USING LARGE-SCALE CLIMATE INFORMATION TO FORECAST SEASONAL STREAMFLOW IN THE TRUCKEE AND CARSON RIVERS

by

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

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Thesis directed by Assistant Professor Balaji Rajagopalan

Water managers in the Truckee and Carson River Basins depend on seasonal forecasts to assist with oeprations and decision-making. Current forecasting techniques, however, are not skillful enough and do not provide adequate lead-time to effectively manage the system. In this study, we develop a seasonal forecasting model to assist with water resources decision-making in the Truckee-Carson River System. We utilize large-scale climate information as a spring runoff predictor to improve the skill and lead-time of the forecasts. Nonparametric stochastic forecasting techniques are used to provide ensemble (probabilistic) forecasts that aid in decision-making. We demonstrate the utility of the improved forecasts by coupling them with a simplified seasonal policy model and analyze the resulting decision variables.

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Chapter 1

Introduction

Water managers in the western U.S. and throughout the world are facing the increasing problem of meeting water demands for a wide variety of purposes including municipal, industrial, agricultural, power production, and environmental. Strict planning is necessary to meet demands on water quality, volume, timing and flowrates. This is particularly true in the Truckee-Carson Basin where snowmelt from the Sierra Nevada Mountains is virtually the only water source for the semi-arid desert of western Nevada. With the bulk of the water in the Truckee and Carson Rivers coming in just four months (April, May, June, and July) and a potential evaporation to precipitation ratio of 12:1 in most of the basin, water managers must plan very carefully how they will meet all the demands. Management issues are particularly complex due to the large number or reservoirs, diversions, and varying demands in the basin. The U.S. Bureau of Reclamation (USBR) manages the operations on the Truckee and Carson Rivers. The forecast for the upcoming water year is instrumental to their planning process. Skilled forecasts provide the information necessary to facilitate effective planning of reservoir releases and diversions throughout the system.

1.1 Motivation

One of the key components of water management on the Truckee-Carson river system is the interbasin transfer of water from the Truckee River through the Truckee

Canal to Lahontan Reservoir, on the Carson River, to provide water for the Newlands Project irrigation district and other water users. Water managers use the spring streamflow forecasts for the Truckee and Carson Rivers to determine the amount of water to be diverted through the Truckee Canal. Due to the limited capacity of the canal and the short water season, skilled forecasts of spring flows on these rivers are important for efficient water management in the system.

The Newlands Project is a network of canals, ditches and reservoirs developed by the USBR in the early 1900s to provide the water necessary for the successful development of agriculture in western Nevada. Key to the Newlands Project's success is the 32.5 mile (52 kilometer) Truckee Canal. The primary operating criterion for the Newlands Project is to maximize use of water from the Carson River and minimize diversions of Truckee River water into the Truckee Canal. If managers divert too much water into the Truckee Canal, they leave insufficient flows in the Truckee River to support other water users, including endangered fish populations, along the last reach of the river. Yet, if managers divert too little water, farmers in the Newlands Project district will have insufficient water to sustain their crops. The USBR Lahontan Basin Area Office utilizes spring streamflow forecasts for the Truckee and Carson Rivers to determine the allowable diversions through the Truckee Canal.

The USBR Lahontan Basin Area office needs an improved forecasting model to use for watershed management and decision-making. Accuracy of forecasts has become evermore important in the water-stressed Truckee and Carson River Basins. Recently implemented policies limit diversions through the Truckee Canal and require specific reservoir releases to aid in the protection of the endangered fish populations. These policies depend heavily on the seasonal streamflow forecast. The current USBR forecasting model is limited in the skill, the lead-time, and the quantification of uncertainty in the forecasts it offers. The current forecasting method uses linear regression based on the existing snowpack. Though the basin is predominantly snowmelt driven, using only snowpack information in the forecast means the forecast is not available until the beginning of January-after a reasonable amount of snow has fallen. Furthermore, because this forecast only incorporates weather that has already occurred (i.e., snow that has already fallen) it cannot do a good job of projecting the accumulation season's total snow, and hence, runoff to come. An improved seasonal forecasting model is necessary to strengthen seasonal planning strategies in the Truckee and Carson Basins.

1.2 Study Area

The Truckee and Carson Rivers originate high in the California Sierra Nevada Mountains and flow northeastward down through the semiarid desert of western Nevada. A map of the adjacent basins is shown in Figure 1. The vast majority of both basins' surface area and demands for water resources lie within the State of Nevada. Most of the precipitation and high alpine storage reservoirs, however, are located in the State of California (Horton, 1996). (See Figure 2.) Historically, the rivers have been used for fishing, logging and paper making, mining, ice production, irrigation, power production, and municipal and industrial (M & I), among other uses (Horton, 1995). The two basins are connected by the one-way Truckee Canal which brings water from the Truckee Basin into the Carson Basin. The individual river basins are described in detail below.

1.2.1 Truckee Basin

The Truckee River Basin encompasses an area of approximately 3,060 square miles in the States of California and Nevada. Of the total basin area, approximately 790 square miles, or almost 26 percent of total area, lie within the State of California. The remaining 74 percent lies in the State of Nevada. The Truckee River originates as outflow from Lake Tahoe in California, runs northeastward approximately 105 miles, and terminates in Pyramid Lake in Nevada. The Truckee River has an average annual

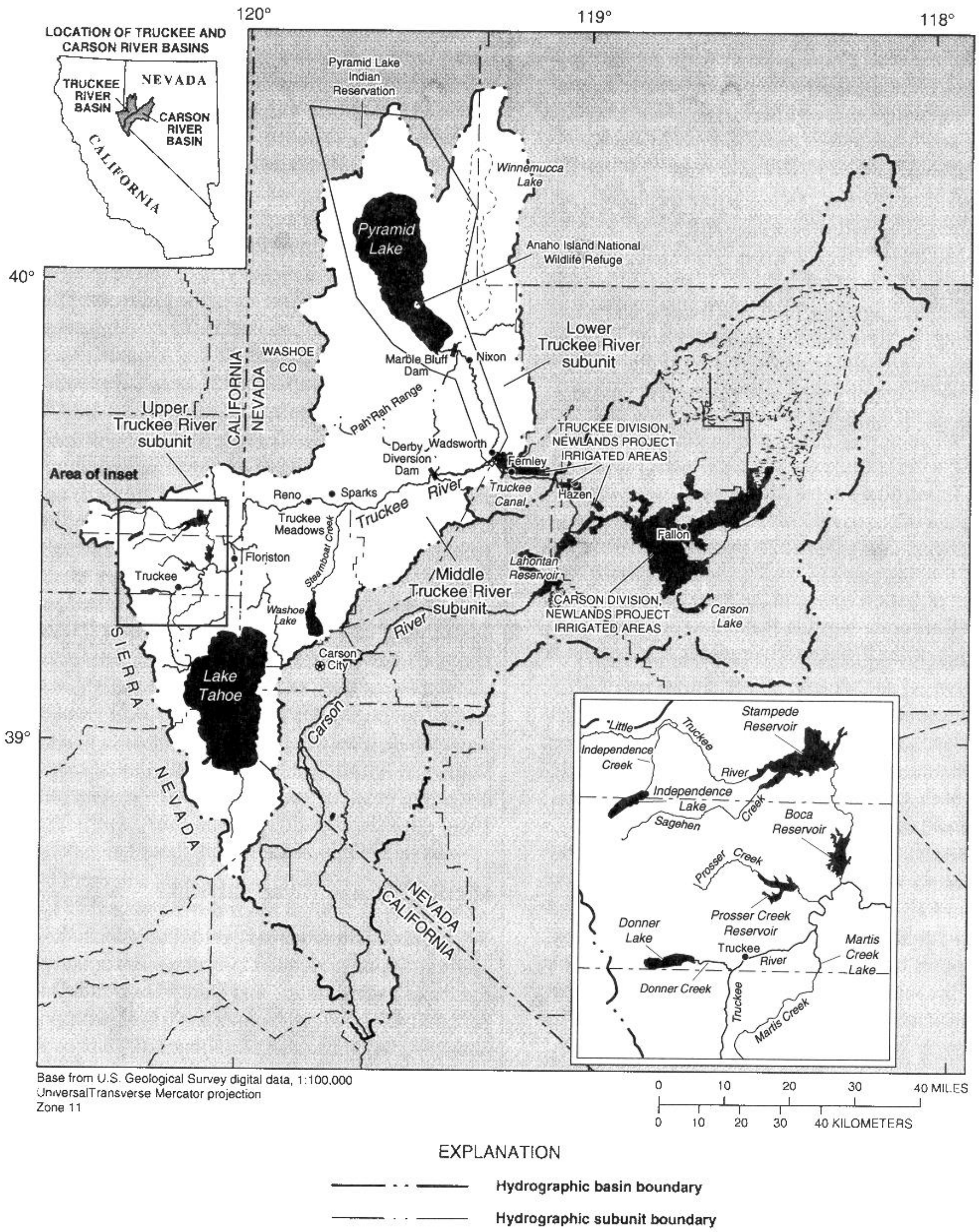


Figure 1: Study Area

flow of 548,200 acre-feet (1973-1994 period of record) crossing the California-Nevada border at the Farad gaging station. (Horton, 1991)

The upper Truckee basin is steep, high alpine or forested land with elevations reaching 9,000 to 10,000 feet (Horton, 1995). This area receives the greatest precipita-

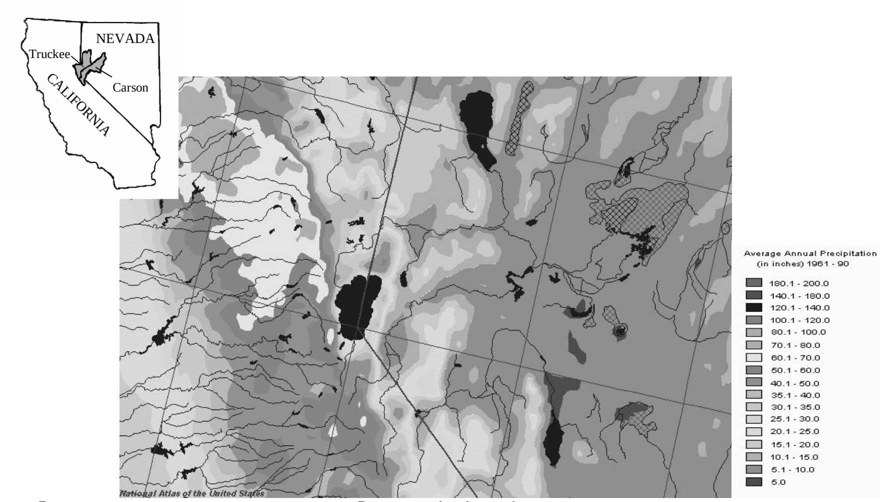


Figure 2: Study Area Average Annual Precipitation

tion in all the basin: 30 - 60 inches a year mostly in the form of snow (Taylor, 1998). The Truckee River has seven major storage reservoirs in the upper part of the basin: Lake Tahoe, Donner Lake, Independence Lake, Martis Creek Lake, Prosser Creek Reservoir, Stampede Reservoir, and Boca Reservoir. These reservoirs are used for both flood control and storage of water for downstream uses.

The Truckee River originates as outflow from Lake Tahoe, the subbasin of which comprises 24 percent of the total Truckee River Basin. The Lake Tahoe Basin is fed by 63 creeks and streams and is a major contributor to flows in the Truckee River. After Lake Tahoe, numerous streams join the Truckee River in the 15 mile stretch between Tahoe City and the town of Truckee. These streams include Bear, Squaw, Deer, Silver, Pole, Deep, and Cold Creeks. Between the towns of Truckee and Boca, major tributaries include Donner, Martis, and Prosser Creeks and, the largest tributary, the Little Truckee. The Little Truckee River is vitally important to the Truckee River Basin due to the fact that several crucial water storage systems--Boca and Stampede reservoirs, and Independence Lake--are located within its drainage basin.

After its confluence with the Little Truckee, the Truckee River flows down a steep canyon into Nevada and down to the Truckee Meadows that encompass the cities of Reno and Sparks, Nevada. The Truckee Meadows is in the rain shadow of the Sierra Nevada Mountains and receives less than 8 inches of precipitation a year (Taylor, 1998). Though once an agricultural area, the Truckee Meadows is now nearly consumed by the expanding cities of Reno and Sparks. Consequently much of the water from the Truckee is used for municipal and industrial (M&I) purposes. Used M&I water, treated at the Truckee Meadows Wastewater Reclamation Facility, is released into Steamboat Ditch and eventually returns to the Truckee River.

Downstream of Reno/Sparks, the Truckee River flows across an arid plateau. At Derby Dam, an annual average of almost 187,000 acre-feet of Truckee River Water is diverted through 32.5 mile Truckee Canal. With a nominal capacity of 900 cfs, the Truckee Canal transports water from the Truckee Basin into Lahontan Reservoir in the Carson Basin for use in the Newlands Project irrigation district. In dry years, such as the 1988-1994 period, this diversion can withdraw up to two-thirds of the total Truckee River water. Arguably, this interbasin transfer represents the single greatest controversy within the Truckee and Carson River Basins. The Newlands Project diversion comprises the most significant single withdrawl of the Truckee River's waters.

The portion of the river that is not diverted to the Truckee Canal continues through desert before emptying into Pyramid Lake within the Pyramid Lake Indian Reservation. Two culturally and economically important fish to the Pyramid Lake Paiute Tribe live in Pyramid Lake: the endangered cui-ui and the threatened Lahontan cutthroat trout. These fish must migrate upstream to spawn. Low flows and shallow depths in Truckee River below Derby Dam, however, have inhibited spawning, egg incubation, and survival of these species (Taylor, 1998).

1.2.2 Carson Basin.

The Carson River Basin boarders the Truckee River Basin to the south, is roughly the same size and has very similar topography. The Carson Basin comprises an area of 3,360 square miles , 15 percent of which lies in California (Horton, 1996). The Carson River runs northeastward 184 miles from its headwaters approximately fifty miles south of Lake Tahoe to its terminus in the Carson Sink in Nevada. The average annual flow in the Carson River, as gaged at Ft. Churchill above Lahontan Reservoir, is 266,420 acre-feet (Horton, 1996).

Much like the Truckee Basin, the Carson Basin receives most of its precipitation in the form of snow, high in the Sierra Nevada Mountains in California. At its headwaters, the Carson River consists of two forks: the East Fork and the West Fork. The East Fork Carson is roughly twice as long as the West Fork Carson (65 miles compared with 33 miles) and the average annual discharge is 255,560 acre-feet, roughly 3.2 times that of the West Fork (Horton, 1996). The upper basin of the Carson River is significantly less developed than the Truckee. The Carson Basin has several relatively small storage reservoirs in its upper basin. Due to their size, these reservoirs do not play as integral a role in policy and management decisions as do the reservoirs in the Upper Truckee Basin.

The east and west forks of the Carson River flow down from the steep mountains into the Carson Valley. The Carson Valley serves as a natural catchment basin for the many short streams which feed the East and West Fork Carson and often flood the basin. The East and West forks join near the western part of the Valley, though the exact location changes from year to year. The valley is rich in farmland (over 35,000 irrigated acres) and is consequently marked by significant diversions. Here the waters of the Carson River are rapidly diminished by extensive irrigation diversions, though the exact depletion is not known.

In the lower basin, the Carson River flows northeast from the town of Carson City toward Lahontan Reservoir in Lahontan Valley. The arid Lahontan Valley is in the rain shadow of the Sierra Nevada Mountains and receives an average of only five inches of precipitation a year. In contrast, the average potential evaporation here exceeds 60 inches, with rates recorded as high as 70 inches per year (Horton, 1996).

Water diverted from the Truckee River pours into Lahontan Reservoir via the Truckee Canal to provide water for the Newlands Project. The Newlands Project consists of approximately 73,000 water-righted acres, of which about 59,800 are actually irrigated (Horton, 1996). While controversy continues to surround the Newlands Project with respect to its sources of water, the project's efficiency, and the water quality of its return flows, the economic benefits of this reclamation project are indisputable. Agriculture ranks only second (to the Fallon Naval Air Station) in its contributions to local employment, incomes, and spending in Churchill County (Horton, 1996).

Past Lahontan Reservoir the majority of the Carson River splits off into a network of ditches and canals that make up the Truckee-Carson Irrigation District (TCID), which represents Newlands Project farmers. Extensive Newlands Project irrigation has altered the natural flow to wetland areas and modified the hydrologic characteristics of the Lahontan Valley, raising the local water table. The Carson River terminates past the Newlands Project in the area of the Carson Sink. Depending on the time of year and annual runoff from the upper basin, this area can be an extensive labyrinth of interconnected lakes, marshes, and wetlands or a barren, alkali desert and salt flat.

1.3 Policies and Operations on the Truckee and Carson Rivers

The Truckee and Carson Rivers have been, and continue to be, crucial to the sustainment of life in western Nevada. The rivers have played a major role in the settlement and development of the area. Consequently, the policies and operations on these rivers extend back to before the turn of the century and continue to be negotiated to this day. Current negotiations seek to balance the demands of M&I for the cities of Reno and Sparks, irrigation for Truckee Meadows and TCID, power production operated by the Sierra Pacific Power Company in the Truckee Canyon, as well as protection of the cui-ui (an endangered sucker) and Lahontan cutthroat trout (a threatened species). As negotiations over new policies continue, the USBR and Federal Water Master implement the provisional policies in their daily operations on the Truckee and Carson Rivers (Horton, 1995).

Of primary importance to this research is the Operating Criteria and Procedures (OCAP) for the Newlands Project irrigation district. OCAP was originally established in 1967 to regulate agricultural diversions to the Newlands Project. For many years before this date, water was diverted from the Truckee River to the Newlands Project without restrictions. This water would otherwise have flowed to Pyramid Lake, the river's terminus, on the Pyramid Lake Indian Reservation. Due to these diversions, the water level of Pyramid Lake declined for decades-- over 85 vertical feet between the early 1900s and 1967. This decline in the water level eventually made it difficult or impossible for cui-ui and Lahontan cutthroat trout to swim upstream in the Truckee River and spawn. The Pyramid Lake Paiute Tribe filed a number of suits resulting in the initial establishment of OCAP and further revisions in 1988 and 1997 (Horton, 1995).

The primary goal of OCAP is to maximize the use of Carson River water and minimize diversions of Truckee River water into the Truckee Canal. The USBR Lahontan Basin Area Office uses forecasts of the spring runoff in the Carson and Truckee Basins to assist in achieving this objective.

Newlands Project OCAP specifies the circumstances under which water can be diverted from the Truckee River. Specifically, OCAP allows diversions of up to 1,500 cfs through the Truckee Canal (although the canal's nominal capacity is only 900 cfs) and up to a total of 288,129 acre-feet per year. The actual quantity of water which may be diverted from the Truckee River at Derby Dam varies with the determination of the irrigation entitlement each year, the runoff forecasts for the Carson and Truckee Rivers and water in storage in Lahontan Reservoir. Irrigation entitlements are based on the actual irrigated acreage in any given year: 3.5 acre-feet per acre per year (bottom lands) and 4.5 acre-feet per acre per year (bench lands).

The USBR incorporates these criteria into operations by setting an end-of-month storage targets for Lahontan Reservoir. Monthly storage targets from January to May vary based on both the Ft. Churchill runoff forecast and the TCID water demand. From June through December, the storage targets vary based only on projected TCID water demand.

OCAP also specifies that diversions to the Truckee Canal be coordinated with releases from Stampede Reservoir and other reservoirs, in cooperation with the Federal Water Master, to minimize fluctuations in the Truckee River below Derby Dam in order to meet annual flow regimes established by the United States Fish and Wildlife Service (FWS) for the listed species in the lower Truckee River. Increases in canal diversions which would reduce Truckee River flows below Derby Dam by more than 20 percent in a 24-hour period are not allowed when Truckee River flow, as measured by the gauge below Derby Dam, is less than or equal to 100 cfs. During times when diversions are technically not allowed (e.g., after the monthly storage target on Lahontan has been met), the Truckee Canal must be managed to achieve an average flow of 20 cfs or less.

OCAP also seeks to increase efficiency in the Newlands Project irrigation district. OCAP requires that TCID farmers estimate their demands for the coming growing season and then irrigate at a minimum of 68.4 percent efficiency on that projected demand. If the District fails to meet the targeted efficiency, then a calculation is made as to how much water was used or diverted in excess of what it would have taken if the efficiency target had been met. Once that total excess reaches 26,000 acre feet, OCAP requires that the District reduce the water delivery in the following year to all water users by the amount of that excess. To date the District has not been able to achieve an efficiency any greater than 63 percent (TCID web site, retrieved 10/13/02).

The USBR is responsible for calculating the allowable Truckee River diversions and consulting with interested parties including the Pyramid Lake Paiute Tribe, the U.S. Fish and Wildlife Service (FWS), TCID, and others. During the last week of each month the USBR determines the next month's Truckee Canal diversion schedule based on OCAP and Carson and Truckee River forecasts. USBR water engineers revisit the diversion schedule when necessary, based on observed runoff and forecast revisions in order to meet the end-of-month storage target at Lahontan Reservoir. In some months there is not enough water available, even with diversions, to meet the storage target.

TCID currently operates Derby Dam under a temporary contract with the USBR. The USBR Lahontan Basin Area Office monitors the flows at the U.S. Geological Survey (USGS) gage on the Truckee Canal near Hazen to determine if and when flows are in excess of those needed and works with TCID to bring the flows back into compliance when excessive.

Fish spawning releases are also particularly important to this research. In 1982, the Stampede Reservoir Judgement allotted all of the water and storage in Stampede to protecting, and encouraging the spawning of, the endangered cui-ui and threatened Lahontan cutthroat trout. Releases are based on schedules set by FWS and the Pyramid Lake Tribe. Forecasted runoff, storage values, and time since the last run all affect the annual decision of whether to have a cui-ui spawning run. If FWS and the Pyramid Lake Tribe decide to have a spawning run, the releases from Stampede aim to meet the following flow targets at Pyramid Lake: January 90 cfs, February 120 cfs, March 190 cfs, April 570 cfs, May 1000 cfs, June 50 cfs (Berris 2001).

Other major policies and laws in the basin include the Truckee River Operating Agreement, flood control, Floristan Rates, and the Tahoe-Prosser Exchange. (See Appendix A, "Operating Policy in the Basin" and Appendix B, "Description of Select

Laws" for more details on operations and policies in the Truckee-Carson River System.)

1.4 Current forecasting methods

The USBR Lahontan Basin Area Office currently makes monthly forecasts of streamflow in both the Truckee and Carson Rivers. The Carson forecast is used to determine the natural inflows to Lahontan Reservoir. The Truckee forecasts are used to determine the Truckee River water available for diversion. From a water supply standpoint, the USBR Lahontan Basin Area Office considers the total April through July runoff as the most important component of their forecasts, as this is when the majority of the streamflow comes (Scott, 2002). (The Truckee River receives an average of 66 percent of its total annual flow and the Carson River receives 63 percent of its total annual flow during this time period.) Forecasting the distribution of the spring runoff, however, is also important for scheduling Truckee Canal diversions and setting storage targets on Lahontan Reservoir (Reynolds, 2002).

The current USBR forecasting techniques use linear regression analysis based on snow water equivalent (SWE) information. Lahontan Basin Area Office forecasters typically regress streamflow data against monthly basin average SWE, percent of normal snowpack, total accumulated precipitation, and observed runoff data to develop regression equations for each month. Forecasters then use the monthly regression equations to predict the most probable streamflow value. USBR forecasts also include information from the Natural Resource Conservation Service (NRCS) official forecasts, whenever they are available. The USBR regression equations are always used to forecast the January to March runoff. The NRCS official forecasts are the primary April to July forecasts, if recently issued. If recent NRCS forecasts are not available, the USBR regression equations are used to forecast April to July natural flow. In all cases, the monthly distribution of the forecasted runoff is determined from similar years selected based on forecasted January to March and April to July volume forecasts.

The USBR Lahontan Basin Area Office typically forecasts one key point on each river: the Ft. Churchill USGS gaging station on the Carson River and the Farad USGS gaging station on the Truckee River. Sometimes a separate forecast for the Little Truckee River is also issued. The Carson River forecast is taken as the natural streamflow entering Lahontan Reservoir. The Truckee River forecast for Farad is spatially disaggregated to the various reservoirs upstream. This disaggregation is based on the historical contribution of each subbasin to the total streamflow at Farad.

1.5 Incorporation into a Decision Support System (DSS)

Once a forecast is issued, water managers must decide how to best operate the system given the predicted flow values. The USBR is currently developing a decision support tool using the general-purpose river and reservoir modeling software RiverWare (Zagona et al., 1998 and 2001). The Truckee RiverWare model simulates the movement of water through reservoirs, reaches, and diversions using objects in a graphical user interface. Simulated reservoir releases and diversion schedules are controlled by rules: user-defined, prioritized logic based on the laws and policies of the rivers. The model also includes an accounting network to track water as it moves through the system. It is thus possible to track whether water was released to meet in stream flow targets or for irrigation demands. The rules dictate how much water is released from each reservoir, what account the water came from, and where the water goes. By using different rules to move water through the system, it is possible to simulate flow patterns using different policies. Together with the forecasts, the DSS will be used to assist with daily operations and seasonal and long-term planning in the basin.

1.6 Proposed Research

The USBR Lahontan Basin area office funded part of this research in an effort to obtain an improved seasonal forecasting model to strengthen planning and management in the Truckee and Carson River Basins. This research aims to achieve the objective by utilizing large-scale climate information and nonparametric stochastic forecasting techniques as described below.

The link between streamflow in the Western United states and global climate variables has been strongly supported in the literature. This research uses climate diagnostics to demonstrate that the spring streamflows in the Truckee and Carson rivers are strongly related to atmospheric circulation features over the northern Pacific during the preceding winter and fall. This enhances the prospects for a long-lead forecast. We develop indices from the relevant oceanic-atmospheric circulation variables to be applied in a forecasting mode.

This research utilizes nonparametric stochastic forecasting techniques. We use large-scale climate information together with known streamflow predictors to develop a flexible streamflow forecasting model. The model developed in this research produces ensemble forecasts of spring streamflows. The ensemble forecasts can be analyzed to obtain various exceedence probabilities of interest to water managers in the Truckee and Carson River Basins.

After issuing the forecast, this research tests the utility of the forecast to water resources decision making. Ensemble streamflows used as inputs to a DSS. We then analyze the forecasts' impact on different decision variables in the system.

The overall approach is outlined in the flowchart below. A description of each step in this process follows.

1. Determine large-scale climate features correlated to spring streamflow in the Truckee and Carson Rivers. Verify the physical relationship supporting this correlation. Develop indices for the significant predictors to be used in

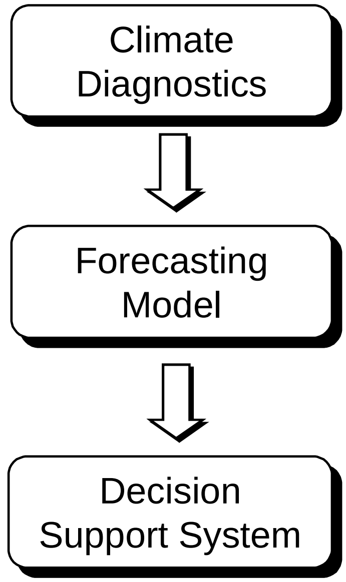


Figure 3: Proposed Research Flowchart

the forecasting model. This step is discussed in Chapter 2, "Climate Diagnostics."

2. Develop an empirically based predictive streamflow model that can be coupled with the DSS. Standard statistical methods are used to validate the model and measure the skill of the forecasts. This is presented in Chapter 3, "Nonparametric Stochastic Forecasting Model."
3. Couple the streamflow ensembles from the stochastic forecasting model with the DSS to determine flows throughout the system. Analyze various decision variables and exceedence probabilities to test the utility of the ensemble forecasts. Steps 3 and is discussed in Chapter 4, "Decision Support System."

1.7 Contribution of this Research

This research produces two tools that can be used to improve forecasting results, and, hence, water resources operations and planning in the Truckee and Carson River Basins. First, we demonstrate that incorporating large-scale climate information in a forecasting model can produce more skillful, longer lead-time forecasts. Second, results show that nonparametric stochastic forecasting techniques used in this study have the added benefit of producing ensemble forecasts which can be analyzed to determine exceedence probabilities. The improved forecasts, when coupled with a DSS, facilitate efficient seasonal planing and management of water in the Truckee-Carson river basin. Finally, this research highlights additional areas that warrant more research.

Chapter 2

Climate Diagnostics

Researchers have gathered an increasing body of evidence to demonstrate the relationship between large-scale climate features and hydroclimatology in the western United States. Much of the work has involved studying climate phenomena such as El Niño-Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) and their impacts on hydrologic variables such as precipitation, temperature and streamflows in the western United States. Researchers have used a variety of techniques, both physically and empirically based, to analyze the atmosphere-ocean-land interactions that influence hydrology in the West. Statistical techniques typically relate the dominant modes of large-scale ocean-atmosphere patterns in sea surface temperatures (SSTs) and sea level pressures (SLPs) to regional hydrologic variables for diagnostics and prediction. Deterministic methods often employ regional watershed models to predict streamflow based on the state of the atmosphere as indicated by large-scale global climate models. Using these approaches, the predictive capability of atmospheric circulation patterns on streamflows has been applied to improve water resources management and planning on several river basins in the West.

There has, however, been little research on diagnosing and predicting the variability of streamflows in the Truckee and Carson Basins. Current forecasting techniques in the Truckee and Carson River Basins do utilize large-scale climate information, though only qualitatively (e.g., in El Niño years, forecasters may subjectively alter the forecast). Given this lack of research and the importance of water resources planning in the basin, there is a need to systematically diagnose the streamflow variability in an effort to improve forecasting. This chapter first reviews past studies of large-scale climate features and hydrologic variability in the western United States then follows up with the authors' analysis of large-scale climate features' influence on streamflow variability in the Truckee-Carson River Basin.

