.97	24.37	1.28	0.68	-	-		
2004	30.00	27.18	9.10	6.27	-31	-31		
2007	30.00	30.00	15.45	15.45	47	47		
2009	27.50	27.50	1.08	1.08	-	-	Yes	Yes
2011	22.69	22.91	0.16	0.38	-	-		Yes
Min.	22.15	20.81	0.00	-0.10	-38	-38		
25%	25.85	23.88	0.74	0.09	-3	0		
Median	30.00	28.75	3.17	0.68	0	0		
75%	30.00	30.00	9.15	7.74	17.50	10.50		
Max.	30.00	30.00	15.87	15.45	63	63		

Table 4.4: Change in discharge characteristics for years in which either shift policy makes a difference from the normal policy. Dashes are used where the difference during that year is zero.

Chapter 5

Conclusions and Key Results

5.1 Future Directions

Many possibilities in this model were left unexplored. A few key areas that should be further explored are:

- A risk based model looking at the impact of a shift to different levels. Using a more refined categorical forecast along with information about the importance of each policy would allow the individual rule forecasts to be incorporated in a multi-objective optimization approach to deciding to which level the reservoir should be evacuated.

- Other approaches for the forecast should be considered, including categorical forecasts looking at fractions of the allowable shift and their impacts, non-parametric methods that may provide better discrimination in predicting the allowable shift.

- A better understanding of the spring water supply forecast, and possible refinements would also improve operations and reduce the possibility of a shift occurring in a bad year.

5.2 Study Conclusions

The shift policy presents a difficult problem to model, as its purpose is rooted in the uncertainty of the water supply forecast. To predict in which years the shift policy should be used, an alternative forecast needs to be developed. Chapter 2 presented an approach using an operational model to figure out which years the policy is appropriate. Through examining which rule was the limiting factor for operations, or a value computed from the model's output, it is possible to develop a preferred decision for each year..

The results from the operational model was combined with a logistic regression model in Chapter 3 to forecast the probability of the policy being allowed. This was shown to be successful in that the model had skill greater at early lead times than a baseline model using the predicted inflow. A logistic regression model can be used for individual goals or rules, either to forecast impacts of a policy decision on particular rules, such as looking at impacts to an environmental flow criteria, or to inform a decision with a cost-benefit analysis. The weaknesses in using a logistic regression approach are for modeling sequences very rare events. Through combining an operational model to look at possible scenarios for each policy, determining which is preferred for each year, and then using a logistic regression approach, otherwise complicated policy decisions can be predicted.

The resulting model can be used to inform operational decisions, and one such approach, shown in Chapter 4 is shown with using the forecasted probability as the fraction of shift to make. It appears that while this may provide some use, the low probability of shift in some years limit's the impact made with respect to the goal of being able to refill the reservoir, but did create a spring freshet in some years. While this process should not replace the decision making process for deciding how much to shift, it should provide additional information. Chapter 4 should be considered as an example for what could be done with a forecast built on a decision variable.

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Appendix A

RiverWare Model Rules

A.1 Policy Rules

RPL Set: C:\Documents and Settings\Administrator\My Documents\Dropbox\Thesis RW Model\dwr_model\ThesisRules.rls
Description:

Policy Group: Mandatory Constraints (Level I)
Description:

Rule: 1kcfs Minimum Flow
Priority: 1
Description:

```
IF ( Dworshak Res.Outflow [ ] < Dworshak Rule Data.MinimumOutflow [ ] ) THEN
   Dworshak Res.Outflow [ ] = Dworshak Rule Data.MinimumOutflow [ ]
   Rule Status.Min Flow [ ] = 1.00000000
ENDIF
```

Rule: 700KAF minimum FC space 15DEC-1APR
Priority: 2
Description:

```
IF ( @"t" <= @"24:00:00 April 1, Current Year" AND Dworshak Res.Storage [ ] > ElevationToStorage ( % "Dworshak Res" ,
                                                                                                  1,600.00000000 "ft" )
     - Dworshak Rule Data.Spring FC Minimum Space [ ] ) THEN
   Dworshak Res.Outflow [ ]
      = Max ( Min ( SolveOutflow ( % "Dworshak Res" ,
                                   Dworshak Res.Inflow [ ] ,
                                   Dworshak Rule Data.Max Storage [ ]
                                   - Dworshak Rule Data.Spring FC Minimum Space [ ] ,
                                   Dworshak Res.Storage [ @"t - 1" ] ,
                                   @"t" ) ,
                    DworshakMaxOutflow ( @"t" ) ) ,
              Dworshak Rule Data.FC_MinimumOutflow [ ] )
   Rule Status.Min FC Space [ ]
      = 1.00000000
ENDIF
```