2.1 Influence of Large-Scale Climate Features on Hydrologic Variability in the Western United States: Past Studies

Precipitation and its resulting streamflow are an important source of water for the semi-arid western United States. El-Ashry and Gibbons (1988) estimate that water consumption in the western US averages 44% of renewable supplies, compared with 4% in the rest of the country. Yet, precipitation in this area varies both inter-seasonally and inter-annually. Given the importance of precipitation and streamflow in the western United States, many research efforts strive to determine the cause of their spatial and temporal variability. Efforts in recent decades have focused on the links between large-scale climate features and hydrology in the West in an attempt to understand this variability.

We have long understood that in the mid-latitudes the jet stream moves moisture laden air masses from the Pacific Ocean eastward over the North American continent. The jet stream is strongest during winter when the equator-to-pole temperature gradients are greatest and, hence, is most active in carrying low pressure systems during this time. As moist air travels eastward and encounters the mountainous regions in the western United States, it rises and cools, forming precipitation.

The strength and location of the jet stream govern the inter-seasonal and inter-annual variability of precipitation over North America. The jet stream typically moves in a sinuous motion from west to east-- with a trough over the North Pacific Ocean, a ridge over the Rocky Mountains, and a trough over the eastern United States. This structure is described by several teleconnection patterns (Wallace and Gutzler, 1981; Barnston and Livezey, 1987; Leathers, et al., 1991). For example, the PNA teleconnection pattern describes variability in four pressure centers over the Pacific Ocean and North America that persist from late summer to spring and are strongest in winter. The PNA is marked by low pressure systems south of the Aleutian Islands (the Aleutian Low) and over the southeastern United States and high pressure systems near Hawaii and over the Rocky Mountains (central Canada) in winter and fall (spring.) These positive and negative pressure systems direct the movement of the jet stream: counter-clockwise near the low pressure systems and clockwise near the high pressure systems, resulting in the sinuous motion seen in Figure 4.

Intensification of the PNA is associated with a deepening of the Aleutian Low and a strengthening over the ridge of the Rockies. This situation deflects storm sys-

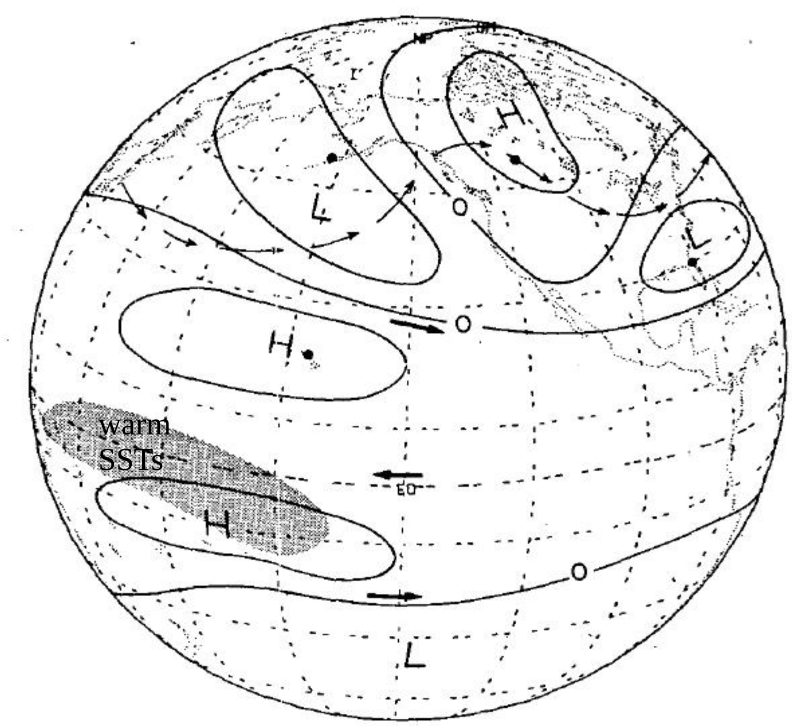


Figure 4: Typical PNA Pattern and its effect on the jet stream

tems north toward Alaska and reduces precipitation over much of the western US. Weakening of the PNA is associated with a weaker Aleutian Low and a weaker ridge over the Rocky Mountains. In this situation cyclonic disturbances can penetrate into the western US, resulting in increased precipitation. Variability in the location and strength of the PNA wave train over North America can have pronounced impacts on local climate in specific regions. These variations are actively forced by slow changes in SST patterns in the tropical and extra-tropical Pacific Ocean. Changes in SST patterns are associated with the ENSO and PDO teleconnections which are described below.

ENSO is a quasi-cyclic phenomenon that occurs in the tropical Pacific Ocean every three to seven years and has pronounced effects on weather around the world. In normal years, easterly "trade winds" in the tropical Pacific drive surface waters westward. This results in warmer waters (6-8° C warmer) in the western tropical Pacific due to longer exposure to solar heating, and cooler waters in the eastern tropical Pacific due to oceanic upwelling. In some years the trade winds weaken, allowing warmer waters off the western Pacific to migrate eastward and eventually reach the South American coast. These situations are knows as El Niño events. The opposite phenomenon, termed La Niña, is characterized by stronger trade winds and colder SSTs in the tropical Pacific Ocean. (Allan, 1996; Dingman, 2002) (See Figure 5.) The Southern Oscillation refers to a see-saw shift in surface air pressure at Darwin, Australia and the South Pacific Island of Tahiti. When the pressure is high at Darwin it is low at Tahiti, and vice versa. El Niño and La Niña occur during the extreme phases of the Southern Oscillation. Climatologists have developed several indices based on SSTs (e.g., Nino3, Nina1+2, Nino3.4, etc.) and SLPs (e.g., SOI, Darwin SLP, etc.) that indicate the strength and phase of ENSO. The indices measure SSTs or SLPs in specific regions of the tropical Pacific Ocean that are strongly influenced by ENSO.

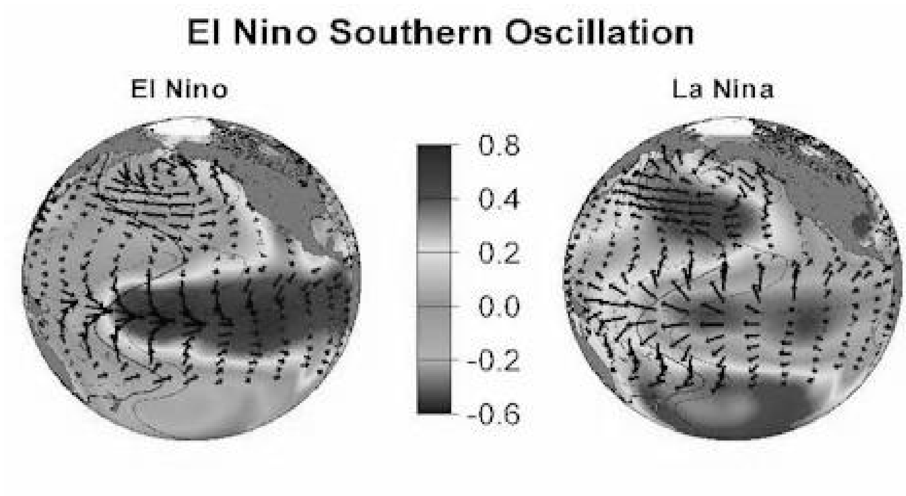


Figure 5: Color comparisons of warm versus cold phase El Niño/La Nina, SST, sea-level pressure, and surface wind stress anomaly patterns

Although ENSO is defined by large-scale oscillations in oceanic and atmospheric conditions in the tropical Pacific, the phenomenon affects weather patterns across the globe. Perhaps the most notable effect for North America is the shift in the jet stream which carries storm systems from the North Pacific across the North American land mass in late fall and winter. In El Niño years warmer than average SSTs cause increased convection and precipitation in the tropics near and east of the date line. La Niña events are marked by decreased convection and precipitation just west of the date line (Hoerling et al., 1997). This change in the magnitude and location of typical convection patterns perturbs the areas of high pressure where air subsides on either side of the equator, in turn altering atmospheric circulation in the mid-latitudes. During ENSO events, the altered PNA pattern shifts the location and strength of the jet stream. (See Figure 6.) The PNA wave train is typically strengthened during El Niño events and a weakened during La Niña events. The overall result is unusually warm or cold winters in particular regions, drought in normally productive agricultural areas, and torrential rains in normally arid regions (Rasmussen, 1985; Ropelweski and Halpert, 1986 and 1989).

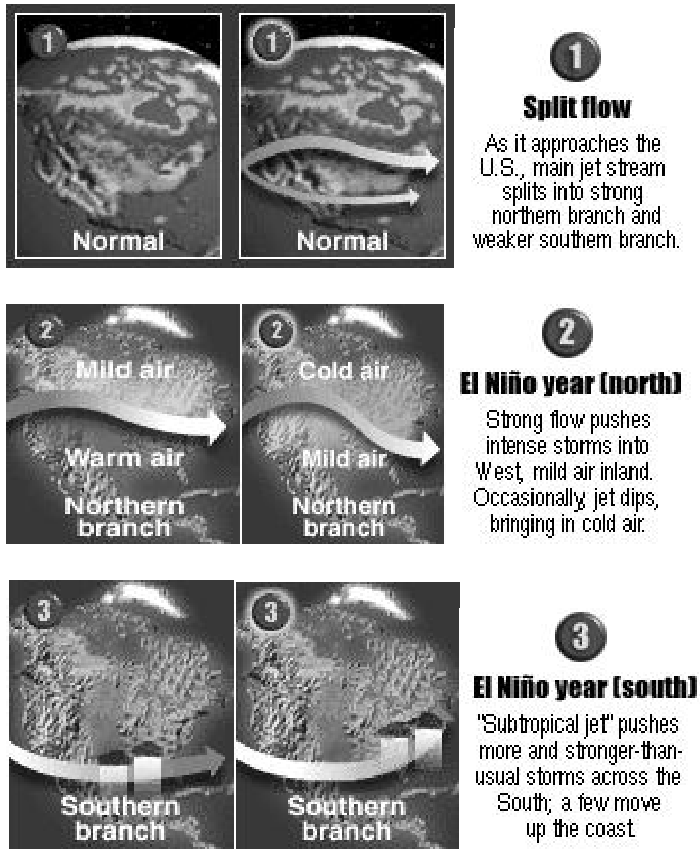


Figure 6: El Niño effect on jet stream

The PDO is a long-term fluctuation in SSTs and sea levels in the northern Pacific Ocean that waxes and wanes approximately every 20 to 30 years (Mantua et al., 1997). Like ENSO, the PDO oscillates between a “warm” (positive) phase and a “cool” (negative) phase. (See Figure 7.) The PDO index, which is based on the first principal component of Pacific SSTs, denotes the strength of the PDO and its phase. (See Figure 8.) Based on atmospheric and oceanic data, scientists believe we have just entered the “cool” phase. The “cool” phase is characterized by a cool wedge of lower than normal sea-surface heights and ocean temperatures in the eastern equatorial Pacific and a warm horseshoe pattern of higher than normal sea-surface heights connecting the north, west and southern Pacific. In the “warm” phase, which appears to have lasted from 1977- 1999, the west Pacific Ocean becomes cool and the wedge in the east warms. Two main characteristics distinguish PDO from ENSO, however.

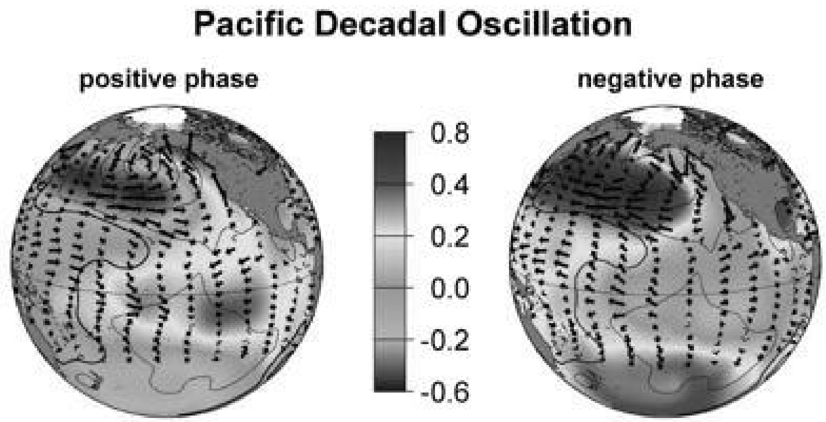


Figure 7: Color comparisons of warm versus cold phase PDO, SST, Sea-level pressure, and surface wind stress anomaly patterns

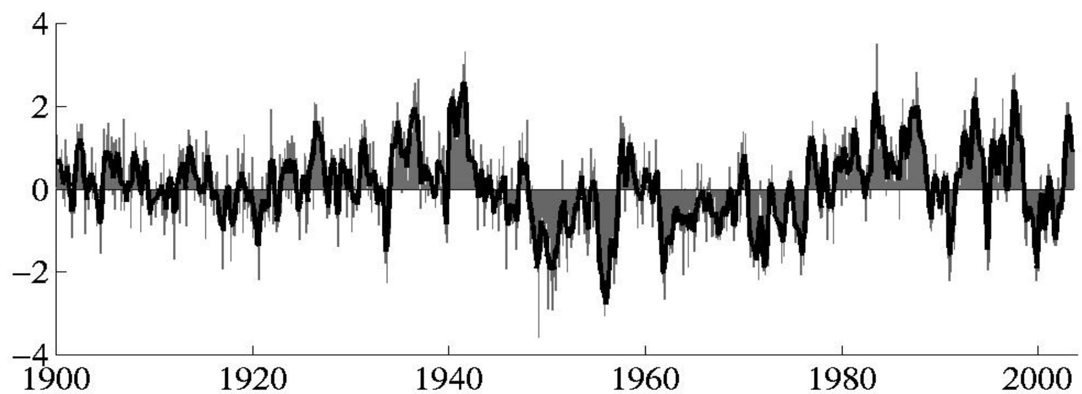


Figure 8: Monthly Values of the PDO index: January 1900-August 2003

First, twentieth century PDO "events" persisted for 20-to-30 years, while typical ENSO events (El Niño or La Niña) persisted for 6 to 18 months. Second, the truly distinguishing climatic features of the PDO are most visible in the North Pacific/North American sector, while secondary signatures exist in the tropics - the opposite is true for ENSO.

The change in location of the cold and warm water masses resulting from a shift in the PDO alters the path of the jet stream. The PDO phase that we appear to have entered will act to steer the jet stream further north over the Western United States. This shift will in turn transport winter precipitation and storm systems further north than what has been the norm for the past 30 years. As can be perceived, the PDO has several attributes in common with ENSO. Hence, the PDO, as an independent phenomenon like ENSO, is an area of active research.

The influence of tropical Pacific climate conditions (such as ENSO and PDO) on North American hydroclimatic variability has been well documented (e.g., Ropelweski and Halpert, 1986; Cayan and Webb, 1992; Kayha and Dracup, 1993; Redmond and Koch, 1991; Cayan and Redmond, 1996; Gershunov, 1998; Kerr, 1998; Dettinger et al., 1998 and 1999; Cayan et al., 1999; Hidalgo and Dracup, 2003). In 1986, Ropelweski and Halpert demonstrated that El Niño events are associated with increased seasonal precipitation in the southwestern and southeastern United States. Several years later, Kerr (1988) suggested that La Niña events can cause drought in the same regions of North America. From this time onward, studies relating atmospheric circulation features over the Pacific to hydrology, particularly in the semi-arid western United States, have abounded.

As most basins in the western US receive the bulk of their annual flow from spring snowmelt (Serreze et al., 1999), many studies focus on the correlation between large-scale climate features and western mountain snowpack. For example, McCabe and Dettinger (2002) used principal component analysis to determine the primary modes of April 1st snowpack and found that the two components which account for 61% of the variance in the western United States are closely related to the PDO and the Nino3 (tropical Pacific) SSTs.

Other studies exhibit a strong correlation between atmospheric circulation patterns and warm season precipitation. Hidalgo and Dracup (2003) investigated the linkages between ENSO and hydroclimatic variations in the Upper Colorado River Basin. The results for warm season precipitation response to ENSO were much stronger than results obtained for cold season precipitation.

Pizarro and Lall (2002) studied the effect of the ENSO and PDO on annual maximum floods in the Western U.S. Their correlations with Nino3 suggested an enhanced probability of winter floods in El Niño years in California and Oregon, spring floods in S. Idaho, N.E. Utah and Colorado, and summer floods in New Mexico and S. Colorado. In Washington, N. Idaho, Montana and Wyoming, the likelihood of flooding appears reduced. However, when they considered the recent weakening of the negative PDO signal, these probabilities changed, stressing the interplay of ENSO and PDO signals. Under the weakened PDO assumption, the probability of floods decreased in California, N. Washington and S. Colorado and increases in the other regions.

Rajagopalan et al. (2000) studied the teleconnection between the winter ENSO and summer drought in the United States. They discovered a strong relationship between ENSO and drought in the southwestern U.S. (e.g., Texas, southern Arizona and California). They determined, however, that this relationship varied spatially and temporally over the twentieth century, thus underscoring the complicated nature of the relationship and the difficulty in forecasting.

Because ENSO and PDO generally persist for several months (to years, in the case of PDO), useful long-range hydrological forecasts can be made in regions that are particularly affected by these patterns. A number of studies have found relationships between streamflows and ENSO cycles (e.g., Dracup and Kayha, 1994). In basins that exhibit strong hydrologic-atmospheric circulation pattern linkages, incorporation of climate information has been shown to improve streamflow forecasts. Clark et al. (2001) examined the effects of the ENSO signal and SWE on streamflow in the Columbia and Colorado River systems. They determined that in basins which exhibit strong ENSO seasonality, a forecast incorporating both the ENSO signal and SWE is more accurate than a forecast based on SWE alone. While SWE is good a measure of initial conditions, the ENSO signal provides information about weather to come throughout the remainder of the winter season.

Several researchers have focused on the possibilities of improving water management through the use of climate information. In their analysis of adaptive management on the Colorado River, Pulwarty and Melis (2001) presented the need for monitoring climate parameters in addition to the April 1st snowpack when analyzing runoff forecasts. They argued that careful application of climatic information could result in enhanced management of water supply, flood control, power generation and environmental issues.

The incorporation of large-scale climate features can also improve the lead-time of forecasts. Because atmospheric-oceanic conditions change slowly from season to season, it is possible to use summer and fall climate information to predict April 1st snowpack (McCabe and Dettinger, 2002) or even summer streamflow (Hamlet et al., 2002). This enhanced lead-time allows for more efficient management of the system. Hamlet, Huppert and Lettenmaier (2002) presented the economic value of the increased hydropower production in the Columbia River Basin as a result of incorporating climate information in the streamflow forecast to increase lead time--in this case, six months earlier.

The effects of large-scale climate phenomenona, however, are non-linear in space and time (Hoerling and Kumar, 1997). Not all El Niño's are the same, nor does the atmosphere always react in the same way from one El Niño to another. An anomalous ENSO signal may have strong effects in one basin and none at all in another basin. Similarly, the signal may correlate strongly with years of high streamflow, but have no apparent link to drought conditions. Furthermore, the interplay of multiple climate patterns such as ENSO, PDO and PNA make the impacts on hydroclimatic variability more complex. Jain and Lall (2000 and 2001) found non-linear relationships between annual maximum floods and ENSO and PDO, particularly when multiple indices were considered. Additionally, the influence of climate indices may only be apparent in years when the indices are at extreme values. Pizarro and Lall (2002) determined that major changes in rainfall or floods occur only for extreme NINO3 and PDO values with the intermediate values leading to no effect. Furthermore, subtle shifts in atmospheric circulation patterns can cause significant changes in precipitation and temperature, meaning that standard teleconnection indices provide a poor descriptor of climate changes in many regions. In order to utilize climate information to forecast in a specific basin, it makes sense to analyze the direct linkages between individual climate features and streamflow (or precipitation) in the given basin.

2.2 Analysis of Atmospheric Circulation Features' Impact on Streamflow in the Truckee and Carson Rivers

Given the influence of atmospheric circulation patterns on hydrologic variability in the western United States, we analyze their direct impact on our basin of interest, the Truckee-Carson Basin. We perform climate diagnostics to determine the relevant large-scale climate features related to streamflow in the Truckee and Carson Rivers. The dominant teleconnection patterns described above (ENSO, PDO, PNA) clearly have a significant impact on hydrology across the western US as a whole. Subtle variations in these patterns, however, can significantly shift the basin-scale area of impact. These patterns, therefore, may not always directly impact the hydrology in the Truckee-Carson Basin. In this study we analyze the dominant teleconnection patterns as well as other large-scale atmospheric variables. We attempt to identify which patterns are most important (dominant or otherwise) and develop indices of these patterns to forecast streamflow. The results from this analysis are later utilized for forecasting seasonal streamflow in the basin, as is presented in Chapter 3, "Nonparametric Stochastic Forecasting Model."

The Truckee and Carson Rivers are spring snowmelt dominated. Serreze et al. (1999) estimate that 67% of annual precipitation in the Sierra Nevada Mountains falls as snow. Mountain snowpack and winter precipitation are key to forecasting on these rivers. The total snowpack, however, is not known until late winter or early spring and earlier snowpack measurements provide lower skill in forecasts. Atmospheric circulation patterns, however, have been shown to be good indicators of what precipitation will come throughout the winter season, and hence offer insight into spring streamflows. In this study, relationships between spring streamflows and climate variables from the preceding winter and fall are identified. Consequently, we identify physical mechanisms governing the interannual variability of streamflow in the Truckee and Carson Rivers and determine their application to forecasting.

2.2.1 Data

The following data sets for the 1949 - 2003 period are used in the analysis:

(i) Monthly natural streamflow data from Farad and Ft. Churchill gaging stations on the Truckee and Carson Rivers, respectively.

(ii) Monthly SWE data is obtained from the NRCS National Water and Climate Center website (http://www.wcc.nrcs.usda.gov). The SWE data is gathered from snow course and snotel stations in the upper Truckee Basin (17 stations) and upper Carson Basin (7 stations) to compute an area average for each basin.

(iii) Monthly winter precipitation data for the California Sierra Nevada Mountains region. This is obtained from the U.S. climate division data set from the NOAA-CIRES Climate Diagnostics Center (CDC) website (http://www.cdc.noaa.gov).

(iv) Monthly values of large-scale ocean atmospheric variables - SST, SLP, wind, etc., for the globe are also obtained from the CDC website. These are extracted from the NCEP/NCAR re-analysis data sets.

The natural streamflow data for Farad and Ft. Churchill is not a direct measurement of the water in the river, but rather, a calculation of what the streamflow would have been without the effects of human development (e.g., reservoirs and depletions).

We use natural streamflow data because our interest lies in forecasting the total water coming into the system before regulation. Once the natural streamflow is forecasted, policies and regulations can be simulated using a DSS, as is addressed later in Chapter 4, “Decision Support System.” We obtain the natural streamflow data for the Truckee River at Farad from the USBR Lahontan Basin Area Office. USBR engineers calculate the natural streamflow in the Truckee River based on inflows to the seven major storage reservoirs near the top of the basin before any significant depletions have been made. Data for the Carson River are scarce; though irrigators deplete significant amounts of water before the Ft. Churchill, these depletions are not monitored, making it extremely difficult to calculate natural streamflow. For Ft. Churchill, the USBR takes the historical flow (i.e., the actual gaged flow in the river) to be the natural streamflow. The historical flow data for Ft. Churchill can be obtained from the USGS website (http://water.usgs.gov). We compute spring streamflow volumes (April to July total) from the monthly natural streamflow data. The UBSR and the NRCS use the April to July time period as the standard for spring runoff and base many operations in the basin on the April to July total volume forecast.

Basin SWE data is gathered from snow course and snotel stations in the upper Truckee and upper Carson Basins. As shown in Figure 2, the vast majority of precipitation, and certainly snow, falls in the upper basins where elevations are highest. SWE measurements from the upper basins, thus, provide a good measure of the total precipitation contributing to spring streamflows in the Truckee and Carson Rivers. Basin averages of SWE are calculated using the method employed for the NRCS web site. The SWE depth from every station in the basin is summed and then divided by the sum of the long-term averages for each of the stations (Tom Pagano, 2003). This average gives more weight to heavier snow producing sites. Because basin averages are measured in terms of percent of normal, this averaging method makes sense in terms of calculating the total spring runoff-- the sites which contribute the most to the total runoff should carry more weight. For example, we compare two hypothetical sites one with a long-term SWE average of 60 inches and the second with a long-term average of 5 inches. If, in a given year, each site receives 5 inches above the average, the 60 inch site would report a 108% of normal snowpack and the 5 inch site would report a 200% of normal snowpack. Clearly, the total basin runoff in this year will be much closer to 108% of normal than to 200% of normal, suggesting that higher value stations should get more weight. The basin average SWE method does not account for missing data (i.e., at specific stations) in any given year. If the data is missing, that site is left out of the average in that year. Also, the method does not account for higher variability sites. These issues could potentially introduce bias into the basin average (Clark et al., 2001). To correct for such baises, Clark et al. (2001) calculate *z* scores for each station (by subtracting the long-term mean and dividing by the stadnard deviation), calculate a basin-wide *z* score and then convert back to SWE units. For comparison with current forecasting tehcniques (which use NRCS basin averages), we use the NRCS averaging method.

For the large-scale atmospheric circulation variables such as SSTs, geopotential heights, and winds, we obtain monthly averages of the NCEP/NCAR re-analysis data (Kalnay et al., 1996) for the 1949 to 2003 time period. These data sets are available from the CDC website given above. The re-analysis data are computed by running a global atmospheric circulation model that is initialized with observed global atmospheric data every six hours. As a result, all atmospheric circulation variables are available on a regular 2.25° grid at several levels - for details refer to Kalnay et al. (1996).

2.2.2 Methodology

Through climate diagnostics, we analyze the influence of large-scale climate features on streamflow in the Truckee and Carson Rivers. The primary purpose for performing these climate diagnostics is to gather information regarding the physical mechanisms that drive spring streamflow in the basins as well as to establish predictors that can be used in a forecasting model.

Though it is well known that these basins are snowmelt dominated, we first analyze their climatology to better establish the timing of precipitation and runoff. We examine the interannual and seasonal variability of streamflow and precipitation and demonstrate the relationship between the two variables. Next, we perform a correlation analysis to resolve which atmospheric circulation features are relevant to the basins. Correlations between spring streamflow in the Truckee and Carson Rivers and various winter and fall atmospheric circulation features are presented as contour maps. The contour maps cover the Pacific Ocean region and the contours represent the correlation values between streamflow and climate variables at every point on the 2.25° grid. Correlations are deemed statistically significant using standard t-test methods as presented by Helsel (1995). The 95% significance level for correlations in this analysis is 0.27--correlations above this level are considered significant. We next perform a composite analysis to establish the physical relevance of the statistically significant variables. A composite analysis takes a group of selected years and presents the dominant atmosphere and ocean circulation patterns during these years. Specifically, we analyze atmosphere and ocean features in high and low streamflow years. The correlation and composite analyses are conducted using the CDC web-based analysis tool available at the CDC website given above. All correlation and composite images are generated using this analysis tool. Finally, based on the above analyses, we establish indices to be used as predictors in the forecasting model. Climate indices are taken as area averages of the regions of highest correlation for the various relevant climate variables.

2.2.3 Results: Climatology Analysis

Figure 9 presents the average monthly streamflows for the Truckee and Carson Rivers at Farad and Ft. Churchill, respectively. The plot demonstrates that the bulk of the annual streamflow in both rivers comes in the springtime, specifically during the months of April, May, and June. Streamflow in the remaining months is relatively small.

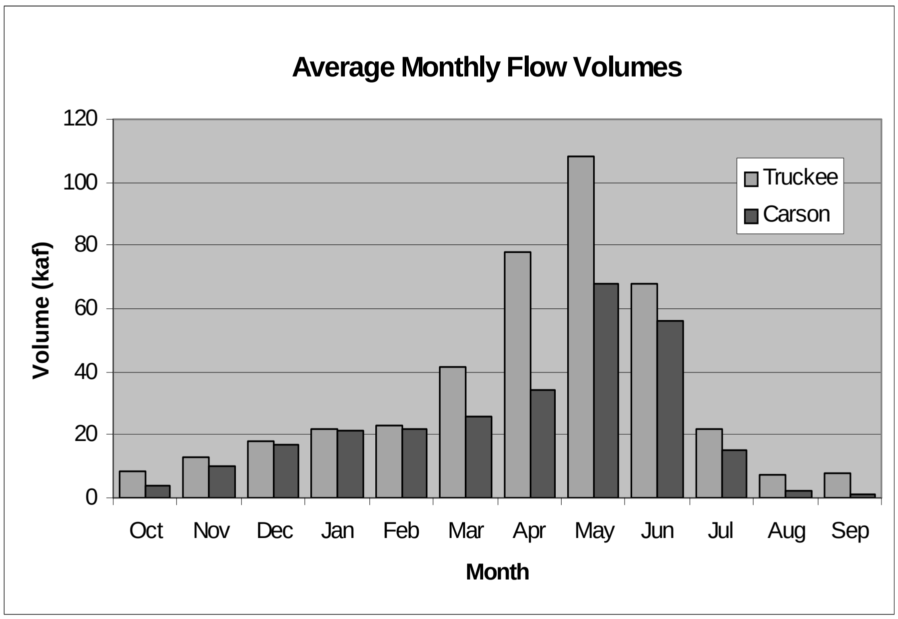


Figure 9: Average monthly streamflow volumes for the Truckee and Carson Rivers (based on the 1949-2003 period)

Figure 10 illustrates the monthly average precipitation for the Sierra Nevada region. Precipitation is highest in the winter months of December to February, with a significant amount also falling in November and March. Based on Serreze et al.'s (1999) estimate that 67% of precipitation in the Sierra Nevada's falls as snow, we deduce that most winter precipitation falls in the form of snow. Precipitation stored as snow in mountains throughout winter is released as runoff in spring when temperatures rise, causing the spring pulse evident in Figure 9.

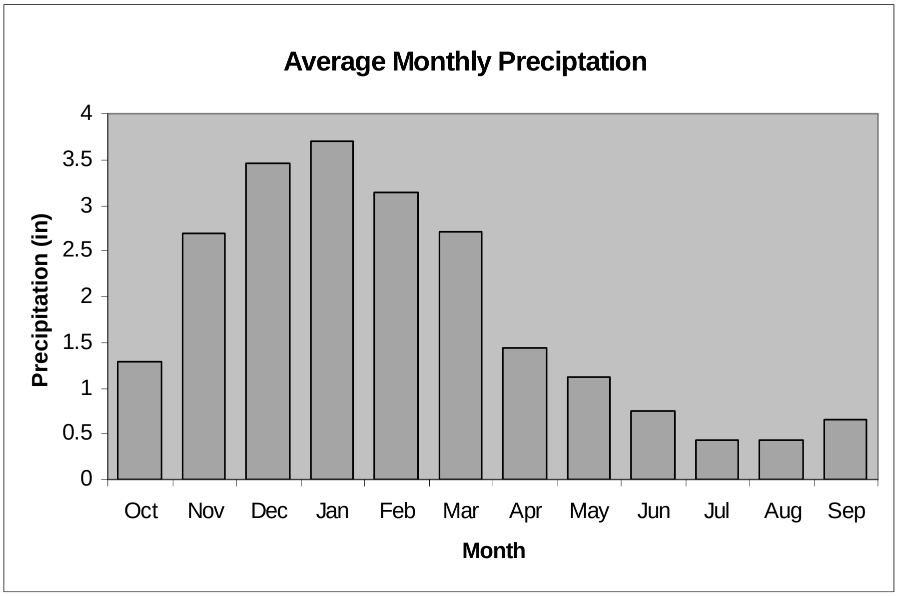


Figure 10: Average monthly precipitation for the Sierra Nevada mountain climate division (based on the 1949-2003 period)

Figure 11 and Figure 12 show the timeseries of spring runoff (measured as total April to July streamflow) and winter precipitation (measured as April 1st SWE), respectively, in the Truckee and Carson Basins for the period 1949-2003. The figures demonstrate the high interannual variability in seasonal precipitation and streamflow. In the water-stressed basin, where all available water is allocated, there often isn't enough water to meet demands. Water managers in the basin must understand and predict the variability in the supply in order to efficiently manage the basin.

Figure 13 presents the scatterplot of end of winter SWE and spring runoff in the Truckee and Carson rivers. There is a high degree of correlation between winter SWE and spring runoff. The top figures represent the correlations for the Truckee River; the bottom for the Carson River. The left figures are for March 1st SWE; the right for April 1st. Not surprisingly, April 1st SWE correlates better with spring runoff than March 1st SWE. Correlation values are 0.80 for the Truckee with March 1st SWE, 0.81 for the Carson with March 1st SWE, 0.93 for the Truckee with April 1st SWE and 0.90 for the Carson with April 1st SWE. April 1st SWE provides a more

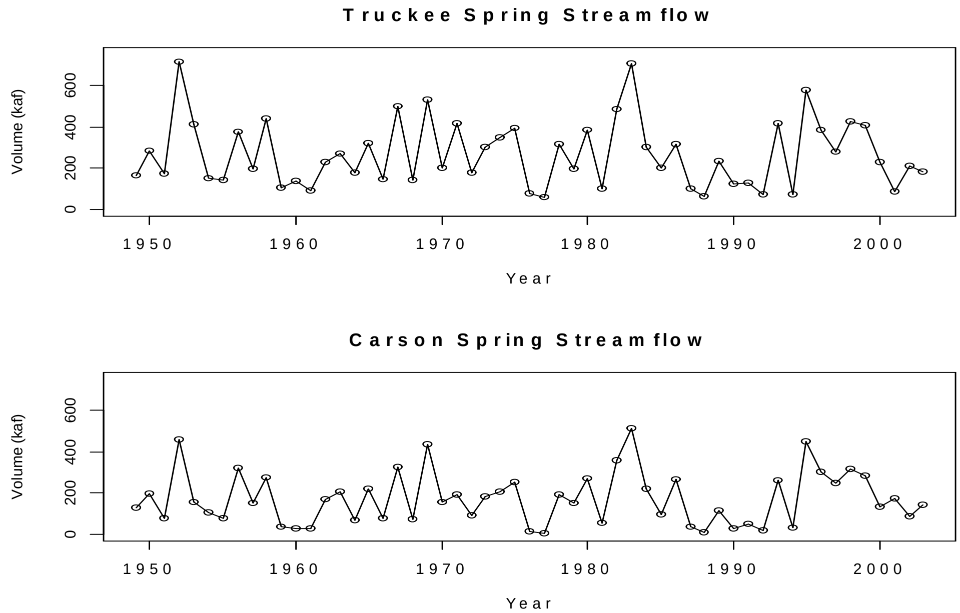


Figure 11: Spring streamflow in the Truckee and Carson rivers for the period 1949 to 2003. The top figure shows the Truckee River spring streamflow; the bottom show spring streamflow for the Carson River. The spring streamflow is taken as the total volume for the months April to July

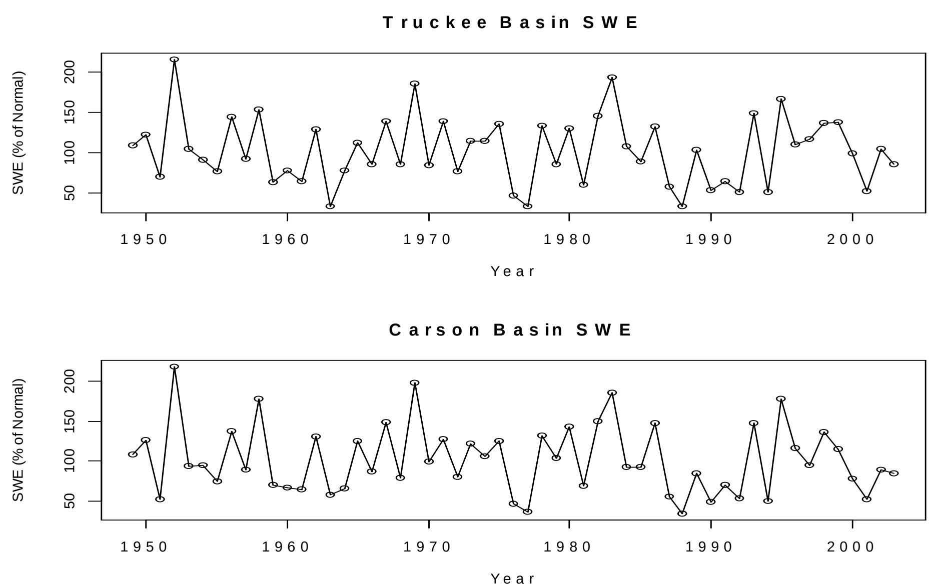


Figure 12: April 1st SWE in the headwater regions of the Truckee and Carson rivers for the period 1949 to 2003. SWE is taken as a basin-wide average and represented as a percent of normal value.

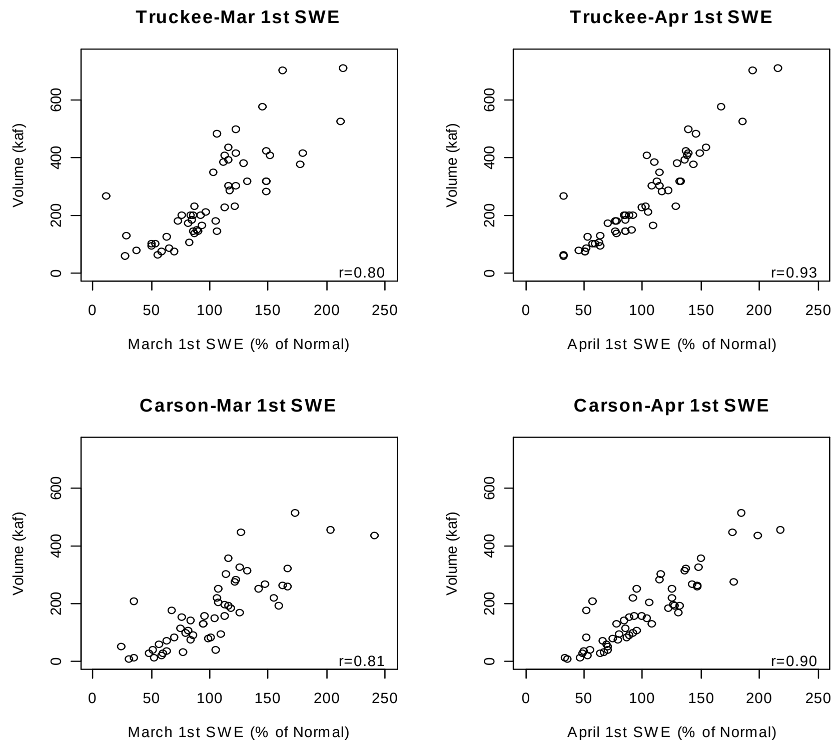


Figure 13: March 1st (left) and April 1st (right) SWE versus spring runoff volume in the Truckee (top) and Carson rivers for the period 1949 to 2003. SWE is taken as a basin-wide average and represented as a percent of normal value.

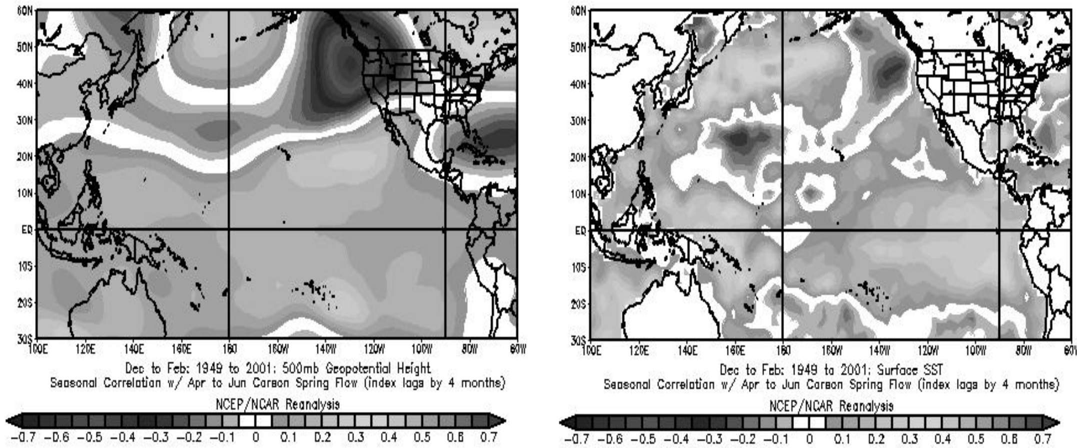
accurate representation of the total snow available for runoff in the April to July season. March 1st SWE, however, also correlates well with spring runoff and offers the opportunity for an earlier forecast. The scatter for the Truckee River is tighter than that for the Carson River. One possible reason for the lower correlation in the Carson is that the Carson Basin has significantly fewer snow measurement stations than the Truckee Basin (7 stations for the Carson versus 17 for the Truckee), limiting the accuracy of a basin-wide SWE value. The USBR is currently coordinating with the NRCS to install more snotel stations in the Carson Basin. Another potential source of the lower correlation values is that the natural streamflow values for the Carson are, in fact, the gaged streamflow values at Ft. Churchill. With over 35,000 irrigated acres before the Ft. Churchill gaging station, it is unlikely that the gaged streamflow is a precise representation of natural streamflow. Having noted this, the plots nevertheless portray a strong correlation between SWE and the total spring streamflow at both Farad and Ft. Churchill. These correlation values are statistically significant, indicating the potential for using SWE as a predictor to spring runoff in both rivers.

2.2.4 Results: Correlation Analysis

In the correlation analysis, we correlate spring streamflows in the Truckee and Carson Rivers with winter indices of the dominant teleconnection patterns (i.e., ENSO and PDO) as well as general oceanic and atmospheric circulation variables (e.g., SST and pressure). Correlations between spring streamflow and the dominant winter teleconnection indices Nino3, Nino3.4, SOI and PDO are not statistically significant. This is not surprising, given that climate (and streamflow) anomalies in specific regions are sensitive to subtle shifts in atmospheric circulation patterns; shifts that are not well described by the standard teleconnection indices. We therefore analyze the oceanic and atmospheric circulation variables related to these larger dominant teleconnection patterns: SST and pressure. The winter SSTs and 500mb geopotential height pressure variables over the Pacific Ocean correlate strongly with spring streamflows in the Truckee and Carson Rivers. We use the 500mb geopotential height pressure variable because it is smoother than the SLP variable. Results from the analysis of these variables are presented below.

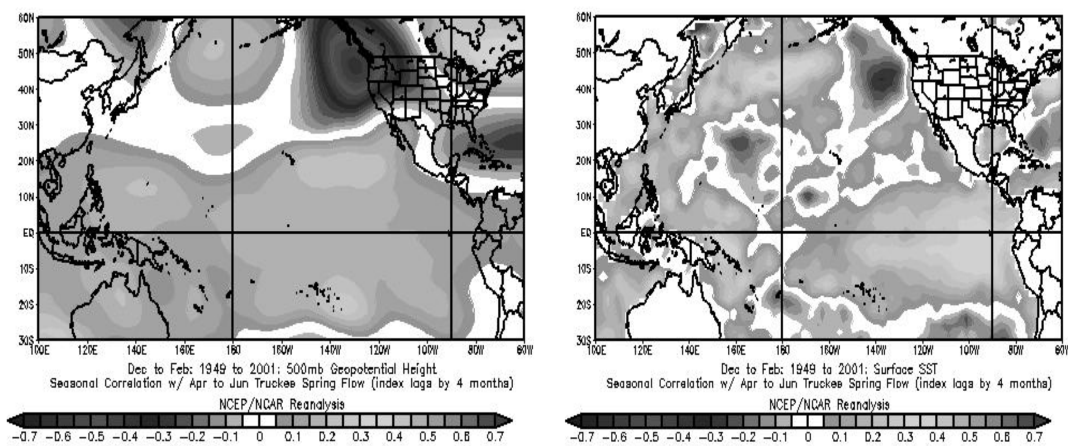
Figure 14 presents the correlations between the oceanic and atmospheric variables over the Pacific Ocean in winter (December to January) and the runoff during the following spring (April to June) in the Carson basin. Figure 14(a) illustrates the 500mb geopotential height correlation and Figure 14(b) depicts the SST correlation. Figure 15 similarly, presents the correlations for the Truckee basin.

Figure 14 and Figure 15 demonstrate that winter climate over the Pacific Ocean correlates strongly with streamflow in the Truckee and Carson Rivers in the following spring. In particular, the 500mb geopotential height pressure variable off the



(a) (b)

Figure 14: Carson River spring streamflow correlated with winter (a) geopotential height 500mb and (b) sea surface temperature



(a) (b)

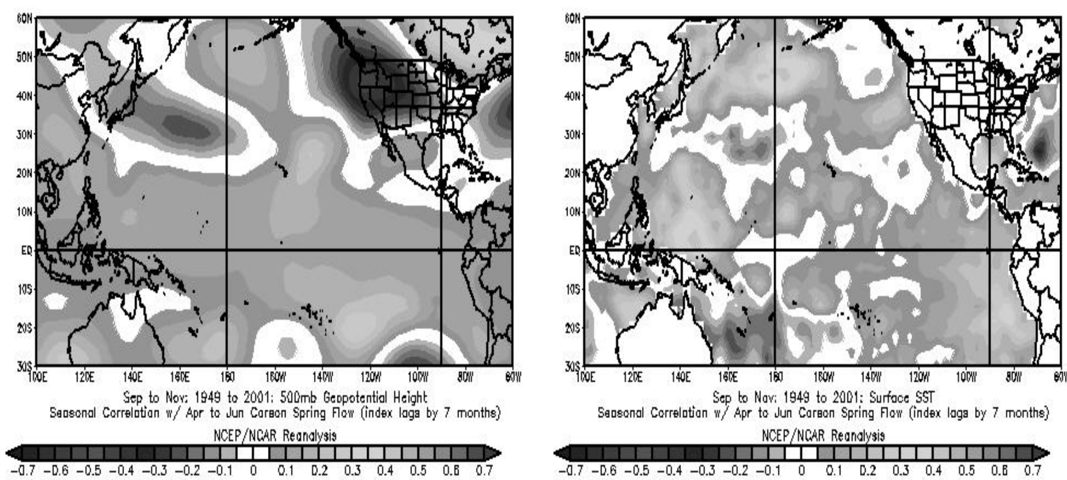
Figure 15: Truckee River spring streamflow correlated with winter (a) geopotential height 500mb and (b) sea surface temperature

coast of Washington has a strong negative correlation (-0.7) with spring streamflow. This means when pressure in this region is below average in winter, streamflow in the Truckee and Carson Rivers the following spring will likely be above average. Similarly, the sea surface temperature in the northern mid-Pacific Ocean in winter has a strong positive correlation (0.5) with spring runoff; above average sea surface temperature in this region in winter indicate above average runoff the following spring in the

Truckee and Carson Rivers. To the east of this region, the SSTs exhibit a negative correlation with the spring streamflows. The physical significance of these correlations will be described in the following section.

It is not surprising that the climate correlation patterns are very similar for both rivers. Because the headwaters to the Truckee and Carson Rivers are very close in proximity, they are affected by many of the same weather patterns.

Correlations between spring streamflows and climate variables from the preceding fall are shown in Figure 16. The correlations in fall, though somewhat weaker than those for winter (-0.5 for the geopotential height 500mb and 0.4 for the SST), could provide early information about streamflow to come the following spring--before SWE data is even available. It can be seen that these patterns are similar to the winter patterns (Figure 14). This persistence in atmospheric circulation patterns enhances the possibility of longer lead-time forecasts.



(a) (b)

Figure 16: Carson River spring streamflow correlated with fall (a) geopotential height 500mb and (b) sea surface temperature

It is generally believed that the large-scale ocean-atmospheric patterns are persistent over time. To confirm that the patterns provide important information over time, we correlate the spring streamflows with the large-scale climate variables in successive three month seasons starting with the preceding July (e.g., July-Sept., Aug.-Oct., Sept.-Nov., etc.). For each map we take the correlation value for the geopotential height and SST regions discussed above. We then plot the correlation values as they increase with time. This is shown in Figure 17. Though correlations are strongest for the winter months, Figure 17 illustrates that correlations are significant in fall and even late summer.

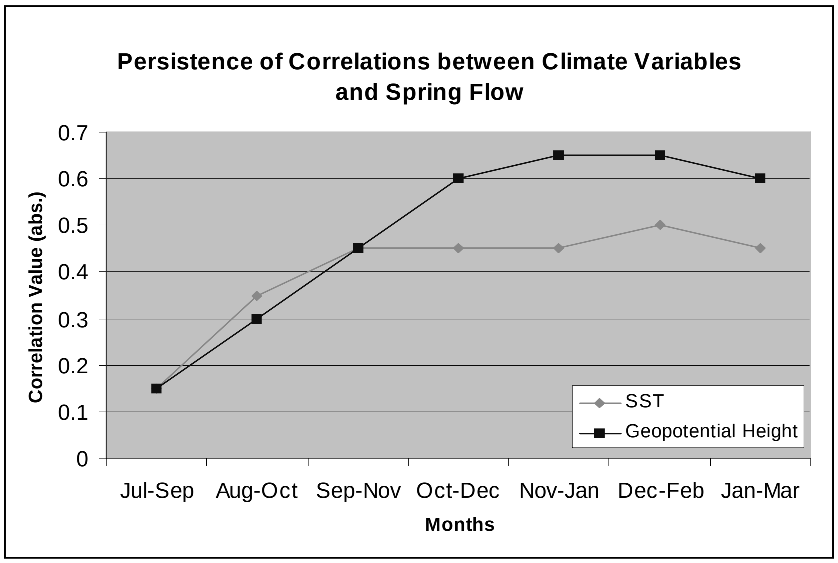


Figure 17: Persistence of geopotential height and SST correlations for months prior to spring runoff

This approach of developing correlation maps and identifying the relationship to large-scale climate variables is much more comprehensive than correlating with standard indices such as the Nino3, Nino3.4, SOI, PDO, etc. In the latter, if the correlation is weak with these indices, one might erroneously conclude a lack of relationship with the large-scale climate phenomenon when in fact the correlation maps with SSTs and geopotential heights might indicate otherwise. For instance, the correlation between the spring streamflows in Truckee and Carson are very low (statistically insignificant) with winter Nino3, Nino3.4, SOI and PDO indices. However, the spatial correlation maps clearly indicate a relationship with northern Pacific geopotential heights and SSTs which are part of the general PNA, PDO and ENSO patterns. The standard teleconnection patterns describe variations in the amplitude of the PNA wave train in specific locations. These variations may not be important in the Truckee-Carson Basin, therefore we find the exact patterns that are important.

2.2.5 Results: Composite Analysis

To understand the physical mechanisms driving the correlation patterns seen above we perform a composite analysis. In this analysis, years are grouped according to flow characteristics (i.e., the six years above the 90th percentile of streamflows and the six years below the 10th percentile of streamflows). Average ocean-atmospheric patterns for the selected years are obtained for each grid point around the globe. Specifically, we examine the SSTs and vector winds in the northern Pacific and plot the patterns in high streamflow years and again in low streamflow years. The resulting patterns provide insights into the physical link between the geopotential heights and SSTs and spring streamflows in the Truckee and Carson rivers. The SSTs are shown as colors, while the vector winds are shown as arrows-- the length of the arrows indicate the strength of the winds.

Figure 18 presents the vector winds in the six highest streamflow years (a) and the six lowest streamflow years (b). Figure 19 similarly presents the SSTs in high (a) and low (b) streamflow year. Figure 20 illustrates the difference of vector winds and SSTs between high and low streamflow years. (For the high minus low composite plot, an average SST or wind vector is computed at each grid point for the high years, again for the low years, and then the two values are differenced.) The SST plots exhibit a similar pattern to that in the correlation plots (Figure 14)-- warm SSTs in the north mid-Pacific in high streamflow years and cool SSTs in this region in low streamflow years. The high minus low composite map shows that the SSTs across the north Pacific exhibit a dipole pattern of warmer SSTs to west and cooler SSTs to the east--

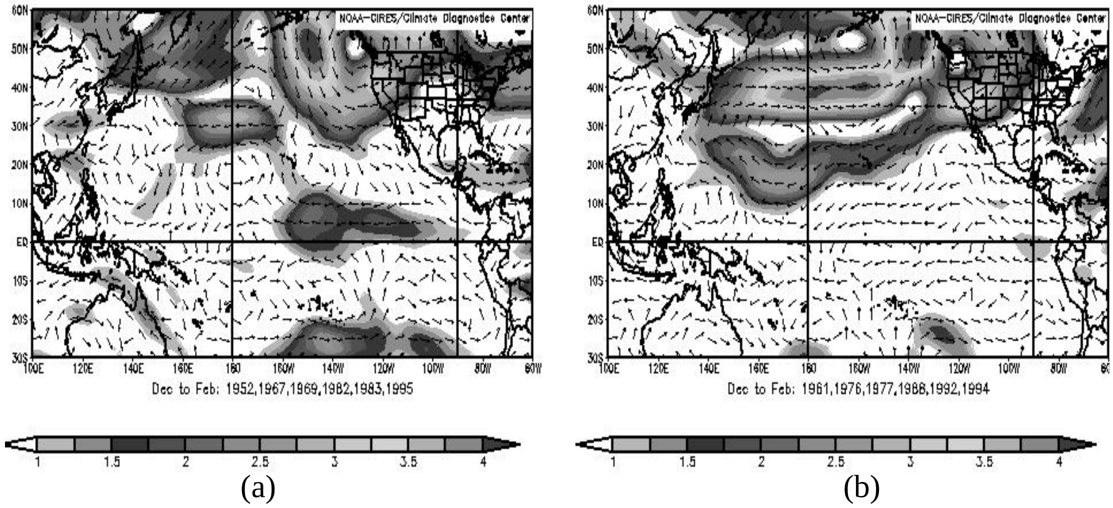


Figure 18: Climate composites: vector winds in high (a) and low (b) streamflow years

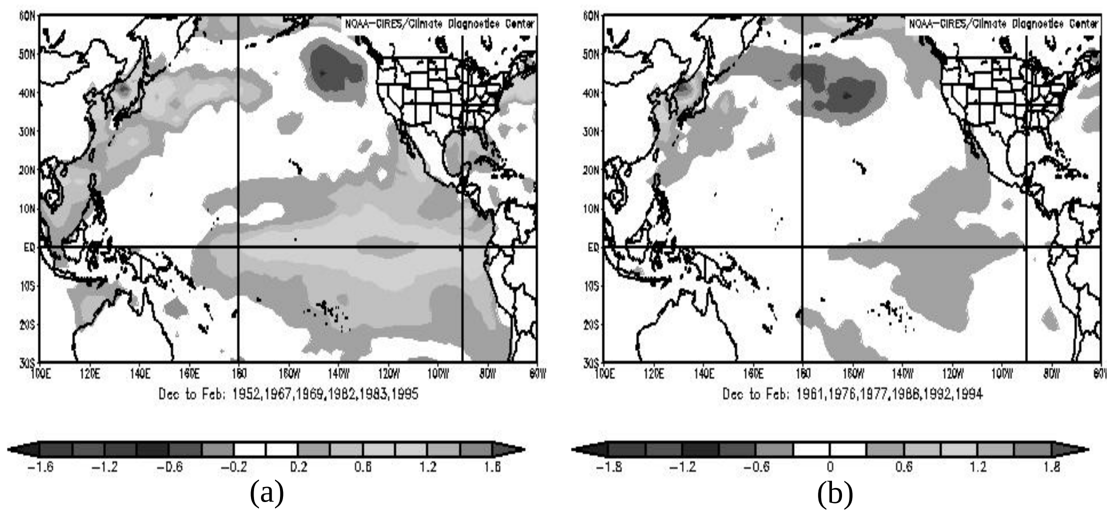
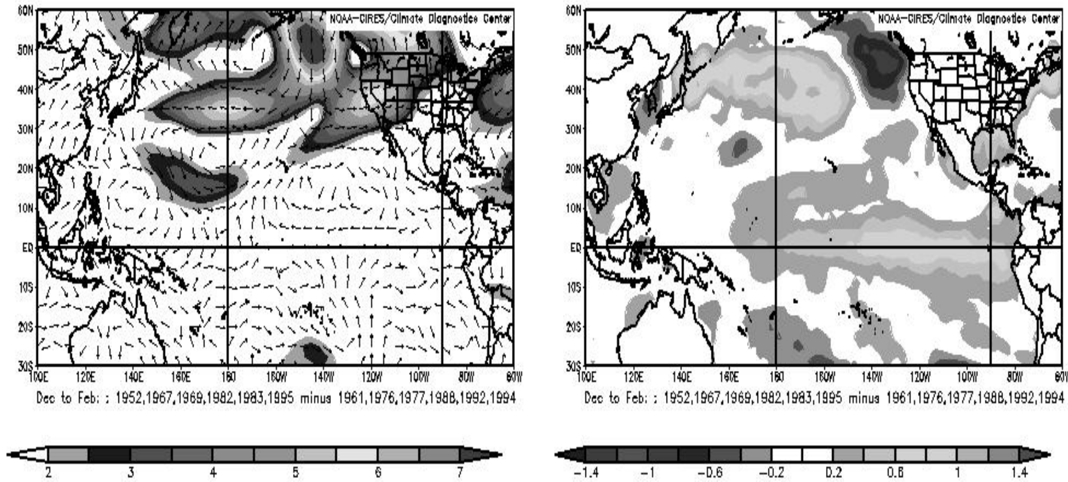


Figure 19: Climate composites: SSTs in high (a) and low (b) streamflow years

also seen in the correlations analysis (Figure 14). The winds in high streamflow years show a counterclockwise rotation around the region off the coast of Washington-the region of highest correlation detected in the correlation analysis (Figure 14). The opposite wind rotation is seen in low streamflow years.

The Coriolis Force causes winds in the northern hemisphere to move in a counterclockwise rotation pattern around a region of low pressure. This can be seen in the



(a) (b)

Figure 20: Climate composites: high minus low streamflow years (a) sea surface temperature and (b) vector winds

low pressure region off the coast of Washington. This process enhances southerly winds to the area southeast of the low pressure region-- in this case the headwaters of the Truckee and Carson Rivers. Southerly winds carry warm, moist air, thereby increasing the chance of precipitation (in this case snow) when the air rises and cools as it encounters the Sierra Nevada Mountains. Increased snowfall consequently increases spring streamflows. This explains the physical significance of the negative correlation between pressure and streamflow in the Truckee and Carson Basins.

The SST pattern, on the other hand, is a direct response to the pressure and winds. The winds are generally stronger to the east of a low pressure region-- this increases the evaporative cooling and also increases upwelling of deep cold water to the surface. Together, they result in cooler than normal SSTs to the east of the low pressure region. The opposite is true on the west side of the low pressure region. Thus, in the mid-latitudes it is typical to see a low pressure region lying between cooler than normal SSTs to the east and warmer than normal SSTs to the west. A schematic of this plausible physical mechanism is shown in Figure 21.