Rule: Reduce Surcharge
Priority: 3
Description:

```
IF ( Dworshak Res.Pool Elevation [ ] > Dworshak Rule Data.SurchargeElevation [ ] ) THEN
   Dworshak Res.Outflow [ ] = Min ( SolveOutflow ( % "Dworshak Res" ,
                                                   Dworshak Res.Inflow [ ] ,
                                                   Dworshak Rule Data.Max Storage [ ] ,
                                                   Dworshak Res.Storage [ @"t - 1" ] ,
                                                   @"t" ) ,
                                    DworshakMaxOutflow ( @"t" ) )
   Rule Status.Reduce Surcharge [ ] = 1.00000000
ENDIF
```

Rule: Snow Covered Area Limit on FC Space
Priority: 4
Description: Not implemented due to a lack of historical data

```
IF ( Dworshak Res.Storage [ ] > ElevationToStorage ( % "Dworshak Res" ,
                                                     1,600.00000000 "ft" ) - scaStorageReq ( ) ) THEN
   Dworshak Res.Outflow [ ] = Max ( Min ( SolveOutflow ( % "Dworshak Res" ,
                                                         Dworshak Res.Inflow [ ] ,
                                                         Dworshak Rule Data.Max Storage [ ] - scaStorageReq ( ) ,
                                                         Dworshak Res.Storage [ @"t - 1" ] ,
                                                         @"t" ) ,
```

```
                    DworshakMaxOutflow ( @"t" )
                Dworshak Rule Data.FC_MinimumOutflow [ ]
    Rule Status.SCA Limit [ ] = 1.00000000
ENDIF
```

Policy Group: Major Constraints (Level II)
Description:

Rule: Rate of change in release - Stage at Peck
Priority: 5
Description:

```
IF ( Abs ( GetHourlyChangeInflow ( ) ) > Abs ( GetMaxChangeInFlow ( ) ) ) THEN
    Dworshak Res.Outflow [ ] = Max ( Min ( IF ( GetHourlyChangeInflow ( ) > 0.00000000 "cfs" ) THEN
                                             Min ( Dworshak Res.Outflow [ ] ,
                                                   Dworshak Res.Outflow [ @"t - 1" ] + 24.00000000 * GetMaxChangeInFlow ( ) )
                                          ELSE
                                             Max ( Dworshak Res.Outflow [ ] ,
                                                   Dworshak Res.Outflow [ @"t - 1" ] - 24.00000000 * GetMaxChangeInFlow ( ) )
                                          ENDIF ,
                                          DworshakMaxOutflow ( @"t" ) ) ,
                                    Dworshak Rule Data.FC_MinimumOutflow [ ] )
    Rule Status.Change in Release [ ] = 1.00000000
ENDIF
```

Rule: Evacuation below ability to refill to 1570 by July 1 w/ 95% certainty
Priority: 6
Description:

```
IF ( @"t" != @"24:00:00 July 1, Current Year" ) THEN
    IF ( Dworshak Res.Storage [ ] + Dworshak Rule Data.ForecastedSpringInflow [ ] < ElevationToStorage ( % "Dworshak Res" ,
                                                                                                          1,570.00000000 "ft" ) ) THEN
        Dworshak Res.Outflow [ ]
          = Min ( DworshakMaxOutflow ( @"t" ) ,
                  Max ( SolveOutflow ( % "Dworshak Res" ,
                                       Dworshak Res.Inflow [ ] ,
                                       ElevationToStorage ( % "Dworshak Res" ,
                                                            1,570.00000000 "ft" ) - Dworshak Rule Data.ForecastedSpringInflow [ ] ,
                                       Dworshak Res.Storage [ @"t" - 1.00000000 "day" ] ,
                                       @"t" ) ,
                        Dworshak Rule Data.FC_MinimumOutflow [ ] ) )
        Rule Status.Evacuation Below 95p Refill [ ]
          = 1.00000000
    ENDIF
ENDIF
```

Policy Group: Normal Operations
Description:

Rule: Fill at 4kcfs
Priority: 7
Description:

```
IF ( Dworshak Rule Data.SpaldingFloodingFlag [ ] == 2.00000000 ) THEN
    Dworshak Res.Outflow [ ] = Min ( Dworshak Rule Data.RecedingOutflow [ ] , DworshakMaxOutflow ( @"t" ) )
ENDIF
```