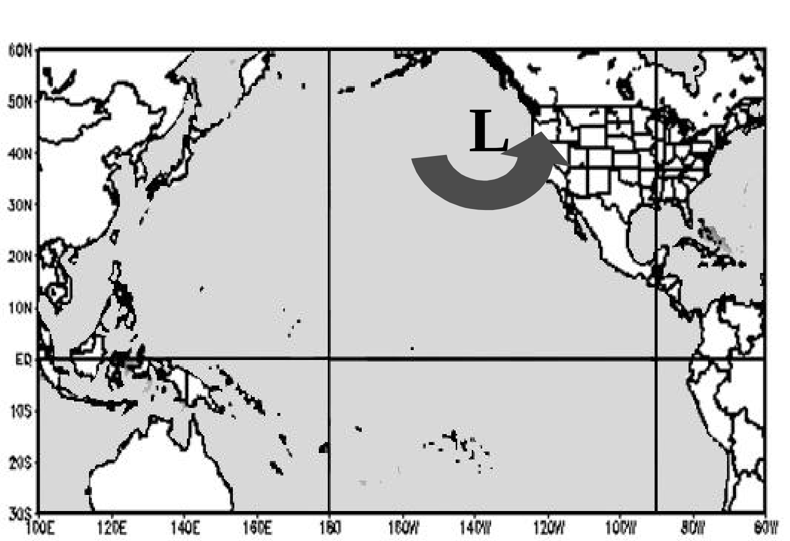
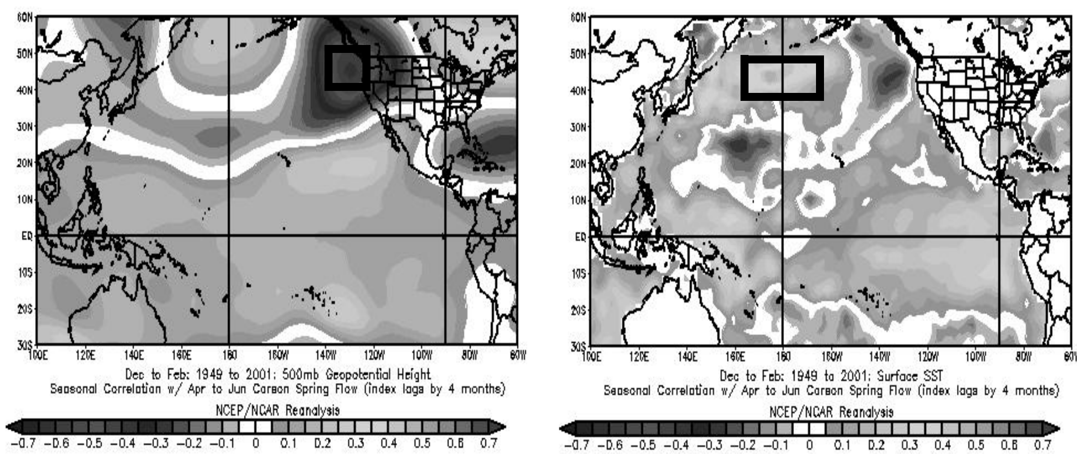


Figure 21: Schematic of physical mechanism relating a low pressure pattern in winter in the northern Pacific to spring streamflows in the Truckee and Carson Rivers.

2.2.6 Predictor Indices

Based on the correlation and composite analyses, we develop climate indices by averaging the ocean-atmospheric variables over the areas of highest correlation. Figure 22 illustrates the making of the geopotential height and SST indices. We com-



(a) (b)

Figure 22: Geopotential height (a) and SST (b) correlation plots. The boxes indicate the regions used in creation of the indices

pute area averages for the regions inside the boxes depicted in Figure 22. Specifically, the gridded geopotential heights over the region 225-235° E and 42-46° N and the SSTs over the region 175-185° E and 42-47° N are averaged for each year - thus, resulting in a time series of the indices. For the winter index, we compute December to February averages, and for the fall, September to November averages.

Figure 23 shows the scatterplot of the geopotential height index (fall and winter) versus runoff the following spring. We use local regression (Loader, 1999) to fit

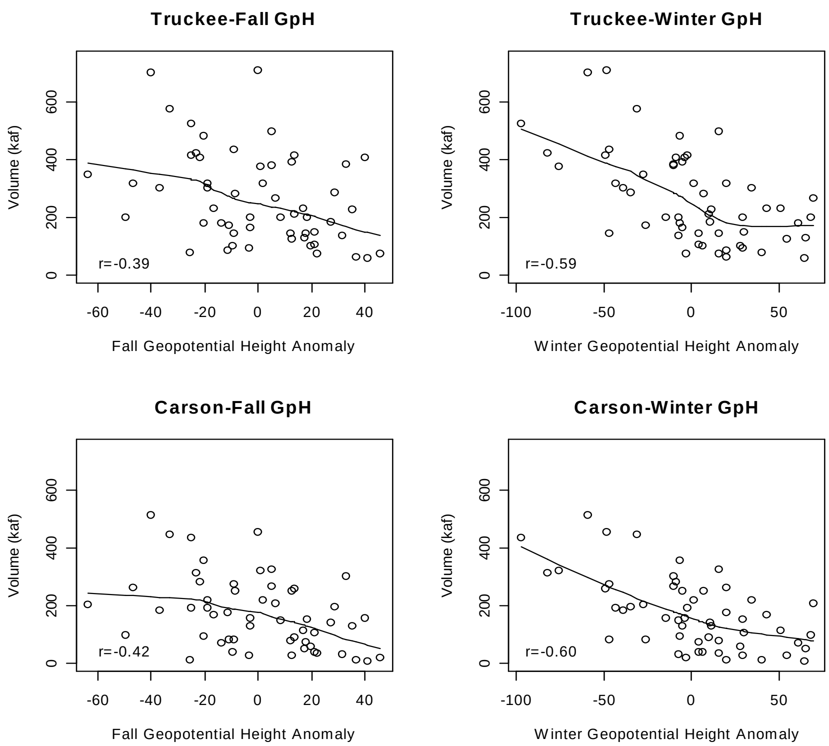


Figure 23: Scatter plots of winter (left) and fall (right) geopotential height index and spring runoff in the Truckee (top) and Carson (bottom) rivers.

the spline shown in the scatterplot. (Details of this method are provided in Chapter 3, "Nonparametric Stochastic Forecasting Model.") A strong relationship exists between the spring streamflows and both winter and fall indices. The relationship, however, is not directly linear. While normal and above normal streamflow values express a nearly-linear negative relationship with the geopotential height index, the relationship breaks down for lower streamflow values - thus providing a non-linearity. The tightness of the scatter and the high correlation value signify the potential for using the index as a predictor to streamflow in a forecasting mode.

Figure 24 presents the relationship between the SST index and runoff the following spring. Though correlation values are statistically significant, the relationship is nonlinear. A large amount of scatter for the normal SSTs indicates that the index may not be as useful in forecasting in normal SST years.

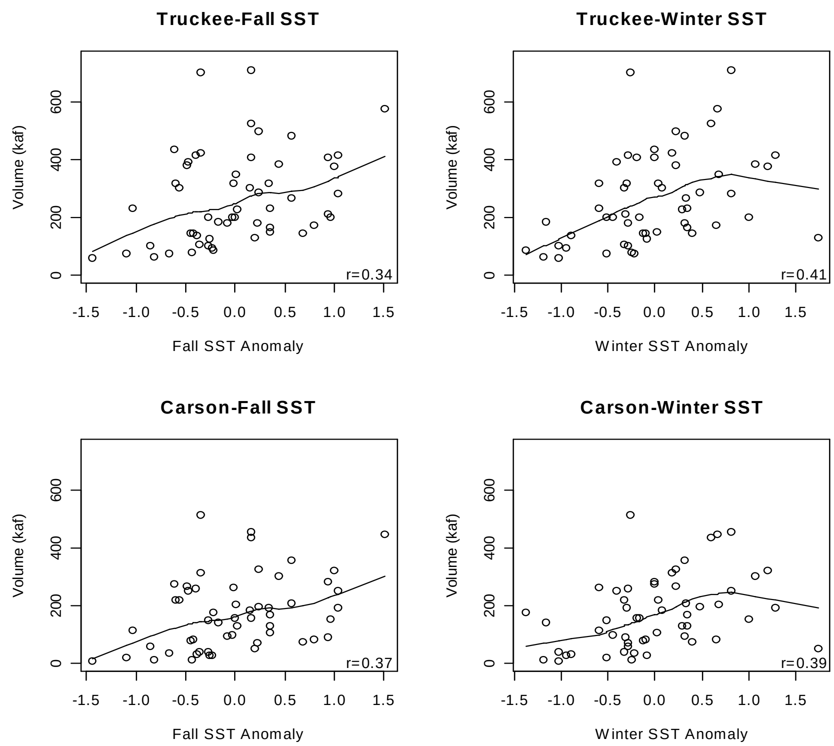


Figure 24: Scatter plots of winter (left) and fall (right) SST index and spring runoff in the Truckee (top) and Carson (bottom) rivers

Figure 25 shows the surface plot of the geopotential height index, the SST index and the Truckee River spring runoff. Results are similar for the Carson. The nonlinearities among all three variables are apparent in the undulations of the surface plot. If the relationships were linear, the plot would appear as a flat sheet. The SST

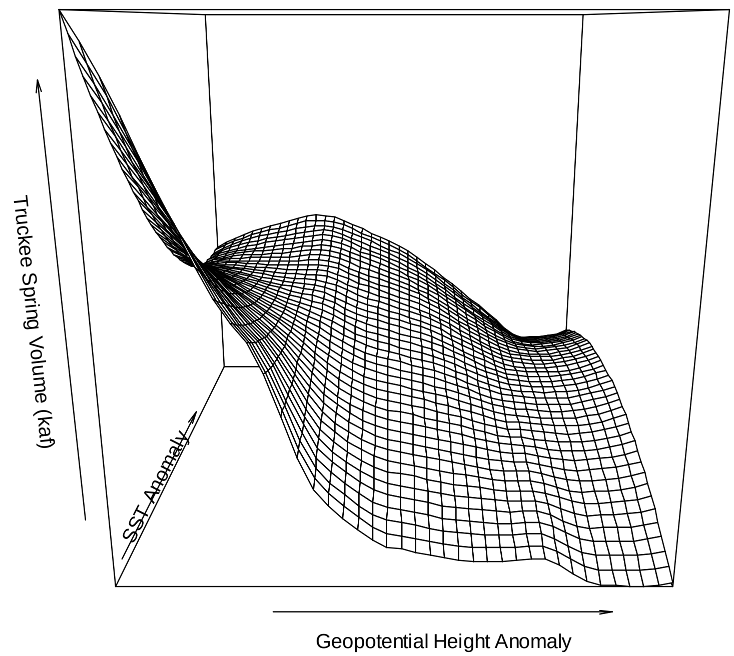


Figure 25: Three dimensional plot of geopotential height index, SST index and spring runoff in the Truckee River

has a stronger relationship with streamflow when geopotential height index is low. When the geopotential height index is high, streamflow does not vary significantly with the SST index. Similarly, the geopotential height index has a stronger correlation with spring runoff when the SST index is low, and a weaker correlation with spring runoff when the SST index is high. The nonlinearities evidenced in this plot underscore the complex relationship between the SST index, the geopotential height index, and spring runoff in the Truckee River. The use of local regression techniques is necessary if any useful information is to be gleaned from these indices.

2.3 Summary and Conclusions

Growing evidence from past studies supports the hypothesis that large-scale atmospheric circulation patterns affect the hydroclimate in the western United States. Researchers have conducted many studies that demonstrate various atmosphere-ocean-land relationships. Many of the studies focus on large-scale patterns (such as ENSO and PDO) that impact weather around the globe. Several studies demonstrate a link between these climate patterns and flooding and drought in various regions of the western United States. Other studies have utilized the relationships for forecasting precipitation and streamflow. Research shows, however, that these relationships are highly nonlinear and their physical mechanisms are not fully understood.

We conduct our own analysis to determine the prominent patterns that affect hydroclimate in the Truckee and Carson basins. The basins are clearly snowmelt dominated, thus we analyze winter atmospheric circulation patterns to glean useful information that may affect runoff the following spring. Correlation analysis results show that winter large-scale ocean-atmospheric patterns over the Pacific Ocean strongly modulate the year to year variations of spring runoff in the basins. Particularly, 500mb geopotential height and SST demonstrate a strong relationship with the spring runoff. The persistence of these circulation patterns into fall enhances the prospect of a longer-lead forecast using the large-scale climate information. The composite analysis provides a physical explanation of the pressure-streamflow relationship. Based on our analysis we develop climate indices to be applied later in a forecasting model.

Chapter 3

Nonparametric Stochastic Forecasting Model

An improved model is required to predict spring runoff in the Truckee and Carson Basins to better facilitate operation and management of the rivers. Specifically, the seasonal forecasting model will help establish allowable diversions through the Truckee Canal to the Newlands project as well as reservoir releases for fish. The spring forecast is of particular importance in the Truckee-Carson river system. Because runoff from spring snowmelt accounts for nearly two-thirds of the total annual streamflow, forecasting this total volume is imperative. It is also important to disaggregate this volume into monthly values throughout the season, as monthly forecasts determine storage targets for Lahontan Reservoir. Furthermore, the forecasting model should quantify the uncertainty of the forecast to allow water managers to plan for extreme scenarios. Finally the model must be easy to use and to implement into the existing operational procedures. This chapter describes the development of a nonparametric stochastic model for forecasting spring runoff. The model uses the large-scale climate predictors identified in Chapter 2 and provides ensemble forecasts of spring streamflows, thus quantifying the uncertainty of the forecast. This chapter presents the forecasting model, its predictive ability and the results obtained from it.

3.1 Introduction

3.1.1 Need for an improved forecasting model

The USBR Lahontan Basin Area Office (LBAO) is currently searching for an improved forecasting model to use for watershed management and decision-making. Accuracy of forecasts has become evermore important in the water-stressed Truckee and Carson River Basins. With the implementation of revised OCAP in recent years, the release of water quality credit water for fish, as well as diversions through the Truckee Canal, depend heavily on the seasonal forecast. The current USBR forecasting model is limited in its skill, estimation of uncertainty, and lead-time. The model does not always predict the spring runoff to a required accuracy level and in certain situations can adversely affect the efficiency and management of the basin. Though flexibility has been built into the system to accommodate for errors, it is not uncommon to divert or release too much or too little water based on an inaccurate forecast. The lead-time provided by the USBR forecasting model also leaves room for improvement. The model employs snowpack information as the basis of the forecast, therefore spring runoff can be predicted from January 1st at the earliest. Though current basin policies do not require a seasonal forecast earlier than January, water managers could benefit from advance notice of the coming water season (Scott, 2002). Furthermore, the January forecast is highly provisional due to the fact that only a small proportion of the total seasonal snow has fallen by the end of December. A forecasting model that is not limited to solely snowpack information could provide better skill in the early winter months. Finally, there is a need to improve the quantification of uncertainty in the forecasts. While the current forecasting methods do provide probabilistic forecasts, these forecasts are based on the assumption that the data are normally distributed and do not capture the true probability distribution. The importance of planning for extreme events such as floods and droughts underscores the need for a reliable stochastic model. In this study, we develop a forecasting model to address all these needs.

3.1.2 Background

Streamflows can be modeled and forecasted by a number of different methods, including physically-based (deterministic) methods and statistically-based (empirical) methods. The streamflow in the Truckee River, for example, is currently being modeled using the deterministic Precipitation Runoff Modeling System (PRMS) (Leavesley et al., 1996) as well as the empirical regression models of the USBR and the NRCS. Deterministic models such as PRMS aim to emulate hydrologic processes by modeling basin response (e.g., streamflows and sediment yields) to various combinations of precipitation, climate, and land use. Deterministic models, however, typically have several parameters to be calibrated, thus requiring large amounts of data. Empirical models developed by the USBR and the NRCS seek to capture the underlying relationship between various hydrological parameters (e.g., streamflows and snowpack) through statistical methods such as linear regression. While each of the models currently used in the Truckee-Carson Basin has its advantages, the forecasts produced are not as accurate as needed for efficient and effective management of the system and the USBR LBAO is seeking an improved model.

This research develops a nonparametric statistical forecasting model. We choose a statistical model because, in general, statistical models require less initial data and parameters and do not need to be calibrated like deterministic models do. The model developed in this research aims to improve on existing models not only by improving the accuracy of the forecast, but also by providing a longer lead-time and better quantifying the uncertainty of the forecast. Because the model utilizes snowpack information as well as large-scale climate information, it can forecast from fall and provide water managers with an early perspective in planning for the coming water season. Later forecasts increase in skill and can be used operationally. The model produces ensemble forecasts which provide reliable exceedence probabilities to be used in planning for extreme events. The forecasting technique has no underlying data assumptions, and hence can better capture the probability distribution of the forecast. Existing statistical forecasting methods are briefly discussed, followed by a description of the methods employed in this study and the results from the application to the Truckee-Carson Basin.

Effective river basin planning and management requires the ability to model streamflow variability. Stochastic models capture streamflow variability by generating ensembles-- multiple scenarios of plausible streamflow values which include extreme events such as floods and droughts and which preserve the statistics of the observed data. The ensembles can be used to quantify the uncertainty of the forecast and to calculate exceedence probabilities. Both statistically-based and physically-based models can generate ensemble forecasts. For example, PRMS utilizes the National Weather Service's Ensemble Streamflow Prediction (ESP) method to couple multiple scenarios of precipitation (specifically, all data from the historical record) with initial conditions (e.g., soil moisture) to generate multiple runoff timeseries. Empirically-based stochastic models often selectively sample from the range of past streamflow data to generate ensembles. In both frameworks, the models operate on the premise that the statistics (mean, standard deviation, lag (1) correlation, and skew) of the historical flow (or precipitation) are likely to occur in the future, i.e. the stationary assumption.

Traditional statistical forecasting techniques fit a regression, often linear, between the response variable (e.g., spring streamflows) and the independent variables (e.g., predictors). They are of the form:

$$y_t = a_1 x_{1t} + a_2 x_{2t} + \ldots + a_p x_{pt} + e_t \qquad \text{Eq. 3.1}$$

Where the coefficients a_1, a_2,…, a_p are estimated from the data. The error, e, is assumed to be normally distributed with mean 0 and standard deviation 1.

In the above model, the independent variables can be past values of the response variable itself:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + a_p y_{t-p} + e_t \qquad \text{Eq. 3.2}$$

These models are termed autoregressive moving average (ARMA) and periodic autoregressive (PAR) models. Hydrologists have developed and used such models for streamflow simulation and forecasting for many years (Salas 1985, Yevjevich 1972, and Bras and Iturbe 1985).

These traditional modeling techniques are termed “parametric” because they are based on estimating parameters (e.g., determining the coefficients) to fit the model. Parametric models inherently assume that the time series is normally (Gaussian) distributed (Salas, 1985). Typically, streamflow data do not fit a Gaussian distribution, thereby violating this assumption. To address this, the data are transformed to a normal distribution using a log or power transformation before fitting a parametric model to the transformed data (Sharma et al., 1997). The forecasted values are then back-transformed into the original space. This process of fitting the model on the transformed data and then back transforming it often does not guarantee the preservation of statistics (Sharma et al., 1997; Salas, 1985; Bras, 1985; Benjamin, 1970). There is rich literature for fitting and testing such models and software packages are extensively available (Helsel and Hirsch 1992). Such models have been widely used for hydroclimate forecasting in the US (e.g., Piechota et al., 2001 and Cordery and McCall, 2000). While parametric models generally preserve the mean, variance, and auto-correlations of a data set, skewness is approximated and further uncertainty is introduced through estimating model parameters. The inability to reproduce skew and bimodality, as well as the model uncertainty introduced through parameter estimation can significantly influence model results.

Nonparametric forecasting models were developed to address the drawbacks of parametric models. Nonparametric models, unlike parametric models, are assumption free and are driven by the data alone. Nonparametric models do not assume any underlying distribution in the data. No parameter estimations or data transformations are necessary. Nonparametric models estimate the marginal and conditional probability density function locally and hence capture any arbitrary relationship in the data, linear or nonlinear, Gaussian or non-Gaussian. Several types of nonparametric models exist for streamflow forecasting. These include the kernel based (Sharma et al., 1999), nearest neighbor based (Lall and Sharma, 1996), and hybrid parametric/nonparametric models (Srinivas and Srinivasan, 2001). This research employs nonparametric forecasting techniques, the further benefits of which will be expanded upon later in this chapter.

3.2 Seasonal Forecasting Model

3.2.3 Modified K-NN Method

The seasonal forecasting model developed in this study utilizes the nonparametric modified k-nearest neighbor (K-NN) approach developed by Prairie (2002) to generate ensemble forecasts of streamflow. The forecasts draw on the strong statistical correlations and physical relationship between winter (and fall) large-scale climate signals and the total spring runoff in the Truckee and Carson Rivers. The modified K-NN model fits a nonparametric relationship using local polynomials (Loader, 1999) between the predictors (500mb geopotential height, SST, and basin averaged SWE) and the spring streamflows. For the given winter (or fall) predictors, the fit is used to estimate the mean streamflow for the following spring. The residuals of the fit are then resampled and added to the mean forecast to obtain the ensemble forecast. A weighting scheme is used in the bootstrap of the k-nearest regression residuals, giving more weight to the closest neighbors, less weight to the farthest.

The local polynomial fit for the mean forecast (an assumption free, nonparametric approach) has the ability to capture any arbitrary (linear or nonlinear) dependence structure. The coupling of this with the residual resampling provides the capability to capture any arbitrary dependencies and probability density functions exhibited by the data, unlike conventional methods that can capture only linear dependence and Gaussian probability density functions. Once the ensemble of the total spring runoff is obtained, we apply similar techniques to disaggregate the total volume into monthly values which are used to set storage targets on Lahontan Reservoir.

The modified K-NN algorithm, adapted from Prairie (2002) to work with multiple predictors in this research, is outlined below:

1. A local polynomial is fit to the flow regressed on the three predictors, x, y, z:

$$Y_t = f(x, y, z) + e_t \qquad \text{Eq. 3.1}$$

2. The residuals (e_t^*) from the fit are saved.
3. Given the three predictors for the current winter (or fall), the mean flow from Equation 3.1 is estimated.
4. The Euclidean distance between the current set of predictors and the sets of predictors for all other years is calculated and k-nearest neighbors are selected.
5. The neighbors are weighted using the weight function:

$$\frac{y_j}{\sum_{j=1}^{k} y_j} \qquad \text{Eq. 3.2}$$

This weight function gives more weight to the nearest neighbor and less weight to the farthest neighbor. The weights are normalized to create a probability mass function or "weight metric". Other weight functions with the same philosophy- i.e., more weights to nearest neighbors and lesser weights to farther neighbors can be used as well. Prairie (2002) found little or no sensitivity to the choice of the weight function.

6. Bootstrap the residuals. One of the neighbors is resampled using the "weight metric" obtained from Equation 3.2 above. Consequently, its residual (e_t) is resampled and added to the mean estimate.

7. Repeat 6 to obtain as many simulations as required (in this case, 100 simulations provided reproducible ensemble statistics.) Repeat steps 1 through 6 for other years.

Figure 26 and Figure 27 can be utilized to better visualize these steps. Figure 26 shows the scatter plot of the historical area-averaged winter geopotential height index and spring runoff for the Carson River at Ft. Churchill. The solid line shows a local (or nonparametric) fit through the scatter. The nonparametric fit is a

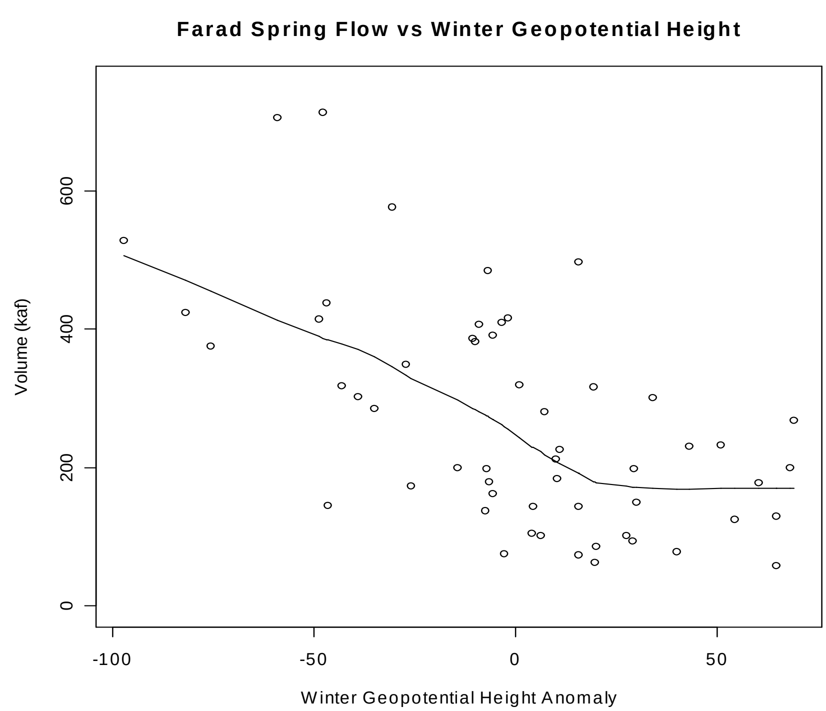


Figure 26: Local regression fit

locally weighted regression scheme (Loader, 1999; Rajagopalan and Lall, 1998). At any point in the regression, a local polynomial is fit to the k nearest neighbors. The size of the neighborhood (i.e., k) and the order of the polynomial are obtained using an objective criteria called Generalized Cross Validation (GCV). This estimation is at several points to obtain the solid line in Figure 26. We used the statistical package LOCFIT developed by Loader (http://cm.belllabs.com/cm/ms/departments/sia/project/locfit/) for fitting local polynomials. Because the forecasting model developed for this research uses three predictors, the local regression fit is in a four-dimensional space. The concept is the same as described for the two-dimensional example shown in Figure 26.

Figure 27 depicts the bootstrapping of the residuals for the ensemble forecast. Using the local regression we first obtain the expected (or mean) value for the forecast.

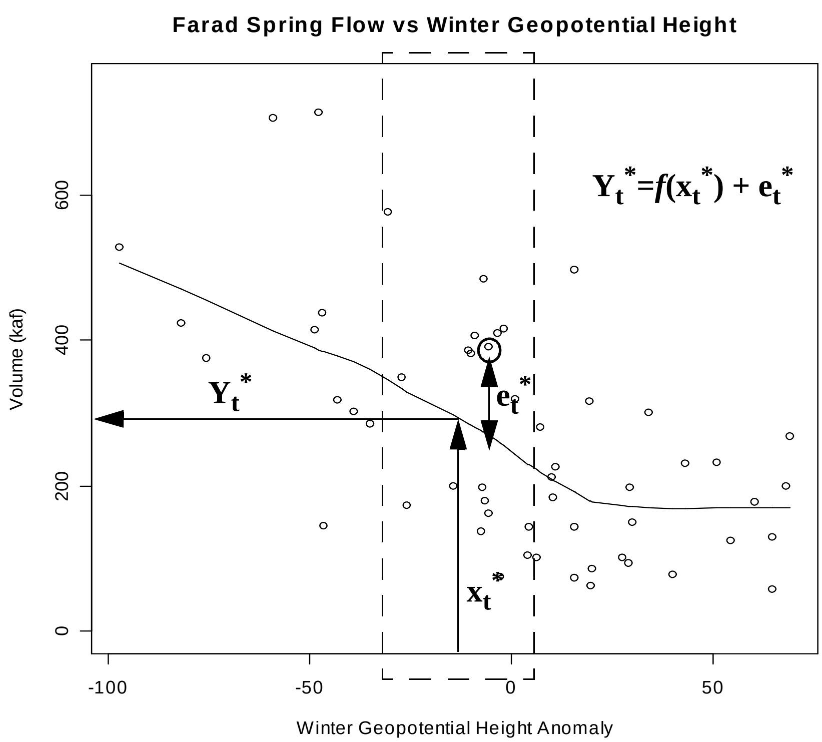


Figure 27: Residual resampling

Given the current state of the system (i.e., the current winter geopotential height, SST and SWE), we determine the spring runoff associated with this value (Y_t^*). In the two-dimensional example, this is obtained by taking the current geopotential height value on the x-axis, moving vertically up to the local regression line and finding the y-value associated with that point on the regression. This y-value is the expected value of the spring runoff. Next, using a heuristic scheme, we define the "neighborhood" around the current x-value to capture the k-nearest points, where k is defined as:

$$k = \sqrt{n} \quad \text{Eq. 3.3}$$

A point is next picked from the "neighborhood" with the stipulation that the points with values closer to the current x-value (in this figure, the geopotential height) have a greater chance of being selected and those further away have a lesser chance. The residual (e_t^*) from the local regression associated with the selected point is then added to the mean forecasted value (Y_t^*) to obtain the first member of the ensemble forecast. This process of resampling the residuals is repeated several times (here, 100 times) to obtain an ensemble forecast with 100 members. This is often referred to as "bootstrapping" the residuals. We tested various ensemble sizes and found little difference in forecast skill or ensemble statistics when the residuals were resampled more than 100 times.

One significant advantage of the K-NN (or modified K-NN) framework is that variables can be easily added in the predictor set--e.g., the number of predictors is not limited and hence forecasts can incorporate hydrologic initial conditions (SWE or accumulated precipitation), large-scale climate information, and any other relevant predictors of streamflows in the basin.

The flexibility of the method allows it to be used within any timestep framework-- e.g., monthly forecasts as done by Prairie (2002), seasonal forecasts (from either winter or fall) as presented in this chapter, etc. Seasonal forecasts can easily be updated monthly to incorporate new initial conditions. Because nonparametric techniques are data driven rather than distribution-fit driven, there is no need to re-parameterize the model for each updated forecast.

The modified K-NN model is an improvement on the traditional K-NN model in that it is able to generate values not seen in the historical record. This modification was first presented in Prairie (2002) and was briefly mentioned in the conclusion of Lall and Sharma (1996) and Rajagopalan and Lall (1999). The traditional K-NN resamples the actual points in the neighborhood, rather than adding the residuals associated with neighbors to the mean forecast. Desouza and Lall (2003) used the traditional K-NN approach to streamflow forecast in northern Brazil and obtained very good results.

A drawback of the modified K-NN technique, however, is that due to residual resampling it is possible to produce negative flow values in extremely dry streamflow years. If the expected value (mean forecast from the regression fit) is close to zero and negative residuals are added to this, it is possible to produce negative ensemble members. A method to address this drawback is to take a log transformation of the data before fitting the model and then transforming the forecasted values back into the original space. It is worth noting that nonparametric techniques such as the modified K-NN, though capable of producing negative flow values, are bounded by the tails of the probability distribution. The lowest possible value is the lowest historical value plus the largest negative residual. For comparison, parametric techniques, which assume a Gaussian distribution, are inherently unbounded in the possibility of streamflow values. Because the tails of a Gaussian distribution extend from $-\infty$ to $+\infty$, it is possible to produce highly negative or positive streamflow values.

3.2.4 Model Verification and Skill Measure

In order to validate the forecasting model, we use standard cross-validation techniques. We remove a streamflow value from the data set before fitting the model and then use the model to produce an ensemble forecast of the "unknown" value. The skill of the forecast is a measure of how adequately the model reproduces the "unknown" value. Boxplots of ensemble forecasts with the observed values overlaid on top provide a visual comparison of how well the ensembles capture the observed values. In addition to this visual comparison, we use three skill measures to evaluate the model performance:

(i) Correlation coefficient of the median of the ensemble forecast and the observed value.

(ii) Ranked Probability Skill Score (RPSS).

(iii) Likelihood Function Skill Score.

The RPSS, typically used by climatologists, is used to quantify the skill of ensemble forecasts. The RPSS verifies multicategory (in this case, above normal, normal, and below normal) probability forecasts by comparing the skill of the forecast relative to climatology. The term "climatology" here refers to the streamflow one would expect based only upon the long-term historical climate data (e.g., precipitation, temperature) for the basin. For example, a climatological forecast in any year will present the historical mean as the most expected streamflow value and a 10% chance of exceeding the 90th percentile of the historical data. By defining the categories above normal, normal, and below normal at the 33rd and 67th percentile of the historical data, climatology presents an equal probability (0.33) of falling into each category. The RPSS ranges from +1 (perfect forecast) to $-\infty$. Negative RPSS values indicate that the forecast has less accuracy than climatology. The RPSS essentially measures how often an ensemble member falls into the category of the observed value and compares that to a climatological forecast. The rank probability score (RPS) of the categorical forecast

P = (P_1, P_2, ... P_k) for a certain time is defined as:

$$RPS(p, d) = \frac{1}{k-1}\left[\sum_{i=1}^{k}\left(\sum_{n=1}^{i} P_n - \sum_{n=1}^{i} d_n\right)^2\right] \qquad \text{Eq. 3.1}$$

for k mutually exclusive and collectively exhaustive categories. The vector d (d_1, d_2, ... d_k) represents the observation vector such that d_n equals one if class n occurs, and zero otherwise. The RPS has a range of zero to one and is positively oriented (the higher the value, the better the forecast). (Toth, 2002)

The RPS is then used to calculate the rank probability skill score, RPSS:

$$RPSS = 1 - \frac{RPS(forecast)}{RPS(standard)} \qquad \text{Eq. 3.2}$$

(Toth, 2002).

The likelihood function is also used to quantify the skill of ensemble forecasts. As with the RPSS, we classify three categories for the likelihood function: below normal, normal, and above normal with divisions at the 33rd and 67th percentiles. The likelihood function compares the likelihood of the ensemble forecast falling into the observed category against climatology to develop a skill score. The likelihood skill score for the ensemble forecast in any given year is calculated as:

$$L = \left(\frac{\prod_{t=1}^{N} \hat{P}_{j,i}}{\prod_{t=1}^{N} P_{c_{j,i}}}\right)^{1/N} \qquad \text{Eq. 3.3}$$

Skill scores range from 0 to the total number of categories-- 3 in this case. A likelihood score of zero indicates no skill, a score of 1 indicates the same skill as climatology, and a skill score between 1 and the number of categories represents skill better than climatology. The likelihood measure is generic and is related to information theory (Rajagopalan et al., 2001).

3.2.5 Results

We first determine the optimal set of predictors by evaluating a model that uses all three predictors (SWE, SST, and 500mb geopotential height) against a model based on SWE and 500mb geopotential height data alone. Results show little or no improvement in forecast skill when the SST index is included in the predictor set. Therefore, in the interest of parsimony, we do not include the SST in the final forecasting model. Though SST correlations coefficients determined in Chapter 2 are statistically significant, the SST pattern is, at least in part, a response to the atmosphere-- hence providing little independent information. It is possible that the SST pattern contains a component which acts independently as a driving force for streamflow in the Truckee and Carson Basins. The relatively low correlation coefficient, however, introduces error in the model, thus decreasing any forecast skill that could be provided by an independent driving force. GCV and other objective criteria can be used to formally select an optimal set of predictors from a large suite of possible predictors. In linear regression, the stepwise regression method is typically used. This research uses only three predictors, therefore making it easy to perform an exhaustive search. All of the forecasting results presented below include only the geopotential height index and SWE in the predictor set. Results indicating the legitimacy of including the geopotential height index as a predictor are also presented.

3.2.5.1 April 1st Forecast

Figure 28 illustrates the modified K-NN model's ability to forecast each year in the historical record using standard cross-validation techniques. This model uses April 1st SWE and the winter (December to February) geopotential height index, mak-

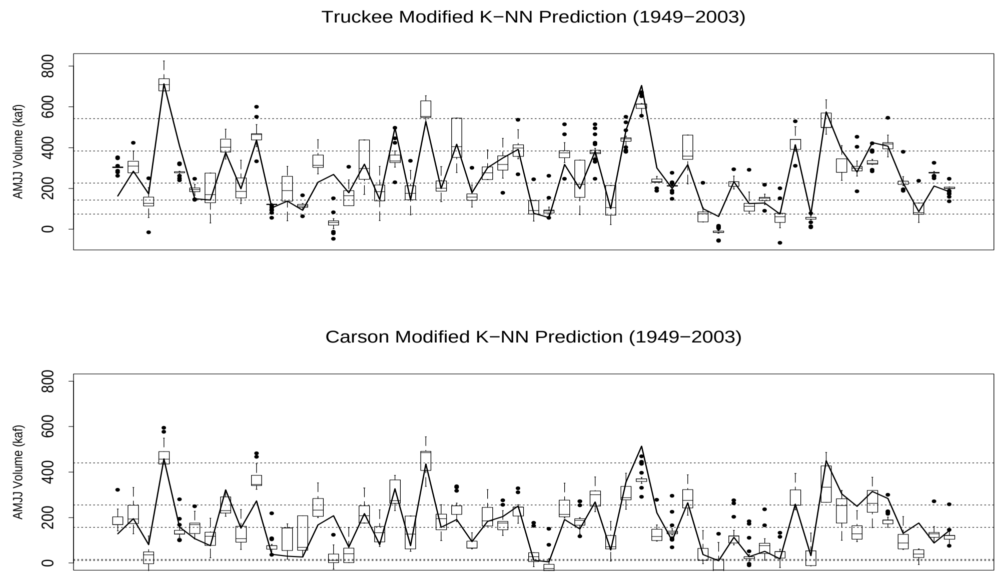


Figure 28: Timeseries of spring runoff with ensemble forecasts for each year (1949-2003). The solid line represents the historical timeseries. The boxplots represent the ensemble forecast issued from April 1st in each year. The dashed horizontal lines represent the quantiles of the historical data (5th, 25th, 50th, 75th, and 95th percentiles). The top figure is for the Truckee River; the bottom for the Carson River.

ing the forecast available April 1st. The solid line in the plots represents the historical timeseries of spring runoff in the Truckee River (top) and Carson River (bottom). The boxplots at each year illustrate the ensemble forecast in that year. The box portion of the boxplots represent the interquartile range of the ensemble forecast (25th to 75th percentile) with the horizontal line inside each box denoting the median of the forecast (most probable value.) The whiskers of the boxplot extend to the 5th and 95th percentiles of the ensemble forecast. Points outside the whiskers are outliers of the ensemble. Larger boxplots indicate greater forecast uncertainty, or a wider range of possible streamflow values in the ensemble. The dashed horizontal lines represent the quantiles (5th, 25th, 50th, 75th, and 95th percentile) of the historical data and help the viewer establish the relative streamflow in each year.

As demonstrated in Figure 28, the model typically captures the observed value within the interquartile range of the ensemble forecast, indicating fairly good skill in the forecast. The fact that the median of the ensemble is not in the center of the box illustrates skew in the ensemble forecast-- a feature that linear techniques cannot produce. Representing skew in the ensemble is important in determining exceedence probabilities of various forecasts.

Figure 29 shows the scatter plot of the median of the ensemble forecast and the observed spring runoff. If the forecast were perfect in every year, the points in the scatter plot would fall directly on the 45 degree lines shown in the figure. A larger amount of scatter denotes more error in the median forecast. The r value of correlation is noted in the lower right corner or each plot.

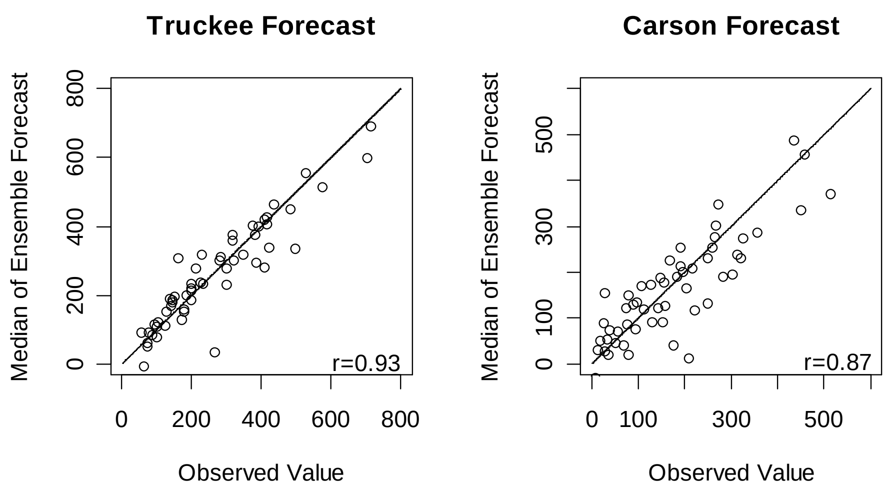


Figure 29: Median of April 1st ensemble forecast vs. observed spring runoff for the Truckee forecast (left) and Carson forecast (right).

The results presented in Figure 29 demonstrate that, even without the added benefit of quantifying uncertainty, the most probable forecasted value falls quite close to the observed value. Forecasting results for the Truckee River (r=0.93) are slightly better than those for the Carson River (r=0.87). As noted in Chapter 2, the correlation coefficient between SWE and spring runoff is slightly lower in Carson Basin than that in the Truckee Basin. Forecasters in the Truckee-Carson Basin historically have had more difficulty forecasting runoff in the Carson River and believe this is partly due to the relative scarcity of snowpack data in the Carson Basin (Reynolds, 2002).

Figure 30 shows the scatter plots of the April 1st NRCS official forecast versus the observed spring runoff. Historic forecast data from the USBR "similar years" model are not available, therefore we analyze the NRCS forecast. The r values are comparable to median of ensemble forecast results presented above: 0.93 for the Truckee River and 0.88 for the Carson River. Based on this comparison, one might argue

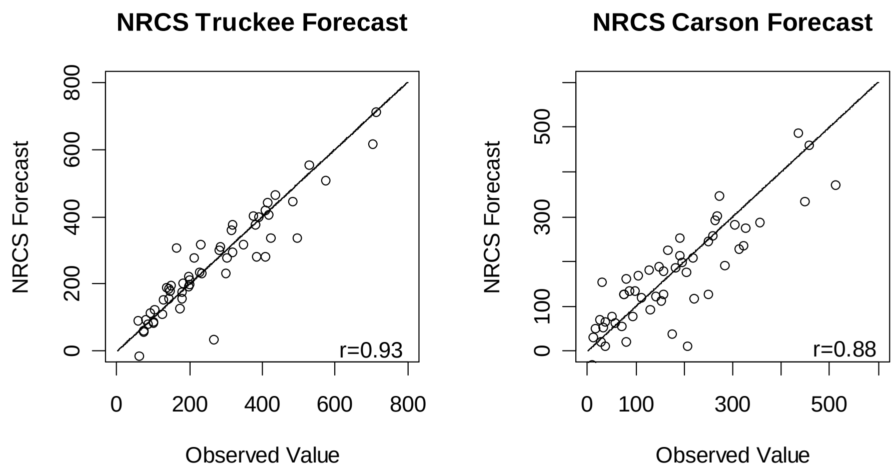


Figure 30: NRCS forecast vs. observed spring runoff for the Truckee River (left) and Carson River (right).

that the model used in the research does not improve on the NRCS forecasting model. This comparison, however, does not evaluate the added benefit of the ensemble forecasts produced in this research. Ensemble forecasts provide important information regarding exceedence probabilities and the uncertainty in the forecast. The official NRCS forecast does provide the 10th, 30th, 50th, 70th and 90th exceedence probabilities. However, the ensemble forecasts generated in this research can be evaluated to find exceedence probabilities for any threshold flow value that may be of particular importance in the basin.

The graphs of Figure 31 and Figure 32 emphasize the model's ability to forecast in extreme years. We select the years above the 90th percentile of the historical

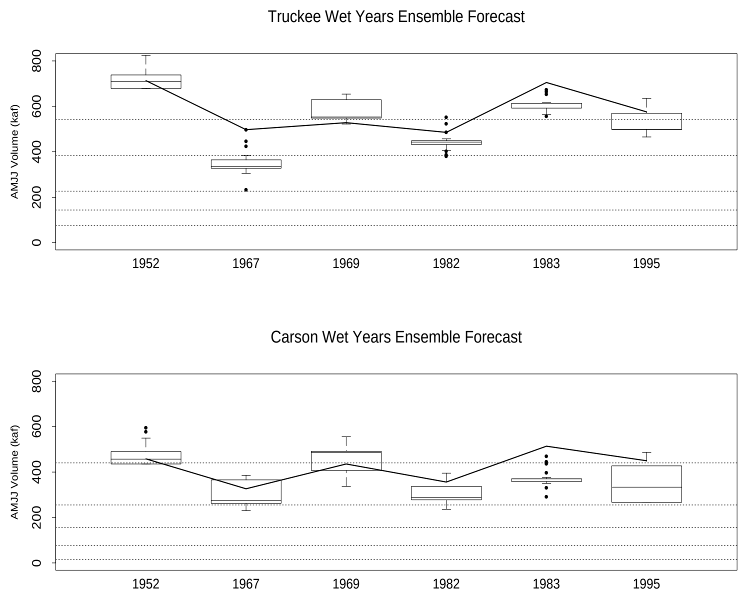


Figure 31: Ensemble forecasts for extremely wet years (above the 90th percentile). The solid line represents the observed spring runoff. The boxplots illustrate the ensemble forecast issued April 1st of each year. The dashed horizontal lines signify the quantiles of the historical data (5th, 25th, 50th, 75th, and 95th percentiles). The top figure is for the Truckee River; the bottom for the Carson River.

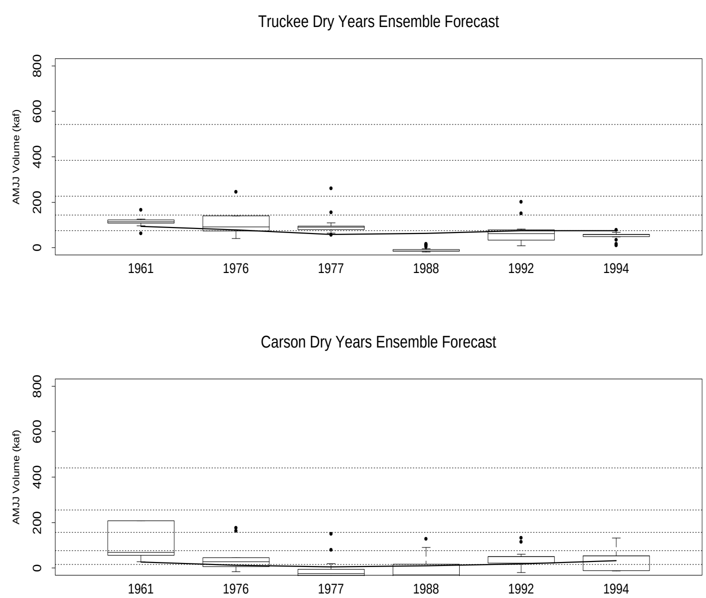


Figure 32: Ensemble forecasts for extremely dry years (below the 10th percentile). The solid line represents the observed spring runoff. The boxplots illustrate the ensemble forecast issued April 1st of each year. The dashed horizontal lines signify the quantiles of the historical data (5th, 25th, 50th, 75th, and 95th percentiles). The top figure is for the Truckee River; the bottom for the Carson River.

record (Figure 31) and below the 10th percentile (Figure 32) to test the model's performance in forecasting extreme wet and extreme dry years. The results demonstrate that the model does a fairly good job of forecasting even these extreme streamflow values. While the model does not always capture the extreme values within the interquartile range of the data, the observed value is not far outside the range of possible streamflow values.

We calculate the RPSS for each forecasted year (i.e., 55 different skill scores) and boxplot the results shown in Figure 33. To ascertain the model's skill in wet and dry years, we boxplot the RPSS of those years separately, as well. We define wet as those years with streamflow above the 75th percentile and dry as years below the 25th percentile.

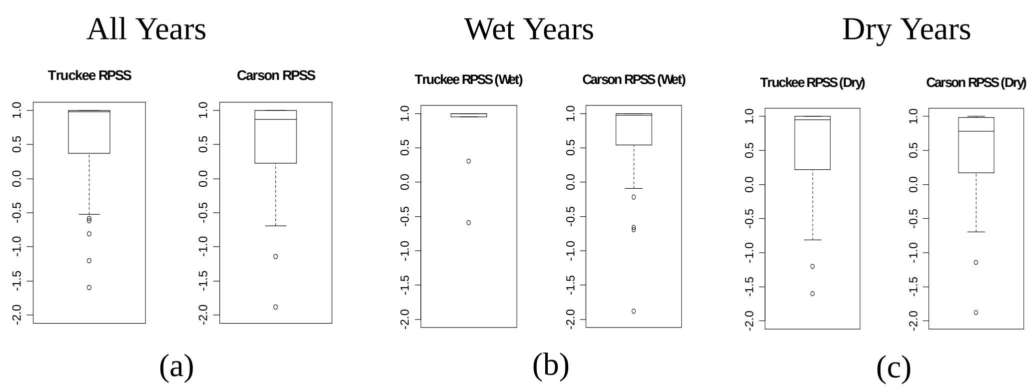


Figure 33: Rank Probability Skill Score (RPSS): all years (a), wet years (b) and dry years (c).

The model performs quite well overall, doing a particularly good job in wet years, with slightly decreased skill in dry years. Note that the scores are heavily skewed toward the upper boundary (1) making the 95th percentile whisker difficult to distinguish. For all categories (all years, wet years, dry years) the interquartile range of the RPSSs is well above 0, indicating that overall, the model performs significantly better than climatology. The median value of the skill scores are presented in Table 1, along with results from the likelihood skill measure.

The results of the likelihood skill measure are presented in Figure 34. Likelihood results also show that the ensemble forecast performs significantly better than climatology. For all categories, the interquartile range of the skill scores lies well above 1.

The median skill scores for the RPSS and likelihood function are presented in Table 1.Both skill measures indicate that the model performs better than climatology in both rivers. The skill score for the Truckee River is slightly higher than that for the Carson River. The model performs best in wet years, with a slight decrease in skill in dry years.

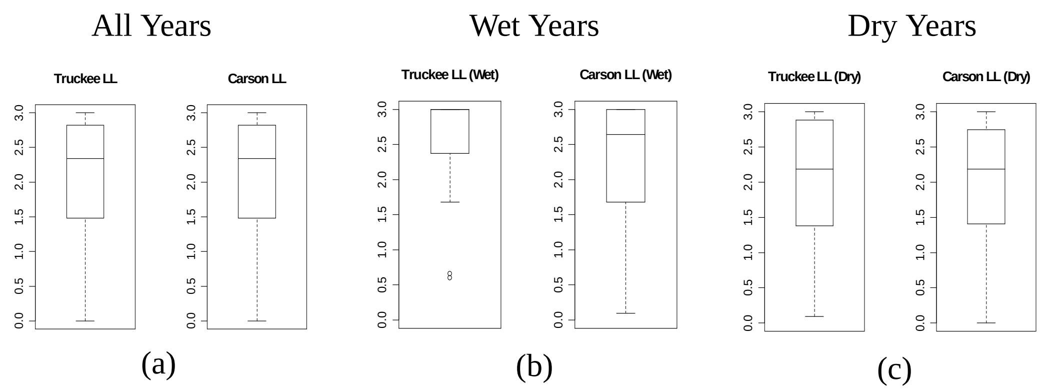


Figure 34: Likelihood skill measure: all years (a), wet years (b) and dry years (c).

	Median Skill Score			
	RPSS		LL	
	Truckee	Carson	Truckee	Carson
All Years	1.0	0.9	2.3	2.3
Wet Years	1.0	1.0	3.0	2.6
Dry Years	0.9	0.8	2.2	2.2
	$-\infty \rightarrow 0 \rightarrow 1$		$0 \rightarrow 1 \rightarrow 3$	

Table 1: Skill measure of the ensemble forecast in all years, wet years, and dry years.

One of the benefits of ensemble forecasts is that they can be used to obtain exceedence probabilities. This can be seen using plots of the probability density function (PDF) of the ensemble. Figure 35 presents the PDF of the ensemble forecast in a below normal streamflow year (1992) on the Truckee River. Figure 36 shows the PDF of the ensemble forecast in an above normal year (1999) for the Truckee River. Plots for the Carson River look similar to those presented for the Truckee. The climatological PDF (i.e., the PDF of the historical data) is overlaid in these plots.

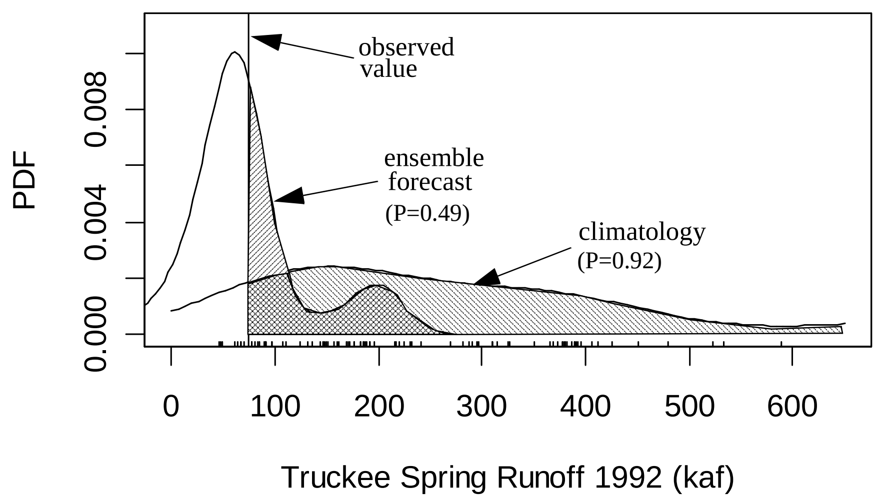


Figure 35: PDF on the ensemble forecast in a dry year (1992)

Notice that in Figure 35 and in Figure 36 the PDF of the ensemble forecast shifts away from climatology, better capturing the runoff in the coming year. In 1992, the streamflow in the Truckee River was 75 kaf, well below the average value. While climatology shows an exceedence probability of 92 percent for that flow, the ensemble forecast supports a much lower exceedence probability (49 percent) for the same flow, more accurately representing the probability of that flow value. Similarly, for the above average flow of 408 kaf in 1999, climatology suggests an exceedence probability of 17 percent while the ensemble forecast shows a much higher probability of exceedence (59 percent), better capturing the probability of the observed flow value.

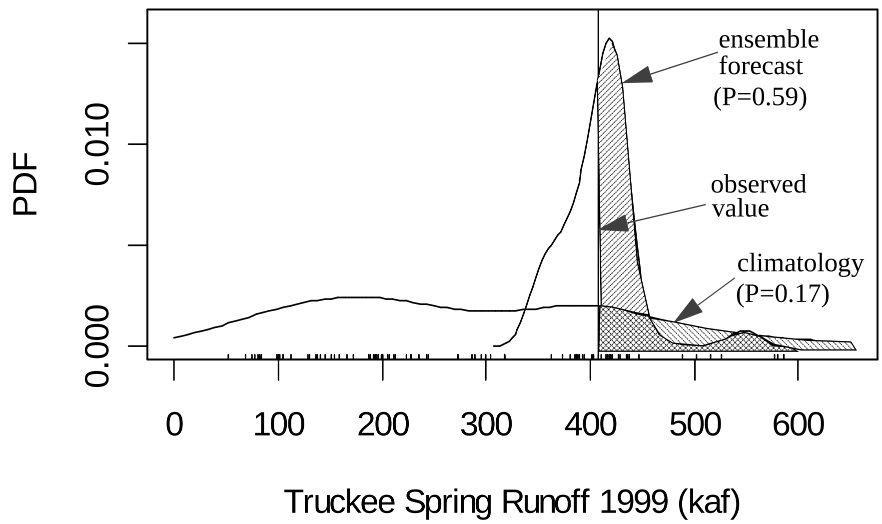


Figure 36: PDF of the ensemble forecast in a wet year (1999)

3.2.5.2 March 1st Forecast

All model results discussed thus far have utilized April 1st SWE in the model. Here, we present results from a forecast based on March 1st SWE. Water managers in the Truckee-Carson river system consider the April 1st forecast the most important for seasonal operations and decision-making, however, preliminary forecasts issued prior to April 1st are also used. Farmers use preliminary forecasts to help estimate their projected seasonal water demand and water managers perform preliminary model runs to get an idea of what policies may have to be implemented in the upcoming water season-- including flood control measures.

Figure 37 shows the scatter plot of the median of the ensemble forecast versus the observed value and demonstrates that a forecast issued at the end of February has considerable skill. The correlation value is 0.76 for the Truckee River and 0.75 for the Carson River. The March 1st forecast skill is less than the April 1st skill; this is expected because as forecast lead time increases, the resulting skill decreases.

Figure 38, Figure 39, and Table 2 display the skill scores for the March 1st forecast in all years, wet years, and dry years. Interestingly, the RPSS demonstrate bet-

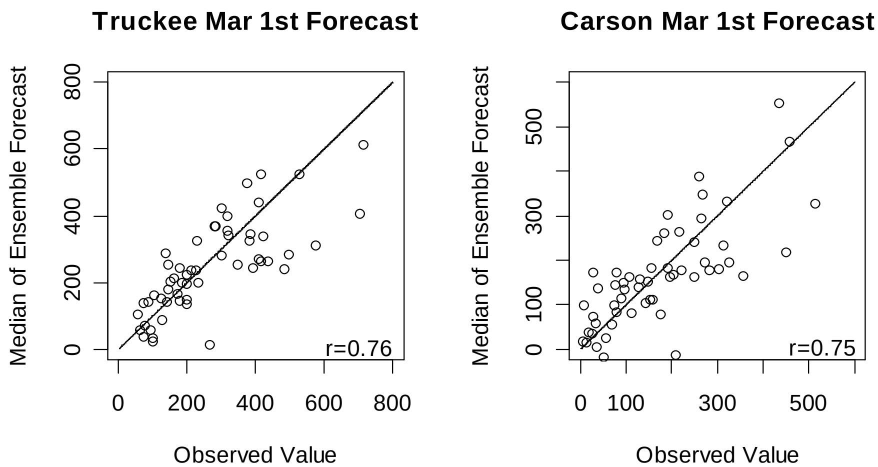


Figure 37: Median of March 1st ensemble forecast vs. observed spring runoff for the Truckee forecast (left) and Carson forecast (right).

ter forecast skill in the Carson than the Truckee, whereas the Likelihood function indicates the opposite. This discrepancy highlights the differences in these skill measures, indicating that various skill measures should be tested to gain true insight into the forecasting skill. Compared with the April 1st results (Table 1), the March 1st results do not show as significant of differences between all years, wet years, and dry years. Overall, the skill scores indicate that the March 1st ensemble forecasts provide significantly greater skill than climatology. This skill can be utilized to better prepare for the coming water season (e.g., releasing water sooner than normal for increased flood storage, or holding back on flood control measures in extreme dry years.)

3.2.5.3 Fall Forecast

Figure 40 shows the fall forecast results: the scatter plot of the median of the ensemble forecast versus the observed value. The forecast, issued at the end of November, uses the September to November 500mb geopotential height index as a model predictor. As SWE data is often unavailable at this time, no snowpack or precipitation information is incorporated in the forecast. The correlation coefficient

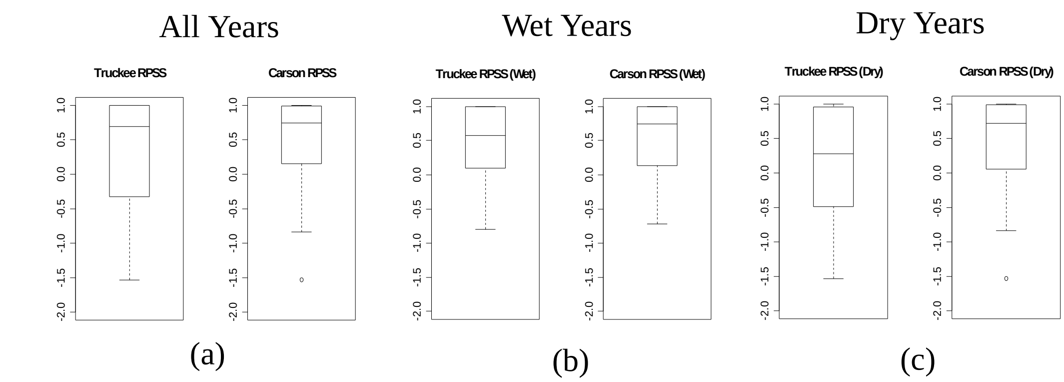


Figure 38: March 1st RPSS: all years (a), wet years (b) and dry years (c).