Rule: Maintain Storage While Inflow > 30kcfs
Priority: 8

Description:

```
IF ( Dworshak Rule Data.SpaldingFloodingFlag [ ] == 1.00000000 ) THEN
  IF ( Dworshak Res.Inflow [ ] > Dworshak Rule Data.ReceedingFlowThreshold [ ] ) THEN
    Dworshak Res.Outflow [ ] = Max ( Min ( SolveOutflow ( % "Dworshak Res" ,
                                                          Dworshak Res.Inflow [ ] ,
                                                          Dworshak Rule Data.ReceedingFloodControlStorage [ ] ,
                                                          Dworshak Res.Storage [ @"t - 1" ] ,
                                                          @"t" ) ,
                                           DworshakMaxOutflow ( @"t" ) ) ,
                                     Dworshak Rule Data.FC_MinimumOutflow [ ] )
  ELSE
    Dworshak Rule Data.SpaldingFloodingFlag [ ] = 2.00000000
  ENDIF
ENDIF
```

Rule: If SpaldingFlag, Limit Flows
Priority: 9
Description:

```
IF ( Dworshak Rule Data.SpaldingFloodingFlag [ ] == 1.00000000 OR Gauge at Spalding.Inflow [ ] > Dworshak Rule Data.SpaldingMaxFlow [ ] ) THEN
  Dworshak Rule Data.SpaldingFloodingFlag [ ] = 1.00000000
  Dworshak Res.Outflow [ ] = Max ( Dworshak Rule Data.FC_MinimumOutflow [ ] ,
                                   Min ( Dworshak Rule Data.SpaldingMaxFlow [ ] - Main Fork Clearwater River.Inflow [ ] ,
                                         DworshakMaxOutflow ( @"t" ) ) )
ENDIF
```

Rule: Follow Rule Curve
Priority: 10
Description:

```
Dworshak Res.Outflow [ ]
  = Max ( Min ( SolveOutflow ( % "Dworshak Res" ,
                               Dworshak Res.Inflow [ ] ,
                               Dworshak Rule Data.Max Storage [ ]
                               - Dworshak Rule Data.Flood Control Space [ LookAheadPeriod ( @"t" ) ] ,
                               Dworshak Res.Storage [ @"t - 1" ] ,
                               @"t" )
                / LENGTH GetDates ( @"t - 1" ,
                                    LookAheadPeriod ( @"t" ) ,
                                    "1 Days" ) ,
                DworshakMaxOutflow ( @"t" ) ) ,
          Dworshak Rule Data.FC_MinimumOutflow [ ] )
```

Utility Group: Dworshak Functions
Description:

Function: DworshakMaxOutflow2
Return Type: NUMERIC
Arguments: (DATETIME time)
Description:

```
MinItem ( { GetMaxOutflowGivenHW ( % "Dworshak Res" ,
                                   Dworshak Res.Pool Elevation [ OffsetDate ( time ,
                                                                              - 1.00000000 ,
                                                                              "1 days" ) ] ,
                                   time ) ,
            MaxReleaseAndSpill ( @"t" ) * 0.90000000 ,
            IF ( Dworshak Res.Pool Elevation [ time - 1.00000000 "day" ] < 1,460.00000000 "ft" ) THEN ,
```

```
SolveOutflow ( % "Dworshak Res" ,
               Dworshak Res.Inflow [ time - 1.00000000 "day" ] ,
               Dworshak Rule Data.Min Storage [ ] + 0.00000000 "KAF" ,
               Dworshak Res.Storage [ time - 1.00000000 "day" ] ,
               time )
ELSE
   MaxReleaseAndSpill ( @"t" ) * 0.90000000
ENDIF
24.00000000 "kcfs"
```

Function: DworshakMaxOutflow
Return Type: NUMERIC
Arguments: (DATETIME time)
Description:

```
Dworshak Rule Data.MaxOutflow [ ]
```

Function: GetMaxChangeInFlow
Return Type: NUMERIC
Arguments: ( )
Description:

```
IF ( GetHourlyChangeInflow ( ) > 0.00000000 "cfs" ) THEN
   TableLookup ( Dworshak Rule Data.IncreasingReleaseLimitAtPeck ,
                 0.00000000 ,
                 1.00000000 ,
                 Gauge at Peck.Inflow [ ] ,
                 @"t" ,
                 FALSE ) * 1.00000000
ELSE
   Max ( TableLookup ( Dworshak Rule Data.DecreasingReleaseLimitsAtPeck ,
                       0.00000000 ,
                       1.00000000 ,
                       Gauge at Peck.Inflow [ ] ,
                       @"t" ,
                       FALSE ) * 1.00000000 ,
         Dworshak Rule Data.MinimumOutflow [ ] )
ENDIF
```

Function: GetHourlyChangeInflow
Return Type: NUMERIC
Arguments: ( )
Description:

```
( Dworshak Res.Outflow [ ] - Dworshak Res.Outflow [ OffsetDate ( @"t" ,
                                                               - ( Dworshak Rule Data.PeckChangeInFlowLookbackWindow [ ] ) ,
                                                               "1 days" ) ] )
-------------------------------------------------------------------------------------------------
                  ( 24.00000000 * Dworshak Rule Data.PeckChangeInFlowLookbackWindow [ ] )
```