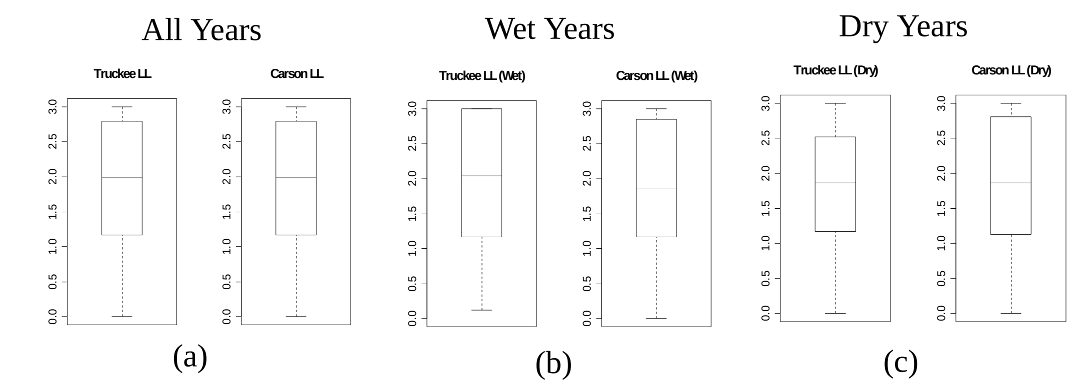


Figure 39: March 1st likelihood skill score: all years (a), wet years (b) and dry years (c).

	Median Skill Score			
	RPSS		LL	
	Truckee	Carson	Truckee	Carson
All Years	0.7	0.7	2.0	2.0
Wet Years	0.6	0.7	2.0	1.9
Dry Years	0.3	0.7	1.9	1.9
	$-\infty \rightarrow 0 \rightarrow 1$		$0 \rightarrow 1 \rightarrow 3$	

Table 2: March 1st skill measure of the ensemble forecast in all years, wet years, and dry years.

between the median forecasted value and observed value is 0.36 for the Truckee River and 0.28 for the Carson River. These correlation coefficients, though much lower than those for the April 1st and March 1st forecasts, are statistically significant and indicate positive skill in the fall forecast.

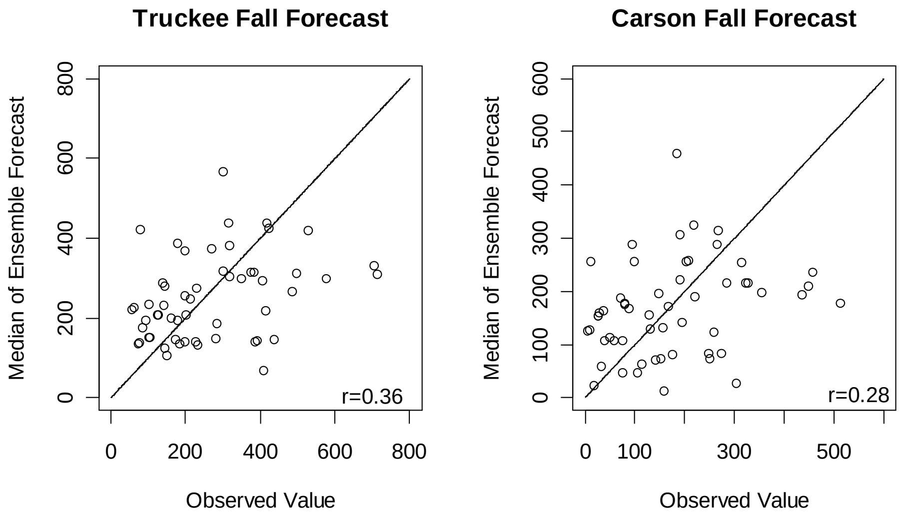


Figure 40: Median of fall ensemble forecast vs. observed spring runoff for the Truckee forecast (left) and Carson forecast (right).

Figure 41, Figure 42, and Table 3 show the skill scores for the fall forecasts in all years, wet years, and dry years.The skill scores indicate that a fall forecast does best in capturing the wet years, with mild improvements over climatology in all years and dry years. The RPSS shows more of an increase in skill in the wet years than the likelihood function. The RPSS also indicates no improvement over climatology in dry years, whereas the likelihood function shows some improvement in every category: all years, wet years, and dry years.

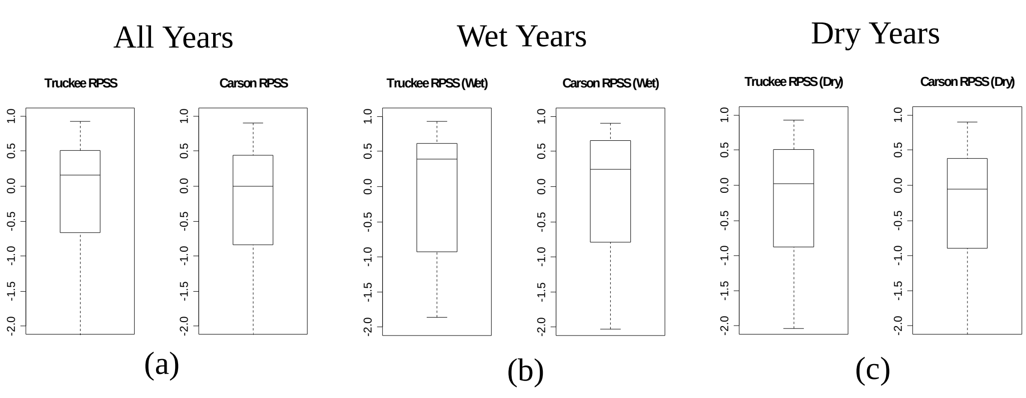


Figure 41: Fall RPSS: all years (a), wet years (b) and dry years (c).

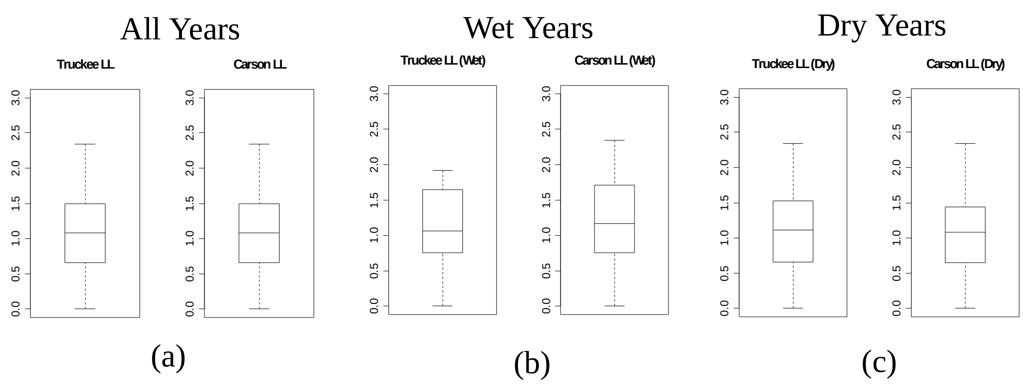


Figure 42: Fall likelihood skill score: all years (a), wet years (b) and dry years (c).

	Median Skill Score			
	RPSS		LL	
	Truckee	Carson	Truckee	Carson
All Years	0.2	0.0	1.1	1.1
Wet Years	0.4	0.3	1.1	1.2
Dry Years	0.0	0.0	1.1	1.1
	$-\infty \rightarrow 0 \rightarrow 1$		$0 \rightarrow 1 \rightarrow 3$	

Table 3: Fall skill measure of the ensemble forecast in all years, wet years, and dry years.

The results and skill scores illustrate that there is substantial and useful skill in the long lead time forecasts (as much as 5 months for forecasts issued in fall). The skill improves significantly as the lead time decreases (i.e., going from fall to spring) and provides useful information about the coming water season. A forecast issued in fall gives water managers a look at the type of runoff season to come. The benefit of a forecast from fall is not that water managers know the exact volume of spring runoff, but that they have an idea of whether the coming season will be above average or below average. Because current forecasting techniques only utilize snowpack information, water mangers do not have the opportunity to utilize a fall forecast in their operations and decision-making. USBR engineers, however, believe that a forecast in fall would definitely be helpful in planning for the coming water season (Scott, 2002).

3.2.5.4 Use of Climate in the Forecast: A Comparison

Though forecasters have used snowpack data in forecasting models for many decades, combining SWE with large-scale climate information to forecast is a relatively new technique (see Chapter 2 for details). We test the utility of including large-scale climate information in the model by comparing the skill of a forecast which includes both SWE and the geopotential height index as predictors against a forecast based on SWE alone.

As extreme wet and dry years affect management and decision making the most, we first present the results for these years. Figure 43 and Figure 44 show the comparisons of incorporating large-scale climate information in the April 1st forecast of extreme wet and dry years. (Extreme wet and dry years are defined as those years with spring streamflow above the 90th percentile and below the 10th percentile, respectively.) Figure 43 demonstrates that including the 500mb geopotential height index in the predictor set significantly improves the forecast in extremely wet years. The improvement in extremely dry years, though not as strong as in wet years, is also apparent in Figure 44. In both cases, the boxplots are tighter for the forecasts that utilize the large-scale climate information, indicating less uncertainty in the forecast.

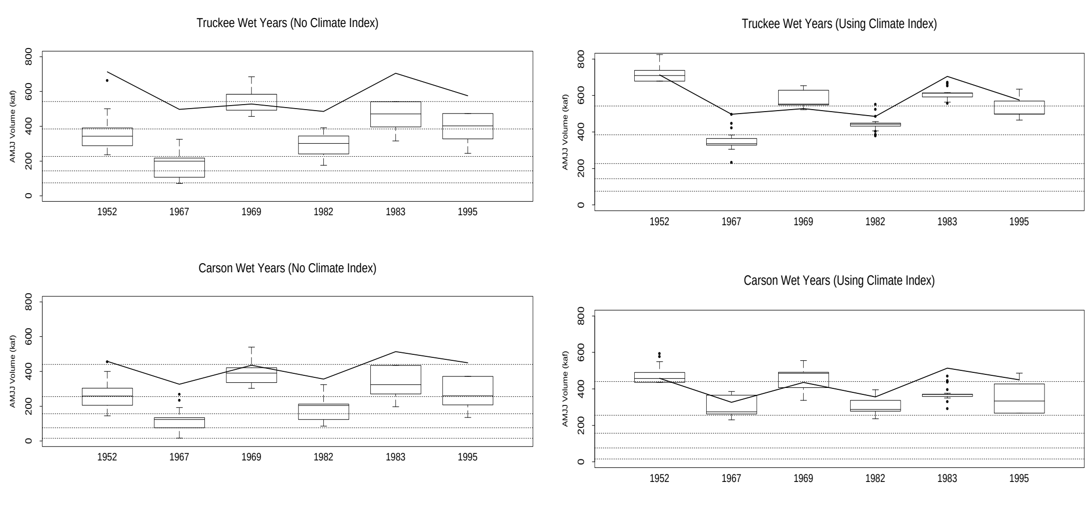


Figure 43: Incorporating large-scale climate information in the forecast: wet years

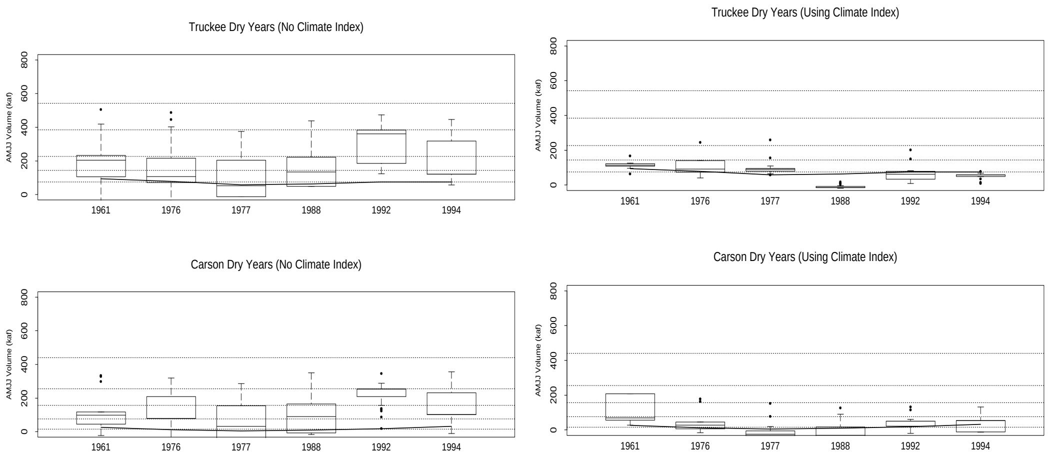
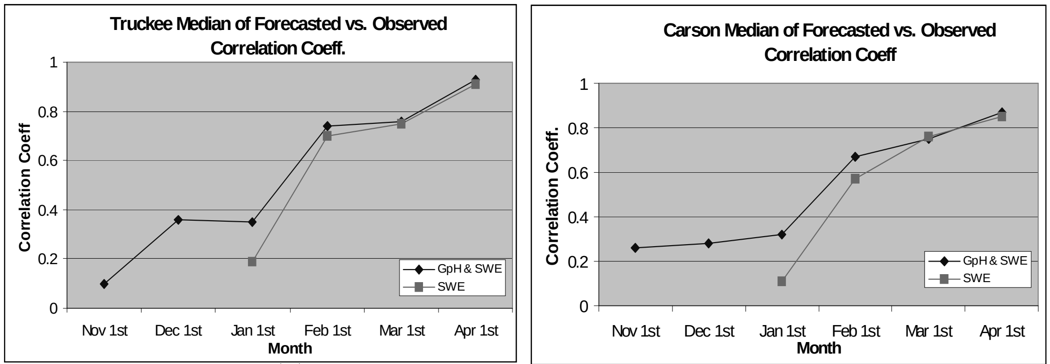


Figure 44: Incorporating large-scale climate information in the forecast: dry years

We next analyze the benefit of including the geopotential height predictor when forecasting all years in the historical record (rather than only extreme wet and dry years). We look at the comparison for each monthly forecast starting from a November 1st forecast through to the April 1st forecast. Forecast skill is presented in terms of (i) the correlation coefficient between median of the ensemble forecast and the observed value, (ii) the RPSS, and (iii) the likelihood function.

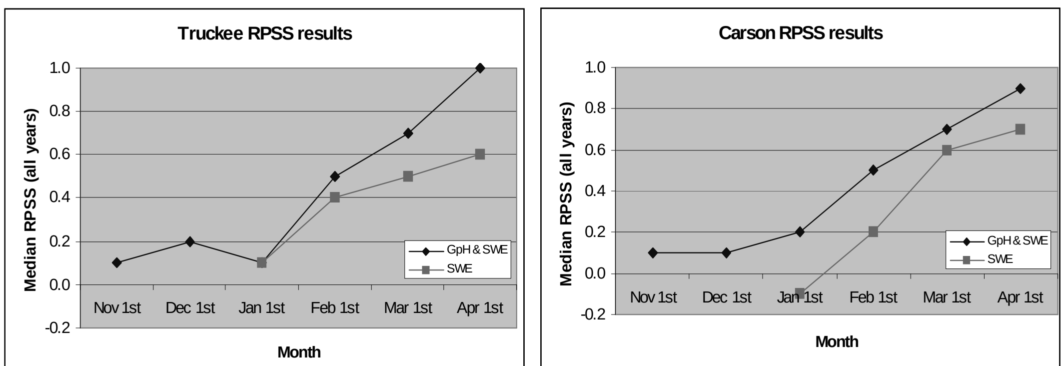
Figure 45 shows the correlation coefficient between the median of the forecasted ensemble versus the observed value for each monthly forecast. The results show that the mean forecast is closer to the observed value if the geopotential height index is included in the set of predictors. This is true for each monthly forecast (though less so in the later months) on both rivers. Note that the November 1st and December 1st forecasts use only the geopotential height index as a predictor. No forecast is available during these months if only SWE information is used. The difference in skill is most pronounced in the long lead forecasts, indicating that initial conditions (i.e., SWE) provide better information later in the forecasting season.

Figure 46 shows the RPSS for all years for each monthly forecast. The RPSS results, too, demonstrate that incorporating the 500mb geopotential height as a predic-



(a) (b)

Figure 45: Incorporating large-scale climate information in the forecast: correlation coefficient for monthly forecasts from November 1st through April 1st for the Truckee (a) and Carson (b) Rivers.



(a) (b)

Figure 46: Incorporating large-scale climate information in the forecast: RPSS for monthly forecasts from November 1st through April 1st for the Truckee (a) and Carson (b) Rivers.

tor adds skill to the forecast. While the correlation coefficient discussed above measures the skill of the mean of the ensemble forecast, the RPSS measures the skill of the entire forecast distribution (i.e., including the spread). It is interesting to note that when the entire ensemble forecast is considered (i.e., as with the RPSS), using both SWE and the geopotential height index produces significantly better results even for the March 1st and April 1st forecasts. One also might note the decrease in skill on the Truckee River when moving from the December 1st forecast to the January 1st forecast. This could be due to the fact that January SWE data is highly provisional and including this information may introduce significant error into the forecast. The decrease could also be due to the January SWE data starting in 1966, rather than 1949, meaning that the January regression contains 17 fewer points than the regressions for other months. Regardless, the results show that including the climate information provides significant skill.

Figure 47 shows the likelihood scores for all years for each monthly forecast. Similar to the RPSS, the likelihood function measures the skill of the entire ensemble forecast. The likelihood skill measure results also show that including the geopotential height as a predictor increases the skill of the forecast.

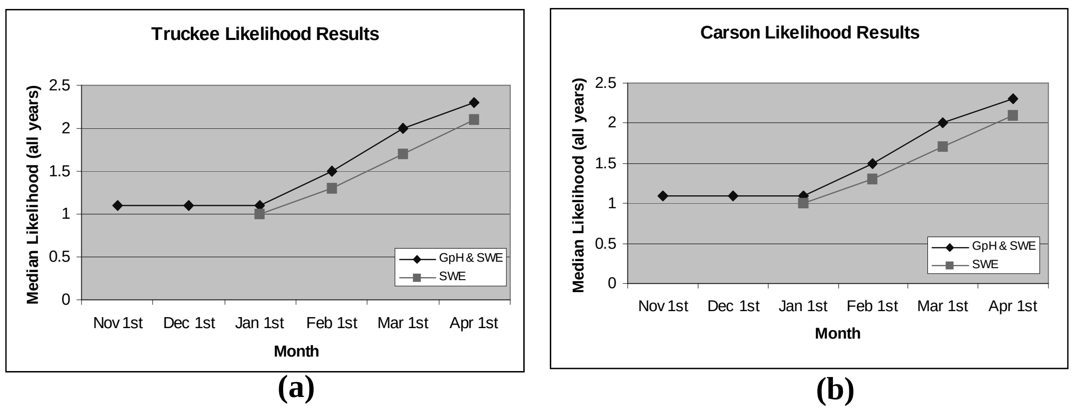


Figure 47: Incorporating large-scale climate information in the forecast: likelihood score for monthly forecasts from November 1st through April 1st for the Truckee (a) and Carson (b) Rivers.

Clearly, including the geopotential height index as a predictor increases the forecast skill. The SWE data provides important information regarding basin initial conditions (i.e., the amount of snow currently available to affect runoff). The atmospheric data, however, provides information about weather yet to come in the basin. The geopotential height, for example, will include information about precipitation in the month of April. This information is not captured in the April 1st SWE measurement, but will nevertheless affect spring runoff. It is thus possible for atmospheric data to increase forecast skill.

3.3 Seasonal to Monthly Disaggregation Model

In practice, for seasonal operations and planning, the monthly breakup (April, May, June, and July) of the spring seasonal runoff is required. The monthly values are used specifically to set target storage values on Lahontan Reservoir. Water managers use the storage targets in determining the allowable diversions through the Truckee Canal. They must establish how much water will come from the Carson River before allowing depletions from the Truckee River. Water managers seek to meet the target values so that Lahontan Reservoir will contain adequate water supplies throughout the irrigation season. Storage targets are based partly on projected demands in the Truckee-Carson Irrigation District (TCID) and partly on the forecasted water availability from the Truckee and Carson Rivers. As stated in Chapter 1, however, sometimes there is not enough water in either river to meet the storage target.

Rather than making monthly forecasts, which may not mass-balance with the total spring runoff forecast, we disaggregate the total volume into monthly proportions. We use the K-NN approach described earlier in this disaggregation. First, monthly fractions of the total spring runoff volume are computed for each historical year. Given the current year's seasonal forecasted runoff, we find *k* neighbors (i.e., historical years) based on their closeness to this forecasted value. One of the *k* years is resampled and consequently, the monthly proportions associated with it. Thus resampled monthly proportions are applied to the current year's seasonal forecast.

3.3.6 Results

Figure 48 displays the results of disaggregating the 1999 total seasonal volume into monthly values. The solid line represents the April to July monthly volumes in 1999. The boxplots illustrate the ensemble forecast in each month. Results in other years are similar. This monthly disaggregation scheme is preliminary and requires validation and testing. However, the results are encouraging.

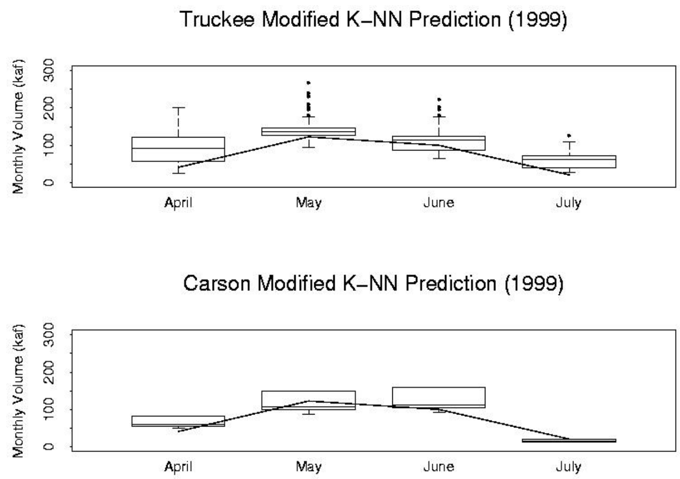


Figure 48: Disaggregation of total seasonal volume into monthly values: 1999. The solid line represents the observed monthly value in that year. The boxplots represent the ensemble forecast for each month.

3.4 Summary and Conclusions

Using the predictors determined in Chapter 2, we develop a nonparametric stochastic model to forecast spring streamflows in the Truckee and Carson Rivers. The nonparametric model uses a local polynomial approach for mean forecast and residual resampling to provide ensembles, thus effectively capturing uncertainty. The method offers a simple and flexible tool to model any arbitrary relationship present in the data. Furthermore, this approach is data-driven with minimal assumptions, unlike the tradition parametric alternatives. The ensemble forecasts provide exceedence probabilities which are useful to water managers. Results show that the incorporation of large-scale climate information, specifically the 500mb geopotential height index, provides skillful long lead time forecasts-- particularly in extreme streamflow years. A simple disaggregation method based on the K-NN bootstrap also demonstrates the flexibility and utility of the proposed approach. The application of these forecasts is demonstrated in Chapter 4.

Chapter 4

Decision Support System

A water resources decision support system (DSS) provides important information to water managers, lawmakers, and stakeholders and aids in operations, planning, and policy-making. The extremely complex operations and policies on the Truckee-Carson river system require the assistance of a DSS. With highly variable flows, multiple storage reservoirs and diversions, demands typically greater than supply, and ever-evolving policies, water managers and policy-makers have much to balance in this basin. Forecasts assist greatly with planning and management, however, after the issuance of a forecast, water managers and policy-makers must determine how to best operate the system given the predicted flow values. DSSs provide the ability to model various flow and policy scenarios to help water managers with operational decision-making in the basin. This chapter describes the DSS currently under development for the Truckee-Carson basin, discusses the application of forecasts in that DSS, and then presents results from a simplified seasonal model developed in this study to test the utility of the forecasts from Chapter 3.

4.1 Truckee- Carson Decision Support System (DSS)

A flexible water resources modeling framework for the Truckee Carson river system is currently under development. USBR managers, partners and stakeholders in the Truckee Carson river basin require this type of DSS to address the complex and rapidly evolving water resources issues in the basin. The USBR Lahontan Basin Area Office and the Truckee River Water Master's Office will use the DSS to make management decisions as well as to formulate operational strategies to satisfy the ever-changing legal requirements and multiple purpose water demands of this basin. The operational capabilities of the model will allow both managers and stakeholders to make decisions for storage, release and exchange of water. The USBR Lahontan Basin Area Office has been building the DSS in collaboration with partners from the USBR Technical Service Center, the US Geological Survey, the Bureau of Indian Affairs, the Truckee River Operating Agreement planning coordinator, the Fish and Wildlife Service and the Pyramid Lake Tribe.

The USBR Lahontan Basin Area Office is developing the Truckee-Carson DSS using the general-purpose river and reservoir modeling software RiverWare (Zagona et al., 1998 and 2001). The Truckee RiverWare model simulates the movement of water through the river system using objects in a graphical user interface. (See Figure 49 below.) The laws and policies of the river are implemented with rules. These rules, based on user-defined, prioritized logic, govern simulations of reservoir releases and diversions throughout the network. The model simulates allocation of water rights in the basin using the accounting network which tracks the ownership of the water as it moves through the system. It is thus possible to monitor whether water was released to meet instream flow targets or for irrigation demands. The rules dictate how much water to release from each reservoir, which account the water comes from, and where the water goes. By using different rules to move water through the system, it is possible to simulate flow patterns using different policies.

4.1.1 Incorporation of Forecasts

The USBR couples forecasts with the decision support system to formulate daily operations and seasonal planning in the basin. USBR natural flow forecasts of

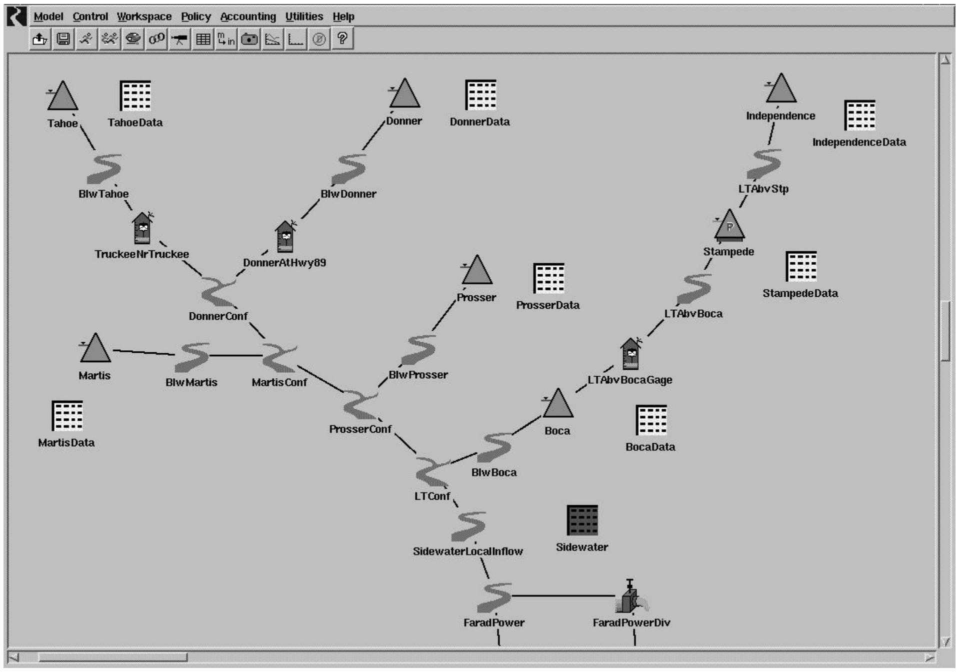


Figure 49: Screenshot of Truckee RiverWare model

seasonal (April to July) runoff volume are used as model inputs at the top of the basin and represent the inflow to the top most reservoirs. The Truckee RiverWare model first spatially disaggregates the forecast for Farad gage to represent the inflow to the various top most reservoirs upstream. Modeling on the Carson River begins at Ft. Churchill, thus no spatial disaggregation is necessary. Next, the model disaggregates the seasonal volume into daily values using a “similar years analysis.” Similar years analysis finds years in the historical record with seasonal flow volumes closest to the current year and applies the associated daily streamflow values in those years to make a timeseries for the current year. Finally, the model takes the daily natural streamflow and implements the policies and operations in the basin to simulate the actual water in the river at any location on any day of the season.

The Truckee RiverWare model simulates three time periods throughout the year: January to March, April to July, and August to December. Because the bulk of the annual streamflow comes from the spring runoff, the April to July forecast dominates most of the operations throughout the year. The April to July natural streamflow forecast directs much of the flood control procedures during the January to March period. For example, forecasts predicting an above average spring runoff will result in larger reservoir drawdowns during the first period of the year, and vice-versa for a drought prediction. The spring forecasts affect the April to July operation period because the bulk of the water moving into and through the system comes in this time period. Managers aim to meet storage targets on Lahontan Reservoir during this period to gear up for the irrigation season. Because very little water enters the system after July, the August to December time period releases storage water built up during the April to July period. In this way, the April to July forecast and observed spring runoff affect operations in the basin throughout the year. Forecasts issued for the January to March and August to December time periods are necessary as inputs to the model, though the accuracy of these forecasts is not nearly as critical as the accuracy of the April to July forecast.

In January each year the USBR Lahontan Basin Area Office issues the April to July forecast for all interested parties in the basin. Irrigators in the Newlands project use this information to determine their projected demand for the irrigation season. U.S. Fish and Wildlife Service (FWS) representatives use the forecast to establish the feasibility of a fish spawning run and to schedule Water Quality Credit Water (WQCW) releases for spawning or to combat low flows. Based on projected demands and forecasted inputs, the USBR runs the Truckee RiverWare model to simulate operations for the entire calendar year. As forecasters update the April to July forecast, the model is run again to simulate operations in the system for the remainder of the year. The USBR uses updated forecasts at the beginning of March and April and then throughout the April to July period. The April 1st issued forecast is particularly important as mangers use these values to set target storages on Lahontan and to set guidelines for operations throughout the runoff season. The FWS uses the updated forecasts, too, in setting a release schedule of WQCW from Stampede reservoir. As very little water comes in the August to December period, forecasters do not update this forecast as regularly. Modelers use new initial conditions (e.g., initial reservoir storage values) as model input at the begin of each new run.

4.1.2 Incorporation of Laws and Policies

The Truckee RiverWare ruleset mimics the laws and policies of the basin. These rules are written in the form of prioritized logic to govern the movement of the forecasted inflow values throughout the system. Flood control algorithms, minimum flow requirements for fish, and allowable diversions for agriculture are examples of rules implemented in the Truckee RiverWare model. Because the policies and laws are expressed as dynamic data (rather than compiled in the model code), managers and policy-makers can easily turn different rules on or off to test the outcome of different policies. In this way, managers and policy-makers can determine the potential impacts of pending laws and policies to help in decision-making.

4.1.3 Incorporation of Physical Mechanisms

The Truckee RiverWare model simulates the physical movement of water through the system using standard hydrologic and hydraulic principles. USBR engineers can select different algorithms to simulate these processes based on available data and the level of detail desired. For example, routing through a reach can be simulated using time-lag, impulse response, muskingum, muskingum-cunge, kinematic wave or storage routing routines. Other selectable algorithms include power generation, tailwater calculation, evaporation and seepage. By modeling the hydrologic and hydraulic mechanisms in the system, the Truckee RiverWare model aims to accurately simulate the total amount of water moving through the system at any place and any time during the simulation run.

4.1.4 Incorporation of Water Rights

The Truckee RiverWare model tracks the legal ownership of water through the water accounting system. The accounting system uses reservoir storage accounts and flow and diversion accounts to simulate water rights, accruals, carryovers and exchanges. The Truckee RiverWare model, for example, tracks how much reservoir storage water belongs to irrigators and how much belongs to fish. The model also tracks who releases are made for. Because water rights drive many of the policies in the basin, account data is first assessed to determine the operating rules driving the simulation.

4.2 Seasonal Operations Model

Because the Truckee RiverWare model is not yet fully operational, we develop a simplified seasonal operations model to test the utility of the forecast results from Chapter 3. The seasonal model incorporates scaled down versions of the major polices and physical structures in the lower Truckee-Carson river system. Primarily, we test the forecasts' influence on diversions through the Truckee Canal and the resulting water available for irrigation and fish. The model operates on a seasonal timescale, and thus does not account for daily operations. To understand the forecasts' influence on daily operations and feedback mechanisms throughout the entire system, we will couple ensemble forecasts with the full Truckee RiverWare model at a later date.

The simplified model, written in the S-plus coding language, takes output from the forecasting model and simulates seasonal policies on the ensemble forecasts. (See Appendix D "Seasonal Operations Model Code" for the policy code.) We analyze three important decision variables: Lahontan Storage Available for Irrigation, Truckee River Water Available for Fish, and the Truckee Canal Diversion. These decision variables are important in both seasonal operations and daily operations. Though the seasonal model does not simulate daily operations, its results provide insight to the necessary daily operations throughout the season. For example, if seasonal model results indicate a high probability of maximizing the total allowed diversion through the Truckee Canal, daily operations will need to start diversions at full canal capacity the first day of the season. Similarly, if the model results show a high probability of minimal diversions through the canal, daily diversions should be small in the beginning of the season to avoid diverting too much water through the one-way canal.

4.2.5 Decision Variables

4.2.5.1 Lahontan Storage Available for Irrigation

Farmers and project managers in the Newlands Project farming district need to know the Lahontan storage available for irrigation before the runoff season starts. Farmers need this information to help establish the size and type of crops they will plant. The new OCAP require that Truckee Carson Irrigation District (TCID) farmers estimate their demands for the coming growing season and then irrigate at a minimum of 68.4% efficiency on that projected demand. If the district does not meet this efficiency standard, the water available for irrigation can be reduced in the coming irrigation season. For this reason, farmers really need to know the Lahontan storage available for irrigation before the runoff season begins. TCID project managers, who currently operate Lahontan Dam under a temporary contract with the USBR, utilize the projected storage information to establish a release schedule from the dam.

4.2.5.2 Truckee Canal Diversion

Water managers (including TCID and the USBR) use projected Truckee Canal diversion information to establish a diversion schedule and inform interested parties of the schedule. Water managers shape the diversion schedule to pass the total projected allowable diversion throughout the entire season. The diversion schedule must consider the 900 cfs canal capacity as well as constraints in diversions during the warm months of July and August when endangered fish are particularly threatened by low flows in the Truckee River and canal diversions must averages less than 20 cfs.

4.2.5.3 Truckee River Water Available for Fish

The FWS and the Pyramid Lake Paiute Tribe (PLPT) use the projected water remaining in the Truckee River to determine the possibility of making a fish run or the need to release Stampede water to combat low flows. If the projected water remaining in the Truckee River is particularly high, FWS will plan a fish spawning run in the coming season. If model results project dangerously low flows, FWS will release WQCW stored in Stampede Reservoir to protect the endangered cui-ui and threatened Lahontan cutthroat trout.

4.2.6 Operational Policies Implemented in Simplified Model

We implement the dominant OCAP policies in a seasonal framework by first streamlining them to work on a seasonal timestep. In reality, the policies are much too complicated to be fully represented in a simple seasonal model; this is why the USBR has invested so many resources to build the Truckee RiverWare model. Several policies, such as those related to projected irrigation demands, require additional data from farmers to exactly reflect implemented procedures. Other polices, such as diversions through the Truckee Canal, have nuances that require modeling on a daily timestep. Nevertheless, the seasonal model, even with the streamlined policies, provides valuable results for analyzing forecasts' impact on decision making and available water for fish and irrigation.

The policies, as implemented in the seasonal model, are described below:

- Water use from the Carson River is maximized before diversions from the Truckee are made.
- Diversion through the Truckee Canal cannot exceed 164 kaf.
- Target storages on Lahontan Reservoir are based on projected April-July

runoff volume for both the Truckee and Carson Rivers as measured at Farad and Ft. Churchill gages, respectively. The target is set at 2/3 the total projected spring runoff for the year.

- The minimum Lahontan storage target is based on average historical flows and demands in the basin. The minimum target is set as 1/3 of average historical spring runoff.

We make several assumptions to streamline the policy in the seasonal model. These assumptions include:

- All water available for irrigation is used in the same season and does not carry over to the next irrigation season.
- All water diverted into the Truckee Canal at Derby Dam reaches Lahontan Reservoir. (In reality, there are diversions and seepage along the canal-- amounting to approximately 25% of the water originally entering the canal.)
- Diversions before Lahontan Reservoir and Derby Dam are neglected (i.e., the simplified policies are implemented on the total forecasted flow).

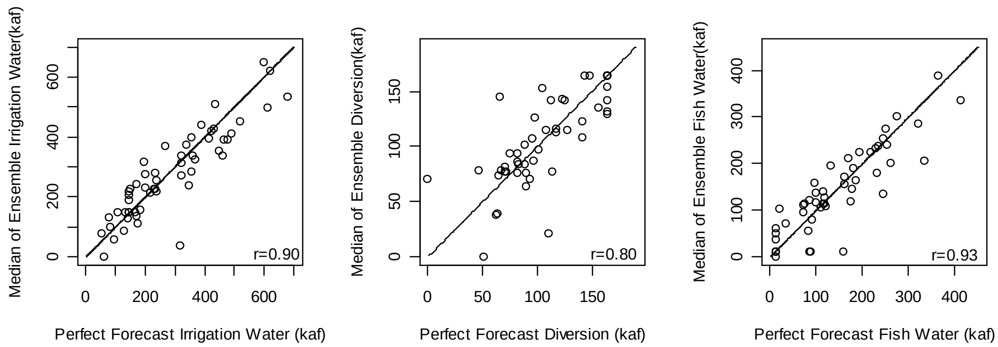
These simplified policies and assumptions do not exactly match reality, however considering the significant simplifications, model results are surprisingly close to observed values. For example, the average annual water avialable for irriagtion in the Newlands Project is 296kaf; model results show an average of 277kaf. Though the simplified policy model does not exactly match reality, it is good enough to be used as a tool to analyze the forecasts' impact on the three decision variables discussed above. Several specific differences between actual basin policy and the simplified policy implemented in this model should be discussed. First, though OCAP allows annual Truckee Canal diversions of up to 288kaf, in practice policies based on actual irrigated acerage limit the April to July diversions to a value closer to 164kaf. Similarly, projected irrigated acerage is used together with the seasonal forecast to set Lahontan storage targets. Because this irrigation data is not available to us, we set the target based on the forecasts only.

4.2.7 Model Testing

To test seasonal operations and the utility of the forecast in any given year, we run each of the 100 forecasted ensemble members through the seasonal operations model. The model's output comes in the form of PDFs for the three decision variables discussed above. Exceedence probabilities of various threshold values can be calculated for each of the variables to assist in decision making. For example, fish biologists have suggested that cui-ui and Lahontan cutthroat trout need 250 cfs of water in the lower Truckee River to survive. A 50% probability of exceeding 60.5 kaf (250 cfs) would alert FWS to plan Stampede releases to augment the low flows. For validation, we also simulate operations on the observed values for spring runoff in each year. A comparison between model results from observed runoff and model results from forecasted runoff validates the forecasts' impact on the decision variables. We do not compare the actual observed values of the decision variables because the assumptions in the seasonal model preclude a direct comparison. The intent behind the simplified seasonal model is not to provide a working decision support system, but rather to demonstrate the utility of including forecast information in a decision support system. For forecasting comparison, we simulate a climatological forecast by bootstrapping the historical data 100 times and then run this ensemble forecast through the seasonal operations model.

4.2.8 Results

Figure 50 presents the seasonal operations model results for observed runoff values versus the median of the model results from the ensemble forecast. We examine each of the decision variables; the simulated values using the observed runoff value (i.e., a perfect forecast) and the values using the ensemble forecasts generated in Chapter 3. Each point in the scatter plot represents the median of the model's output in each year.



(a) (b) (c)

Figure 50: Seasonal operations model decision variables: (a) Lahontan storage water available for irrigation (b) Truckee Canal diversion, and (c) water remaining in the Truckee River available for fish. The scatter plots compare the median of the model's output based on the ensemble forecast with the model's output based on the observed runoff value for that year. Each point represents data for one year.

Correlation values between the perfect forecast model results and median of ensemble forecast model results are 0.90 for the Lahontan storage available for irrigation, 0.80 for the Truckee Canal diversion, and 0.93 for Truckee River water available for fish. These results indicate that operations based on the forecasted runoff ensemble are quite similar to what operations would be given a perfect forecast. Though the skill of the runoff forecast certainly plays an important role in this comparison, flow thresholds and the overall flexibility in operations also affect the model results. It is important to test the streamflow forecast in an operations model to determine how well streamflow forecast skill translates to skill in predicting the values of key decision variables.

Figure 51 presents the seasonal operations model results based on the fall forecast. Correlation coefficients are 0.37 for irrigation water, 0.30 for the diversion, and 0.32 for fish water. Using the standard t-test comparison, these results illustrate posi-

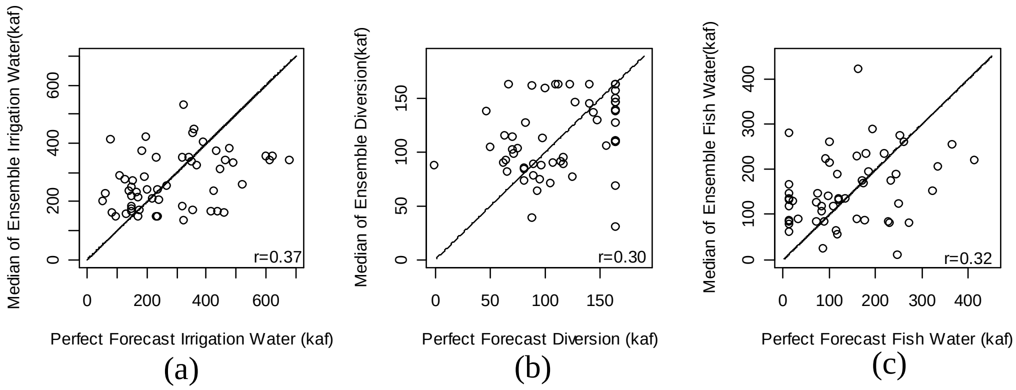


Figure 51: Fall forecast seasonal operations model decision variables: (a) Lahontan storage water available for irrigation (b) Truckee Canal diversion, and (c) water remaining in the Truckee River available for fish. The scatter plots compare the median of the model's output based on the ensemble forecast with the model's output based on the observed runoff value for that year. Each point represents data for one year.

tive skill in simulating the decision variables even as early as fall. Though the skill using the fall forecast is much poorer than that for the April 1st forecast, model simulations using the fall forecast will at least provide some information as to whether these decision variables will be above normal or below normal. The usefulness of using a fall forecast is that it provides water managers with an early look at whether the coming water season will be extremely wet or dry so they can start planning.

The remaining results of the seasonal operations model are presented in the form of PDFs. We present five plots for each year of analysis: Truckee River spring runoff, Carson River spring runoff, Lahontan Storage Available for Irrigation, Truckee Water Available for Fish, and Truckee Canal Diversion. Each plot contains a PDF representing historical observed data (the dashed line), a PDF for the ensemble forecast generated in Chapter 3 (the solid line), a solid circle illustrating results using the observed runoff values, and an open circle illustrating results using the NRCS forecast. We present the Truckee and Carson spring runoff PDFs to assist in the analysis of how the skill of the forecast in each river affects the skill in capturing the various decision variables.

Figure 52 presents seasonal operations model results for a below average streamflow year: 1992. For all decision variables, the PDF representing the ensemble forecast shifts away from the climatological PDF to better capture what would have occurred given a perfect forecast. These results demonstrate that utilizing the ensemble forecast provides water managers with an accurate representation of the decision variables for the coming season. Comparison with the NRCS forecast model results illustrates that in 1992 both the NRCS forecast and the forecast from this research do

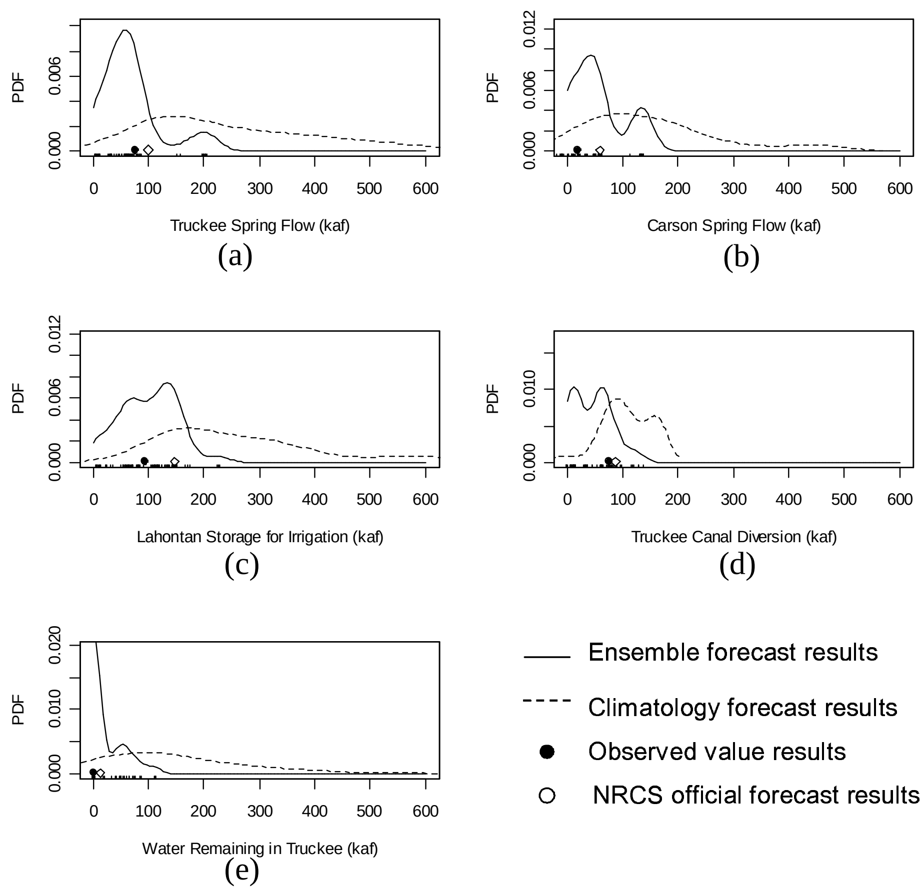


Figure 52: Seasonal Operations Model Results: 1992. Truckee River spring runoff (a), Carson River spring runoff (b), Lahontan storage available for irrigation (c), Truckee Canal diversion (d), and Truckee River water available for fish (e). The solid line represents model results based on ensemble forecasts and the dashed line represents model results based on a climatological forecast. The solid circle illustrates model results using the observed runoff value and the open circle shows the results using the NRCS forecasted value.

a good job in capturing the decision variables. The real benefit of using the ensemble forecasts of this research (rather than the single NRCS forecasted value) comes from the resulting PDFs. Exceedence probabilities obtained from these PDFs will further assist in decision-making. For example, there is a 49% probability that Truckee River water remaining for fish will exceed 60.5 kaf (250 cfs). This probability suggests that flows will likely be close to this threshold value, alerting FWS that they may need to release water quality credit water in the hot summer days. For comparison, using model output of historical streamflow data presents a 85% probability of exceeding the low flow threshold value. Irrigation water available to the Newlands Project farming district averages 296 kaf per year. Model results show a 2% percent chance of exceeding this value in 1992, indicating to farmers that they may need to reduce their planting this year or use low water crops. By comparison, model output of historical streamflow data presents a 50% chance of exceeding this average value. Model results show the most likely (50th percentile) Truckee Canal diversion is 57 kaf, with a 19% chance of the diversions exceeding 100 kaf. Water managers can utilize this information in setting the daily diversion schedule in the Truckee Canal.

Figure 53 demonstrates model results in relatively normal streamflow year: 2003. As in the below normal streamflow example of Figure 52, the PDFs representing the ensemble forecast provide water managers with an accurate representation of the decision variables the coming season. The NRCS results and the results from the ensemble forecast are quite similar in 2003, as well. Analysis of the fish water PDF reveals a 100% exceedence probability for the low flow threshold value of 60.5 kaf (250 cfs). This means that out of 100 simulations, not one value fell below 60.5 cfs. Though FWS will likely monitor the situation throughout the season, this exceedence probability allows them the rest much easier regarding low flows. Model output from historical streamflow data, by comparison suggests a higher probability (15%) of having to release WQCW. Model results show a 6% chance of exceeding the historical

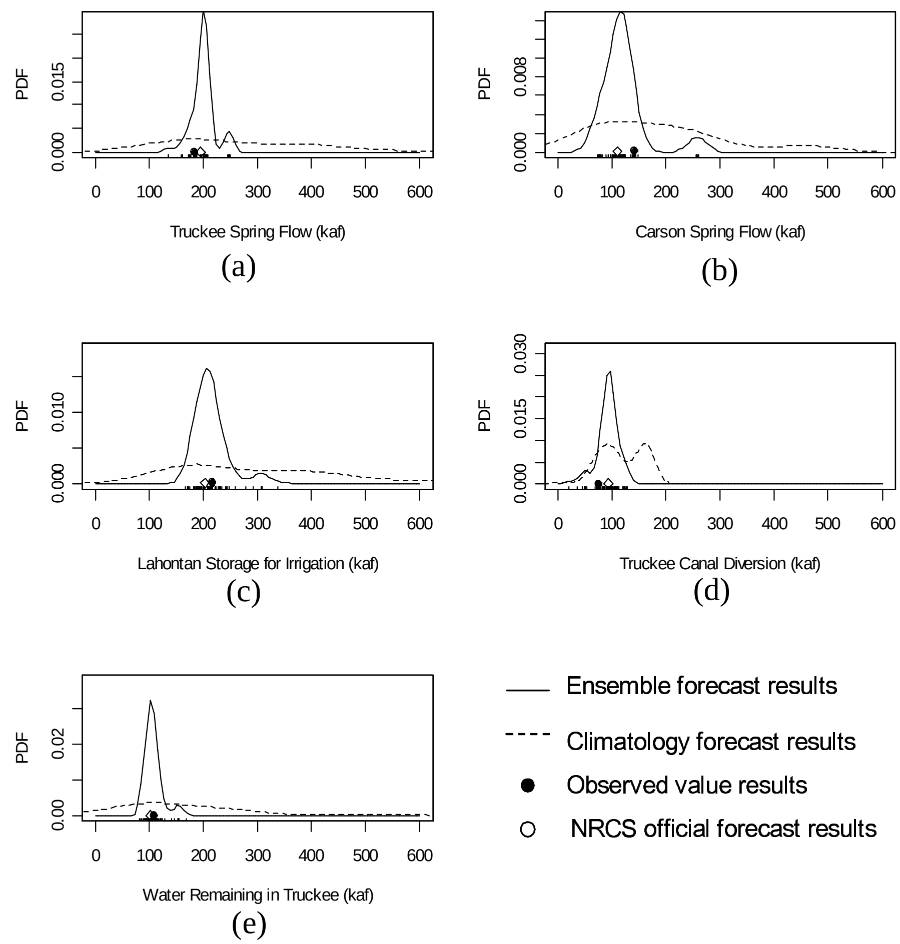


Figure 53: Seasonal Operations Model Results: 2003. Truckee River spring runoff (a), Carson River spring runoff (b), Lahontan storage available for irrigation (c), Truckee Canal diversion (d), and Truckee River water available for fish (e). The solid line represents model results based on ensemble forecasts and the dashed line represents model results based on a climatological forecast. The solid circle illustrates model results using the observed runoff value and the open circle shows the results using the NRCS forecasted value.

average of 296 kaf available for irrigation. The 50th percentile is 209 kaf, indicating to farmers that though it will not be a wet year, drought precautions are not necessary. The most probable Truckee Canal diversion is 94 kaf.

Figure 54 demonstrates results for an above average streamflow year: 1993. In this year, the model results from the ensemble forecast are much better than the NRCS forecast results-- particularly when determining irrigation water and fish water. Model

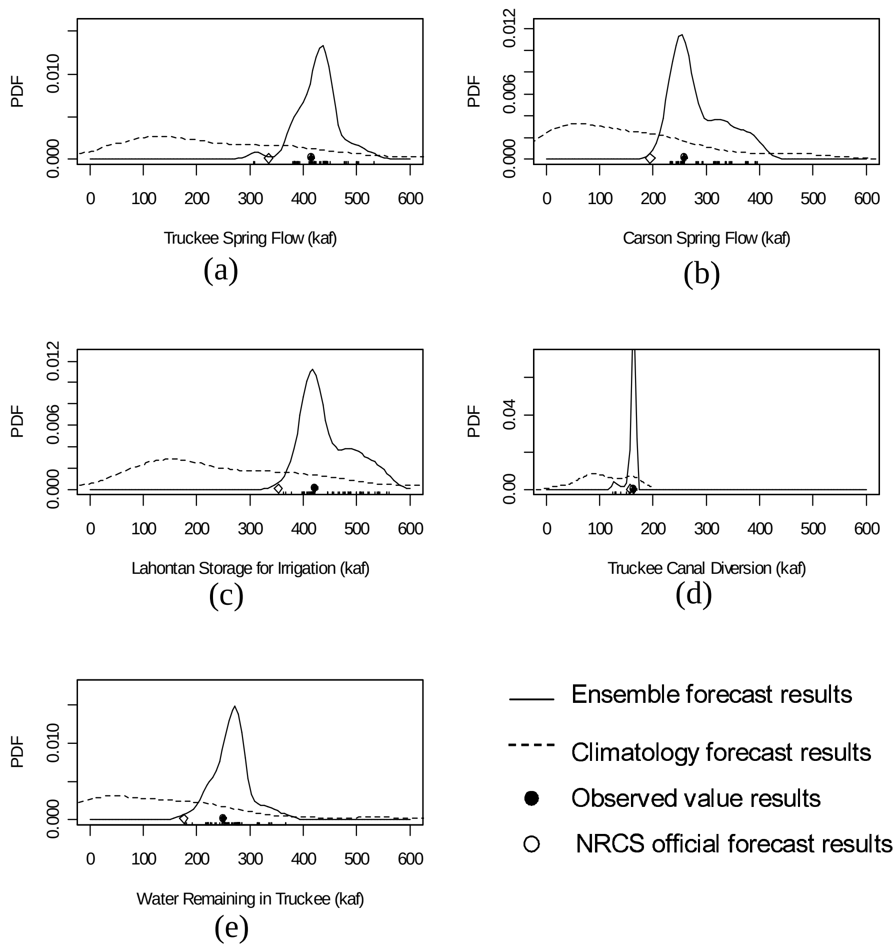


Figure 54: Seasonal Operations Model Results: 1993. Truckee River spring runoff (a), Carson River spring runoff (b), Lahontan storage available for irrigation (c), Truckee Canal diversion (d), and Truckee River water available for fish (e). The solid line represents model results based on ensemble forecasts and the dashed line represents model results based on a climatological forecast. The solid circle illustrates model results using the observed runoff value and the open circle shows the results using the NRCS forecasted value.

results of the ensemble forecast show a 100% chance of exceeding the 60.5 low-flow threshold for fish in the lower Truckee River. In fact, the most probable value is 267 kaf, suggesting to FWS that it is an excellent year to schedule a fish spawning run. Lahontan storage available for irrigation shows a 100% chance of exceeding the 296 average value. TCID farmers can plan on having plenty of irrigation water for this year and will likely consider carryover storage in Lahontan. The PDF for the Truckee Canal diversions is very tight next to 164 kaf--the maximum allowable diversions. Water managers should use this information to schedule diversions at full canal capacity starting from the beginning of the season.

4.3 Summary and Conclusions

While seasonal forecasts help water managers to determine the volume of water available in the coming season, the daily operations on how that water will be divided up to comply with laws and policies in the basin, as well as seasonal and long-term planning strategies, still remains as a large task. DSSs, such as the Truckee River-Ware model, utilize forecasts to determine reservoir releases and diversions throughout the system by modeling the physical river network together with the policies governing operations in the basin. For this study, we develop a simplified seasonal operations model to test the utility of the forecast in different years. Model results for normal, above normal, and below normal streamflow years demonstrate that utilizing the ensemble forecasts from Chapter 3 in a decision support system framework provides water managers with valuable information regarding decision variables in the coming season.

Chapter 5

Conclusions and Recommendations

This section summarizes and concludes this thesis. We review the motivation and original goals of this research, summarize the final results, and draw conclusions from these results. We also make recommendations for future work that will improve and extend this study.

5.1 Summary

As in other western U.S. river basins, water managers of the Truckee and Carson rivers must plan carefully to meet the many demands on water quality, volume, timing and flow rates. Operations on these rivers are particularly complex due to multiple storage reservoirs and diversions as well as the many policies and laws. An important feature in the Truckee-Carson river system is the Truckee Canal, which typically diverts over 1/3 of the annual Truckee River flow to the Carson River basin for use in the Newlands Project irrigation district. Resulting low flows and shallow depths in Truckee River below this diversion have inhibited the spawning and survival of the threatened Lahontan cutthroat trout and the endangered cui-ui. The hydrology of the basins adds to the complexity in operations and management. Snowmelt from the Sierra Nevada mountains is virtually the only water source for the agricultural, municipal, and industrial development of the arid lower basin. Water managers must understand the interannual and interseasonal variability of flows in the Truckee and Carson rivers to enable the sustainment of development in this western Nevadan basin. The USBR utilizes forecasts of the spring runoff to help with operations and planning on the rivers. Current forecasting techniques, however, are not skillful enough and do not provide enough lead-time to optimize management effectiveness.

In this study, we set out to develop a seasonal forecasting model to assist with water resources decision making in the Truckee-Carson river system. We investigate the use of large-scale climate information as a spring runoff predictor to improve the skill and lead-time of the forecasts. We use nonparametric stochastic forecasting techniques to provide ensemble forecasts which can aid in decision making by providing exceedence probabilities. We set out to demonstrate the utility of the improved forecast by coupling them with the DSS and analyzing different important decision variables.

There is growing evidence that large-scale atmospheric circulation patterns affect the hydroclimate in the western United States. In this study, we conduct our own analysis to determine the prominent patterns that affect the hydroclimate in the Truckee and Carson basins. Correlation analysis results show that winter large-scale ocean-atmospheric patterns over the Pacific Ocean strongly modulate the year to year variations of spring runoff in the basins. Particularly, 500mb geopotential height and SST demonstrate a strong relationship with the spring runoff. The persistence of these circulation patterns back to fall enhances the prospect of a longer-lead forecast. Composite analysis results provide the physical explanation of the pressure-streamflow relationship. Based on our analysis we develop climate indices to be applied in a forecasting mode.

We develop a nonparametric stochastic forecasting model to predict the April to July streamflows in the Truckee and Carson rivers. The nonparametric approach is assumption free and can capture nonlinearities as well as linear dependencies in the data. Results show that the incorporation of large-scale climate information improves the skill and lead time of the forecast. The resulting ensemble forecasts provide exceedence probabilities which can aid in water resources decision making. We also demonstrate the ability to use the modified K-NN technique to disaggregate seasonal volumes into monthly values. The true application of these forecasts comes in coupling them with a decision support system.

Water managers in the Truckee Carson river basin are currently developing a decision support system to aid in operations and planning in the basin. The Truckee RiverWare model utilizes forecasts to drive simulations of the physical mechanisms, policies, and water rights in the Truckee-Carson river system. For this study, we develop a simplified seasonal operations model to test the utility of the forecast in different years. Model results for normal, above normal, and below normal streamflow years demonstrate that utilizing the ensemble forecasts from Chapter 3 in a decision support system framework provides water managers with valuable information regarding water available for irrigation and fish in the coming season.

5.2 Conclusions

This research demonstrates that incorporating large-scale climate information in forecasting can produce better, longer lead-time forecasts. Results show that the stochastic forecasting technique has the added benefit of providing exceedence probabilities for various seasonal flow values. The improved forecasts facilitate efficient seasonal planing and management in the complex Truckee-Carson River Basin. Though the process of incorporating large-scale climate information into water resources decision making is applied to the Truckee-Carson river system in this study, the approach is quite flexible and can be extended to other basins throughout the western US.