Function: GetTargetDate
Return Type: DATETIME
Arguments: (DATETIME time)
Description:

```
@"24:00:00 January 1, Current Year"
+ TableLookup ( Dworshak Rule Data.TargetDates ,
                0.00000000 ,
                1.00000000 ,
                IF ( LeapYear ( time ) AND time > @"24:00:00 February 28, Current Year" ) THEN ,
                   GetDayOfYear ( time )
```

```
        - 1.00000000 "day"
      ELSE
        GetDayOfYear ( time )
      ENDIF
      time ,
      TRUE
+ IF ( LeapYear ( time ) AND time > @"24:00:00 February 28, Current Year" ) THEN
    1.00000000 "day"
  ELSE
    0.00000000 "day"
  ENDIF
```

Function: MaxReleaseAndSpill
Return Type: NUMERIC
Arguments: (DATETIME time)
Description:

```
( TableInterpolation ( Dworshak Res.Regulated Spill Table ,
                       0.00000000 ,
                       1.00000000 ,
                       Dworshak Res.Pool Elevation [ time
                                                     - 1.00000000 "day" ] ,
                       time )
  + TableInterpolation ( Dworshak Res.Max Release ,
                         0.00000000 ,
                         1.00000000 ,
                         Dworshak Res.Pool Elevation [ time
                                                       - 1.00000000 "day" ] ,
                         time ) )
```

Function: LookAheadPeriod
Return Type: DATETIME
Arguments: (DATETIME DaysAhead)
Description:

```
NumberToDate ( Min ( DateToNumber ( DaysAhead ) , DateToNumber ( @"Finish Timestep" ) ) )
```

Function: scaStorageReq
Return Type: NUMERIC
Arguments: ( )
Description:

```
TableInterpolation ( Dworshak Rule Data.SCA Flood Control Space , 0.00000000 , 1.00000000 , Dworshak Rule Data.Fraction SCA [ ] , @"t" )
```

A.2 Expression Slot Functions

RPL Set: Expression Slot Functions Set
Description:

Utility Group: Dworshak Functions
Description:

Function: DworshakMaxOutflow
Return Type: NUMERIC
Arguments: (DATETIME time)
Description:

```
MinItem ( { GetMaxOutflowGivenHW ( % "Dworshak Res" ,
                                   Dworshak Res.Pool Elevation [ OffsetDate ( time ,
                                                                              - 1.00000000 ,
                                                                              "1 days" ) ] ,
                                   time ) ,
            MaxReleaseAndSpill ( @"t" ) * 0.90000000 ,
            IF ( Dworshak Res.Pool Elevation [ time - 1.00000000 "day" ] < 1,460.00000000 "ft" ) THEN ,
                SolveOutflow ( % "Dworshak Res" ,
                               Dworshak Res.Inflow [ time - 1.00000000 "day" ] ,
                               Dworshak Rule Data.Min Storage [ ] + 0.00000000 "KAF" ,
                               Dworshak Res.Storage [ time - 1.00000000 "day" ] ,
                               time )
            ELSE
                MaxReleaseAndSpill ( @"t" ) * 0.90000000
            ENDIF
            24.00000000 "kcfs" } )
```

Function: MaxReleaseAndSpill
Return Type: NUMERIC
Arguments: (DATETIME time)
Description:

```
( TableInterpolation ( Dworshak Res.Regulated Spill Table ,
                       0.00000000 ,
                       1.00000000 ,
                       Dworshak Res.Pool Elevation [ time
                                                     - 1.00000000 "day" ] ,
                       time )
  + TableInterpolation ( Dworshak Res.Max Release ,
                         0.00000000 ,
                         1.00000000 ,
                         Dworshak Res.Pool Elevation [ time
                                                       - 1.00000000 "day" ] ,
                         time ) )
```

A.3 Initialization Rules

RPL Set: Initialization Rules Set
Description:

Policy Group: Intialization
Description:

Rule: Set Initial Conditions
Priority: 1
Description:

```
Dworshak Res.Pool Elevation [ @"24:00:00 January 1, Current Year" ]
   = StorageToElevation ( % "Dworshak Res" ,
                          Dworshak Rule Data.Observed Storage [ @"24:00:00 January 1, Current Year" ] )
```

Rule: Zero Rule Status Fields
Priority: 2
Description:

```
FOREACH ( SLOT s IN GetSeriesSlots ( % "Rule Status" ) ) DO
   FOREACH ( DATETIME d IN GetDates ( RunStartDate ( ) , RunEndDate ( ) , "1 days" ) ) DO
      s [ d ] = 0.00000000
   ENDFOREACH
ENDFOREACH
```