5.3 Recommendations for Future Work

Many areas of this research warrant further research and analysis. We present several issues that should be addressed to complete this study as well as possibilities for extending the techniques of this research to new realms.

5.3.1 Coupling ensemble forecasts with the Truckee RiverWare model

The ensemble forecasts generated from this research need to be coupled with the Truckee RiverWare model after its completion. This final step of the study plays an integral role in determining the utility of the ensemble forecasts to water resources decision making in the basin. Results from the simplified seasonal policy model demonstrate that the forecasts provide important information which can be applied to operations and management. However, the full RiverWare model must be tested to determine the exact impact forecasts have on the multiple decision variables in the basin. Using the Truckee RiverWare model will not only allow for daily analysis of all the policies in the entire basin, it will also include the tracking of water rights. The forecasts presumably affect many other decision variables not addressed in the simplified model. Other impacts to analyze in the full DSS include the forecasts' impact on flood control and water rights. The utility of passing entire ensemble forecast through the Truckee RiverWare model, rather than utilizing current methods which only pass the expected value and the 30th and 70th percentiles, should also be explored.

5.3.2 Temporal disaggregation

Further work on developing a temporal disaggregation scheme should be investigated. The temporal disaggreation of the forecasted April to July runoff plays an important role in model simulations. The Truckee RiverWare model requires both daily and monthly streamflow values during the April to July period. Daily values are used as input to drive the simulations in the operations model. Monthly values drive the rules that set target storages on Lahontan Reservoir.

Preliminary results of using the modified K-NN technique to disaggregate the seasonal runoff to monthly values are encouraging. This application of the technique requires more testing and validation.

The Truckee RiverWare model currently uses a “similar years analysis” to disaggregate the total seasonal volume into daily values. It would be interesting to test whether the nonparametric techniques of the modified K-NN method improve the skill of the daily disaggregation.

5.3.3 Forecast Improvements

Streamflow forecasting is not an exact science. Researchers in the field utilize many different techniques that may or may not improve forecasting skill in a given basin. Results from the techniques presented in this study show good forecast skill. However, given that water managers in the Truckee-Carson basin rely heavily upon the spring forecast, any improvement in forecast skill would have pronounced effects throughout the basin.

Improving the predictor selection criteria for the modified K-NN model could possibly increase forecast skill. This study uses correlation analysis and significance tests to determine valid statistical relationships. The composite analysis establishes the physical mechanisms relating various predictors to streamflows in the Truckee and Carson rivers. A more objective criteria could be used to sort through an entire suite of predictors to determine the best set. Methods similar to general cross validation, but applicable in nonlinear models, are available for this purpose.

The potential of issuing a joint forecast to increase forecast skill could also be explored. This study issued forecasts separately for the Truckee River and for the Carson River, relying on the forecasters knowledge that the two rivers are highly correlated. Forecasting the Truckee and Carson jointly may better capture the covariance between the rivers.

As always, the skill of the forecast depends heavily on data quantity and quality. Longer data sets typically provide better model fitting and, hence, forecasting skill. Data sets extending further back than 1949 would likely increase forecasting skill. More accurate SWE data, particularly in the Carson basin, will also improve forecasting results. Other methods of calculating basin-wide SWE could also be explored.

5.3.4 Comparisons with a statistical-physical forecasting model

This study could be extended to compare results from a the statistical model presented in this thesis with a statistical-physical model. The statistical-physical model would couple a stochastic weather generator with the existing physically-based Truckee PRMS model. The weather generator produces ensembles of possible weather scenarios (e.g., precipitation and temperature) using past data. The Truckee PRMS model will use the weather ensembles as input to generate traces of possible runoff scenarios. The skill of the statistical-physical model should be compared to the skill of the forecasting model presented in this study. The ensemble forecasts from both models should be coupled with the DSS to compare their impacts on decision variables in the basin.

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Appendix A

Operating Policy in the Basin

The Truckee-Carson River System is highly regulated and litigated. Over the past century there have been a number of laws, regulations, court cases, and decrees that affect basin operations. Typically, new agreements or laws incorporate the previous policy, so many of the original policies are still in force today. This section briefly describes the river operations of the past, the present and future. A description of the major policies and laws can be found in Appendix B, “Description of Select Laws”.

A.1 Historic and current policy

As in most river basins, flood control is the highest priority operation in the Truckee and Carson River Basins. Except for Lake Tahoe, Donner Lake, and Independence Lake, the reservoirs are operated in accordance with the U.S. Army Corps of Engineers flood control regulations to prevent flooding downstream.

After flood control, the main operating policy is the Floriston rates. The Floriston rates, which were originally established in 1908 and later reaffirmed in the 1944 Orr Ditch Decree, are a set of flow rates that must be met at the Farad USGS gage near the town of Floriston on the border of California and Nevada. These rates vary between 300 and 500 cfs based on the level of Lake Tahoe and the time of year. Operating procedures meet the Floriston rates first by using unregulated flows, then by release storage water from Boca, Prosser, and Tahoe. Municipal, industrial, and agriculture interests downstream all use the water released for Floriston rates.

Donner Lake and Independence Lake are privately owned. The Sierra Pacific Power Company owns all of the storage rights in Independence Lake and half of the storage rights in Donner Lake. TCID owns the other half of the storage rights in Donner Lake. These private entities can schedule releases to use the water they have in storage for municipal, agricultural and industrial purposes. Although these lakes are private, their storage rights do not have higher priority than the Floriston rates; they can only store water when the Floriston rates are met.

Stampede Reservoir was originally constructed to supplement agriculture and municipal water. In 1982, the Stampede Reservoir Judgement decreed all of the water and storage in Stampede to the protection of the endangered cui-ui and threatened Lahontan cutthroat trout. The FWS and Pyramid Lake Paiute Tribe schedule releases based on the projected need to supplement flows for the spawning or survival of these species. Spawning runs are scheduled based on storage values, forecasted flows, and time since the last run. In spawning run years, FWS and the Pyramid Lake Paiute Tribe schedule releases from Stampede to try to meet the following flow targets at Pyramid Lake: January 90cfs, February 120cfs, March 190cfs, April 570cfs, May 1000cfs, June 50cfs (Berris 2001). Because of its more recent construction and therefore junior water rights, Stampede rarely fills completely.

The Truckee Canal diverts Truckee River water into the Carson River Basin for use in the Newlands Project irrigation district. Diversion criteria, as defined by OCAP, are based on forecasted flows on the Carson River and project land that is actually irrigated.

In the upper basin, the Tahoe-Prosser Exchange Agreement helps maintain instream flows below Tahoe Dam by allowing exchanges between Tahoe and Prosser Reservoirs. With the exchange agreement, Tahoe can release water to keep a live stream below the dam even though releases are not required. Meanwhile, Prosser can store inflows which would otherwise have been released. In this way, Prosser stores some of Tahoe’s water-- this is known as an exchange. Exchanges like this also exist between Boca and Donner Reservoirs. These exchanges add flexibility to the system.

A.2 Future policy affecting the Basin

Past policies and procedures will affect how the river operates in the future. The new Truckee River Operating Agreement, if agreed on, will regulate the river in the future while still incorporating many of the past laws and policy. In particular, Floriston rates will still be the main operations goal but those entitled to use Floriston rate water could store some of their water for specific purposes later. The stored water will later be released only to benefit the purpose for which it was stored. (Truckee River Operating Agreement DEIS/DEIR 1998). Another change in TROA is the condition in which stored water can be exchanged with scheduled releases to make operations more flexible for multiple purposes. The new TROA will also allow Floriston rates to be reduced to store WQCW even when cui-ui are not spawning.

Appendix B

Description of Select Laws

The following is a description of some of the major laws in the Truckee-Carson River System. See the Truckee River Chronology (Horton, 1995), the Truckee River Atlas (Horton, 1995), and the Carson River Chronology (Horton, 1996) for a full description of history and laws in the basins.

B.1 Floriston Rates

The Floriston rates were established in 1908 as an agreement between the Floriston Paper Company and the Truckee River General Electric Company. This agreement established mean instream flows of 500cfs between March 1 and September 30 and 400cfs for the rest of the year as measured at Floriston, CA. The Truckee River General Electric Decree of 1915 and the Truckee River Agreement of 1935 amended the Floriston rates to allow for reduced rates based on the level of Lake Tahoe. Between November 1 and March 31, Floriston rates were 350cfs whenever Lake Tahoe was below 6225.0 ft. AMSL and 300 cfs whenever Lake Tahoe fell below 6225.25 ft. Unregulated flow, Tahoe releases, and Boca releases (once it was built) were used to meet these flow requirements. To this day, the reservoirs must be operated such that the Floriston rates are met. (Horton 1995)

B.2 Truckee River Agreement

The Truckee River Agreement (TRA) of 1935 enacted a contract among the federal government, Sierra Pacific Power Company, TCID, and Washoe County Water Conservation District. This agreement reaffirmed the Floriston rates and established rules regarding the use of Lake Tahoe water. The agreement set the natural rim of Lake

Tahoe at 6223.0 ft. AMSL allowing 6.1 feet of storage depth in the lake. This agreement, in conjunction with the Truckee Storage Project, confirmed the need for the construction of Boca Reservoir on the Little Truckee River. (Horton 1995)

B.3 Orr Ditch Decree

The Orr Ditch Decree of 1944 incorporated the provisions of the TRA and delineated Truckee River water rights. In general, the decree established that the Pyramid Lake Paiute Indian Tribe had the most senior water rights to irrigate land. The Decree next permitted the Newlands project to divert up to 1500 cfs through the Truckee Canal. The Sierra Pacific Power Company was given the next water rights for municipal, domestic, and industrial purposes.

B.4 Tahoe -Prosser Exchange Agreement

The Tahoe-Prosser Exchange Agreement of 1959 maintains flows directly downstream of Lake Tahoe during periods when releases from Lake Tahoe are unnecessary to meet Floriston rates. This agreement allowed an equal amount of water released from Tahoe to be stored in Prosser thereby exchanging water between the two reservoirs.

B.5 Newlands Project Operating Criteria and Procedures (OCAP)

Newlands Project OCAP, originally established in 1967, regulate the diversions from the Truckee River to the Newlands Project via the Truckee Canal. The primary objective is to maximize use of Carson River water and minimize diversions from the Truckee River. In 1997, the Secretary of the Interior adjusted the 1988 OCAP to make the Newlands Project less dependent on Truckee River water and to increase the Newlands project water use efficiency.

B.6 Stampede Reservoir Judgement

In 1982, the federal Ninth Circuit Court ruled in Carson-Truckee Water Conservation District v. Watt that all water in Stampede Reservoir be used for threatened and endangered fish in Pyramid Lake until those species are no longer on the Endangered Species List. FWS and the Pyramid Lake fisheries establish the release schedules to protect these listed species.

B.7 Preliminary Settlement Act

The Preliminary Settlement Act of 1989, negotiated between Pyramid Lake Paiute Tribe and Sierra Pacific Power Company (SPPCo), provided 39,500 acre-feet of storage rights to SPPCo when not needed for M&I uses. Excess water in storage could be used for fishery purposes and SPPCo gave up its right to single use hydropower flows. This act allowed for the storage of water to be used for spawning.

B.8 Negotiated Settlement Act: P.L. 101-618

The Negotiated Settlement Act (P.L. 101-618) provided legislation to settle many of the outstanding court cases and disputes over water rights in the Truckee River Basin. The Act provided for protection of wetlands, recovery of endangered and threatened fish, improved management of the Newlands project, settlement of Fallon Paiute-Shoshone and Pyramid Lake Paiute Tribe water issues, and apportionment of interstate water. The act incorporated the conditions set in the Preliminary Settlement Agreement but declared that the act is not effective until a new operating agreement is negotiated and ratified.

B.9 Water Quality Settlement Agreement

In 1996, the U.S. Department of Justice, Environmental Protection Agency, Department of the Interior, Nevada Department of Environment Protection, Washoe County, Reno, Sparks and the Pyramid Lake Paiute Tribe all signed the Truckee River Water Quality Settlement Agreement. This agreement set up a program to improve Truckee River water quality downstream of Reno by augmenting river flows during low flow periods. The Federal government and Washoe County have each agreed to purchase $12 million worth of water rights explicitly for water quality purposes. This water quality credit water (WQCW) is to be stored in the federally controlled reservoirs and released by decision of a committee.

B.10 Truckee River Operating Agreement

The Truckee River Operating Agreement is a negotiated settlement involving all of major entities in the Truckee River Basin. As of November 2003, the agreement has not been approved and is still under negotiations. In general, the agreement will coordinate reservoir releases and storage, improve exchange of stored water, improve efficiency of water and storage space, improve the accounting procedures to track water, and set up the Interstate Allocation.

B.11 Water Rights Acquisition Program (WRAP)

Public Law 101-618 provides for a program to acquire water rights to preserve and enhance wetlands in Lahontan Valley. As a result, the Water Rights Acquisition Program (WRAP) will acquire approximately 75,000 acre-feet of water to help preserve 25,000 acres of wetland in the Stillwater National Wildlife Refuge and Stillwater Wildlife Management Area. Most of this water will come from the Carson Division of the Newlands Project but some of the water could be diverted from the Truckee River via the Truckee Canal.

Appendix C

Glossary

Following is a glossary of important acronyms and terms used in this thesis.

Cui-ui

The cui-ui is an endangered sucker fish that lives in Pyramid Lake and swims up the Truckee River to spawn. Low flows in the Truckee River below Derby Dam have threatened its survival.

DSS

A decision Support System (DSS) is a tool used by water resources managers to evaluate operations and policy alternatives.

Exceedence probability

The probability of exceeding a certain threshold flow value.

ENSO

El Nino-Southern Oscillation.

FWS

U.S. Fish and Wildlife Service.

Lahontan cutthroat trout

The Lahontan cutthroat trout is a threatened fish that lives in the Truckee River and Pyramid Lake.

M&I

Municipal and Industrial (M&I) water is a classification of Truckee River water that is treated and used for domestic or industrial uses.

Natural Flow

The flow that would be present in the river without the effects of human development (e.g., reserviors and diversions).

Newlands Project

Farming district of 65,000 irrigated acres for which Truckee River water is diverterted through the Truckee Canal.

NRCS

Natural Resources Conservation Service.

OCAP

Operating Criteria and Procedures for the Newlands Project Irrigation district.

PCA

Principal Component Analysis.

PDO

Pacific Decadal Oscillation.

PNA

Pacific/North American climate pattern.

RiverWare

RiverWare is a general purpose river and reservoir modeling tool created by the Center for Advanced Decision Support for Water and Environmental Systems at the University of Colorado, Boulder.

SST

Sea Surface Temperature.

SLP

Sea Level Pressure.

SWE

Snow water equivalent. The total water content contained in the snowpack, reported as a depth. SWE data provides useful information for determining the amount of water stored as snow.

TCID

Truckee-Carson Irrigation District. TCID manages all the canals, ditches, dams and reservoirs for the Newlands Project irrigation district.

USBR

U.S. Bureau of Reclamation.

USGS

U.S. Geological Survey.

WQCW

Water quality credit water (WQCW) is created from water rights purchased as part of the WQSA and stored in federally controlled reservoirs.

Appendix D

Modified K-NN Forecasting Code

```
{
#######################################################
#    MODIFIED K-NN METHOD-- FORECAST ALL YEARS
#######################################################

# 1. Use y-hat from the locfit model
#    (fpredicted.loc$fit and cpredicted.loc$fit)
# 2. The residuals from the locfit model will be used
#    (residuals(locf.model), residuals(locc.model))
# 3. Get the distance between the predicted point x values
#    and the x values for all points in the model (will get the
#    Euclidean distance of the normalized values)
# 4. Pick the K (based on heuristic scheme) nearest neighbors
# 5. Weight the K nearest neighbors
# 6. The weighted K-NN residuals will then be used in a bootstrap


# SET UP PARAMETERS
x=matrix(scan("predictors.dat"),byrow=T,ncol=9)  # all 9 possible predictors
     # 1 NCDC Precip
     # 2 Geopotential Height
     # 3 SST
     # 4 Average SWE Mar1
     # 5 Average SWE Apr1
     # 6 Truckee SWE Mar1
     # 7 Truckee SWE Apr1
```

```
     # 8 Carson SWE Mar1
     # 9 Carson SWE Apr1
yfVol=scan("faradNatural.amjj.vol.dat")            # y-values (streamflow at farad)
ycVol=scan("churchillNatural.amjj.vol.dat")        # y-values (streamflow at
churchill)
#nrcsf=scan("nrcsTruckeeApril")                    # 1990-2003 NRCS forecasts
#nrcsc=scan("nrcsCarsonApril")                     # 1990-2003 NRCS forecasts

const=1948               # the year before the data starts

xs=(1949-const)          # the starting position of the data set (change as needed)
xe=(2003-const)          # the ending position of the data set (change as needed)

yp=xe-xs+1               # yp for the number of years to predict at-- predict each year

xx=scale(x)              # normalize the data (so higher magnitude variables
                         # don't get more weight in distance calculation)


# set up matricies to hold ensemble forecast
ensemblef=matrix(nrow=100,ncol=yp)
ensemblec=matrix(nrow=100,ncol=yp)

## TRUCKEE
## Need to make the forecast for every year, so put into loop
#x=cbind(x[,7],x[,2],x[,3])       # swe,geopot,sst
x=cbind(x[,7],x[,2])              # swe,geopot
p=length(x[1,])                   # p for the number of predictors
                                  #  ** NOTE:  If p is not 3, MUST CHANGE number
                                  #  ** of terms in distance calculation
for(i in 1:yp)
```

```
{
    # p1 is the position of the year we're predicting
    p1=i
    xpred=x[p1,]
    yfpred=yfVol[p1]

    if(p1 == xs)
    {
        xmodel=x[(xs+1):xe,]
        yfmodel=yfVol[(xs+1):xe]
    }
     if(p1 == xe)
    {
        xmodel=x[xs:(xe-1),]
        yfmodel=yfVol[xs:(xe-1)]
      }
    if(p1 != xe && p1 != xs)
    {
        xmodel=rbind(x[xs:(p1-1),],x[(p1+1):xe,])
        yfmodel=c(yfVol[xs:(p1-1)],yfVol[(p1+1):xe])
    }
    ym=length(xmodel[,1])

    # DISTANCE CALCULATION
    # calculate the distance between the (predictors of the) point we're predicting
    # and all other points-- use scaled data
    xdist=scale(xmodel)
    distance=1:ym
    for(j in 1:ym)
    {
        # distance[j]=sqrt(((xx[p1,1]-xdist[j,1])^2)+((xx[p1,2]-
```

```
xdist[j,2])^2)+((xx[p1,3]-xdist[j,3])^2))
            distance[j]=sqrt(((xx[p1,1]-xdist[j,1])^2)+((xx[p1,2]-xdist[j,2])^2))
        }

    # RANK the distances
    drank=rank(distance)            # here rank 1 is the nearest neighbor
                                    # (i.e. the smallest distance)
    # DETERMINE K and weight it
    n=length(distance)
    kk=sqrt(n)
    kk=round(kk)
    W=1:kk
    W=1/W
    W=W/sum(W)
    W=cumsum(W)

    # Find the alpha for the locfit model-- take the alpha whith the lowest gcv
    alphaf=seq(0.2,1,by=0.05)
    xxf=gcvplot(yfmodel~xmodel,alpha=alphaf,deg=1,kern="bisq",ev="data")
    zxf=xxf$values
    zzf=order(zxf)
    alphaf=alphaf[zzf[1]]

     # Do the LOCFIT and get the expected value for each of the p  points
    locf.model=locfit(yfmodel~xmodel, alpha=alphaf, deg=1, kern="bisq")
    fit=locf.model

     # Make the mean prediction
            # hack-fix so predict.locfit will work:  make xpred a matrix with
            # the real xpred the first row.  Take first predicted point.
        xpred=rbind(xpred,xmodel)
```

```
        fpredicted.loc=predict.locfit(locf.model, xpred, se.fit=T, band="global")

    # now weight the neighbors and pick one at random (using the weights)
    # do this 100 times
    residualsf=residuals(locf.model)        # get the residuals of the locfit model
    for(k in 1:100)                         # do innerloop 100 times (bootstrap residu-
als)
    {
            rannum=runif(1,0,1)
             xy=c(rannum,W)                 # adds a random number (between 0 and 1)
                                            # to the weight function (CDF)

            rankW=rank(xy)                  # assigns a rank to the random number
                                            # (and W vector)

            pos=order(drank)[rankW[1]] # gives the position in the distance matrix
(and
                                            # corrrespondingly the y matrix for the
selected
                                            # neighbor)

            resids=residualsf[pos]          # Once I get a neighbor, I need to find the
                                            # residual associated with that neighbor

            ensemblef[k,i]=fpredicted.loc$fit[1]+resids
                                            # add that residual to the y-hat from the
                                            # locfit model
        }
}
```

```
## CARSON
x=matrix(scan("predictors.dat"),byrow=T,ncol=9)         # all 9 possible predictors
#x=cbind(x[,9],x[,2],x[,3])          # swe,geopot,sst
x=cbind(x[,9],x[,2])                 # swe,geopot
p=length(x[1,])
for(i in 1:yp)
{
    p1=i
    xpred=x[p1,]
    ycpred=ycVol[p1]

    if(p1 == xs)
    {
        xmodel=x[(xs+1):xe,]
        ycmodel=ycVol[(xs+1):xe]
    }
    if(p1 == xe)
    {
        xmodel=x[xs:(xe-1),]
        ycmodel=ycVol[xs:(xe-1)]
    }
    if(p1 != xe && p1 != xs)
    {
        xmodel=rbind(x[xs:(p1-1),],x[(p1+1):xe,])
        ycmodel=c(ycVol[xs:(p1-1)],ycVol[(p1+1):xe])
    }
    ym=length(xmodel[,1])

    # DISTANCE CALCULATION
    xdist=scale(xmodel)
    distance=1:ym
```

```
for(j in 1:ym)
{
        #distance[j]=sqrt(((xx[p1,1]-xdist[j,1])^2)+((xx[p1,2]-
xdist[j,2])^2)+((xx[p1,3]-xdist[j,3])^2))
        distance[j]=sqrt(((xx[p1,1]-xdist[j,1])^2)+((xx[p1,2]-xdist[j,2])^2))
    }

    # RANK the distances
drank=rank(distance)

# DETERMINE K and weight it
n=length(distance)
kk=sqrt(n)
kk=round(kk)
W=1:kk
W=1/W
W=W/sum(W)
W=cumsum(W)

# Find the alpha for the locfit model-- take the alpha whith the lowest gcv
alphac=seq(0.2,1,by=0.05)
xxc=gcvplot(ycmodel~xmodel,alpha=alphac,deg=1,kern="bisq",ev="data")
zxc=xxc$values
zzc=order(zxc)
alphac=alphac[zzc[1]]

# Do the LOCFIT and get the expected value for each of the p  points
locc.model=locfit(ycmodel~xmodel, alpha=alphac, deg=1, kern="bisq")
fit=locc.model

# Make the mean prediction
```

```
    xpred=rbind(xpred,xmodel)
    cpredicted.loc=predict.locfit(locc.model, xpred, se.fit=T, band="global")


    # now weight the neighbors and pick one at random (using the weights)
    # do this 100 times
    residualsc=residuals(locc.model)
    for(k in 1:100)
    {
        rannum=runif(1,0,1)
        xy=c(rannum,W)
        rankW=rank(xy)
        pos=order(drank)[rankW[1]]
        resids=residualsc[pos]
        ensemblec[k,i]=cpredicted.loc$fit[1]+resids
    }
}

# Write the ensemble forecast matrices to file
# (i.e. write an object from Splus into an ASCII file)
write(t(ensemblef),file="knnFaradAprSWEGpHApr.out",ncol=55)
write(t(ensemblec),file="knnCarsonAprSWEGpHApr.out",ncol=55)

# Make boxplots
plotbeg=1949-const
plotend=2003-const

par(mfrow=c(2,1))
nevals=plotend-plotbeg+1
xevals=ensemblef[,plotbeg:plotend]
xs=1:nevals
```

```
qf=quantile(yfVol,c(.05,.25,.5,.75,.95))
zz=boxplot(split(t(xevals),xs),plot=F,cex=1.0,print=F,cex=1.0,ylim=range(0,800))
zz$names=rep("",length(zz$names))
z1=bxp(zz,xlab="",ylab="",style.bxp="old",cex=1.25)
title(main="Truckee Modified K-NN Prediction (1949-2003)")
title(ylab="AMJJ Volume (kaf)")
lines(z1,yfVol[plotbeg:plotend],lty=1,lwd=2)
for(i in 1:5)
{
    abline(h=qf[i],lty=2)
}

xevals=ensemblec[,plotbeg:plotend]
xs=1:nevals
qc=quantile(ycVol,c(.05,.025,.5,.75,.95))
zz=boxplot(split(t(xevals),xs),plot=F,cex=1.0)
zz$names=rep("",length(zz$names))
z1=bxp(zz,xlab="",ylab="",style.bxp="old",cex=1.25, ylim=range(0,800))
title(main="Carson Modified K-NN Prediction (1949-2003)")
title(ylab="AMJJ Volume (kaf)")
lines(z1,ycVol[plotbeg:plotend],lty=1,lwd=2)
for(i in 1:5)
{
    abline(h=qc[i],lty=2)
}
# end of file
}
```

Appendix E

Seasonal Policy Model Code

```
{
##################################################################
# A simplified policy model for Newland's Project OCAP.
# Solves for storage on Lahontan Reservior, water remaining
# in the Truckee River, and diversion through the Truckee Canal
##################################################################
year=2003          # change value as necessary


# Lahontan minimum storage target is (1/3) of average historical total flow on T and C
minTarget=(1/3)*(mean(yfVol)+mean(ycVol))

# minimum flow that must remain in Truckee for fish-- change to test different policies
fishFlow=0

# max diversion through the Truckee Canal is 164kaf
maxDiversion=164

# get the ensemble for the particular year we want to run
ensemblef=matrix(scan("knnFaradAprSWEGpH.out"),byrow=T,ncol=55)
ensemblec=matrix(scan("knnCarsonAprSWEGpH.out"),byrow=T,ncol=55)
c=year-1948
allf=ensemblef[,c]
allc=ensemblec[,c]
# model does not allow negative flow values from the forecast
for(i in 1:100)
```

```
{
        if(allf[i]<0)
        {
            allf[i]=0
    }
    if (allc[i]<0)
    {
            allc[i]=0
    }
}

# add climatology, to check what managers would do w/o a forecast
# bootstrap the historical data to get climatology
n=sample(1:54, 100,replace=T)
if(c==1)
{
    climf=yfVol[2:55]
    climc=ycVol[2:55]
}
if (c==55)
{
    climf=yfVol[1:54]
    climc=ycVol[1:54]
}
if (c!=1 & c!=55)
{
    climf=c(yfVol[1:c-1],yfVol[c+1:55])
    climc=c(ycVol[1:c-1],ycVol[c=1:55])
}
climf=climf[n]
climc=climc[n]
```

```
allf=c(allf,climf)
allc=c(allc,climc)

# add the observed value, to check what would have occured w/ perfect forecat
allf=c(allf,yfVol[c])
allc=c(allc,ycVol[c])

# set up vectors for decision variables
lahontanStorage=1:201
truckeeDiversion=1:201
truckeeToPyramid=1:201

for(i in 1:201)  # run 100 times (for each set of ensembles) plus one for observed value
{
    # Available for diversion is Truckee water - minimum fish flow water
    faradAvailForDiversion=allf[i]-fishFlow
    if (faradAvailForDiversion<0)
    {
            faradAvailForDiversion=0.0
    }

    # Available for diversion cannot excede maxDiversion
     if (faradAvailForDiversion>maxDiversion)
    {
            faradAvailForDiversion=maxDiversion
    }

  # maximize use of Carson water before diverting from Truckee
  carsonWater=allc[i]
```

```
     #  Lahontan storage target is initially set as (2/3) of total T and C --most probable
forecasted flow
     lahontanTarget=(2/3)*(allf[i]+allc[i])
     if (lahontanTarget < minTarget)
     {
             lahontanTarget=minTarget
     }

     # Set the Truckee Diversion
     # First, divert only what is needed to meet lahontanTarget.
     # If there isn't enough faradAvailForDiversion to meet lahontanTarget,
     # the farmers get shorted (fish get highest priority)

     truckeeDiv=lahontanTarget-carsonWater
      if (truckeeDiv > faradAvailForDiversion)
     {
             truckeeDiv=faradAvailForDiversion
     }
      lahontanStorage[i]=carsonWater+truckeeDiv
      truckeeDiversion[i]=truckeeDiv
      truckeeToPyramid[i]=allf[i]-truckeeDiv
}

#Plot the decision variables
par(mfrow=c(3,2))
sm.density(ensemblef[,c],xlim=c(0,600),ylab="PDF",xlab="Truckee Spring Flow
(kaf)")
sm.density(climf,add=T,lty=2)
points(yfVol[c],.0001,pch=19)

sm.density(ensemblec[,c],xlim=c(0,600),ylab="PDF",xlab="Carson Spring Flow
```

```
(kaf)")
sm.density(climc,add=T,lty=2)
points(ycVol[c],.0001,pch=19)

sm.density(lahontanStorage[1:100],xlim=c(0,600),ylab="PDF",xlab="Lahontan Stor-
age for Irrigation (kaf)")
sm.density(lahontanStorage[101:200], add=T,lty=2)
points(lahontanStorage[201],.0001,pch=19)

sm.density(truckeeDiversion[1:100],xlim=c(0,600),ylab="PDF",xlab="Truckee Canal
Diversion (kaf)")
sm.density(truckeeDiversion[101:200], add=T,lty=2)
points(truckeeDiversion[201],.0001,pch=19)

sm.density(truckeeToPyramid[1:100],xlim=c(0,600),ylab="PDF",xlab="Water
Remaining in Truckee (kaf)")
sm.density(truckeeToPyramid[101:200], add=T,lty=2)
points(truckeeToPyramid[201],.0001,pch=19)

# end of file
}
```