THE MISINTERPRETATION OF CLIMATE FORECASTS AND THEIR ECONOMIC IMPACTS TO THE AGRICULTURE SECTOR

By

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STATEMENT BY AUTHOR

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Abstract

This thesis uses climate forecasts conducted by the Climate Prediction Center to analyze the economic effects on the agriculture sector in the Western United States. We use a variety of different skill scores alongside a water consumptive use model developed for the Lower Colorado River irrigation area. Using various skill scores to evaluate the effectiveness of a given climate forecast, we attempt to model the factors that affect skill scores. Our results show climate forecast skill has not uniformly improved in the last twelve years. We also discovered forecast skill did not differ between climate divisions when forecasting precipitation; however it did when forecasting temperature. We then use our results along with an agriculture water use model to simulate possible decisions urban water managers must make on water purchases and the economic ramifications of their decisions. We found regardless of planning method, managers cannot rely completely upon current climate forecasts.

Chapter 1: Introduction

The ability to have more accurate predictions of future weather and climate patterns has always been a goal of the agriculture and energy sectors. Climate forecasting is a method of predicting shifts in weather patterns months to years into the future. Instead of saying it will rain or be hot tomorrow, climate forecasts aim to predict the weather some months in advance, on a long term scale. Accurate forecasts would be very useful to farmers, who need to know how much water will be needed for irrigating. They would also be important for decision makers in the energy sector, as previous research has shown a direct link between climate variables and demand for electricity (Tanimoto, 2008). In the past, it was not feasible to predict the climate more than three months in advance (Barnston and Van Den Dool, 1994). Scientists did not have the tools or knowledge to understand long term weather patterns. Instead predictions were typically based on past weather patterns. A simple analysis of historical weather and current conditions were used to predict situations months in advance. At the time this was an acceptable practice. However, these methods are not suited to shifting regional climate and more drastic changes in climate recently.

Climate change research has become a hot topic over the last fifteen years. With keener awareness of global warming and the El Nino/La Nina phenomenon researchers have begun to develop models to analyze and predict the possible upcoming climate. With all of the focus on climate, new innovations and methods have been developed by scientists, allowing us to analyze and predict these patterns. The science of climate forecasting took on an entire new role beginning in mid-December of 1994 as the

National Weather Service (NWS) and Climate Prediction Center (CPC) began issuing more climate forecasts. They began issuing 3 month forecasts, with different lead times varying from 1 month to 12.5 (13) months (Livezey, 2008). The ability to conduct these forecasts with such large lead times was accredited to the El Nino Southern Oscillations (ENSO) phenomenon, as well as advances in computer capabilities and data mining procedures (Van Den Dool, 2007). It was thought that skillful forecasts could be made 6 to 9 months in advance, a feat not possible in previous decades.

A current issue with climate forecasts is their overall usefulness. Many decision makers see them as unreliable, while others see them as useful, but only in certain situations (Mjelde and Fuller, 2000). However, another problem with forecasts in today's time is how they are misinterpreted by decision makers. A water manager for instance could take a climate forecast to be a definite prediction thinking of them as weather forecasts which are made days or weeks in advance. The problem with this is that climate forecasts are given as probability distributions, where one set of future conditions is simply 'more likely' than others. This does not guarantee a certain outcome, and decisions must be made with knowledge of forecast uncertainty. The climate forecasts we are analyzing are provided with three separate categories and probabilities. Above, normal and below are the three forecast categories, and each one is assigned a probability between 0 and 1. These three probabilities will sum to 1, and whichever is the most likely will be given the highest probability. If none of the three are most likely, this is referred to as a 'climatology' forecast, or one of 'equal chances'.

This thesis uses climate forecasts performed by the CPC to analyze the potential economic effects of forecasts on an urban water manager. Using a variety of different skill scores alongside a water diversions model developed for the Colorado River irrigation area, the economic consequences associated with forecast skill and interpretationcan be determined. We first determine four descriptive skill scores; the Ranked Probability Score (RPS), the Brier skill score (BS), the False alarm rate (FR), and the Surprise rate (SR) (Pagano, 2001). Using these four scores to evaluate the effectiveness of a given climate forecast, we analyze the factors that affect skill scores using a fixed effects regression model. Such factors include location (climate division), the Oceanic Nino Index (ONI), lead time (from 1 to 13 months) and forecast season (three month seasonal blocks from January through December). We use this model along with our Colorado River water diversions model to simulate possible decisions water managers must make on water purchases. These decision makers receive forecast information and make decisions on how much water will be needed in the future.

Our results show the ONI only affects forecast skill when extreme values are observed. Extreme values are associated El Nino and La Nina climate periods. These periods typically exhibit better forecast skill. When the ONI does not reach extreme values, it is typically insignificant in forecast skill. We found that the ONI plays a larger role in temperature forecasts than in precipitation. However, it can still play a large role in both. The interpretation is basically that climate forecasters find the El Nino and La Nina weather phenomenon present better climate conditions in terms of prediction. We also found that both the lead time and issue year independent variables are typically insignificant or have a negative effect on overall forecast skill. Our interpretation is that forecast methods have not yet developed well enough to predict temperature and precipitation more accurately six to twelve months in advance.

We also use a simulation model to analyze possible choices made by urban water managers based on different planning methods. Using a Lower Colorado River Agriculture water consumption model developed at The University of Arizona (described in detail in chapter 3), along with various planning methods, we predict the amount of water consumption by a particular irrigation district in a given season, under specific temperature and precipitation conditions. Using these values we then find the amount an urban water manager may need to acquire and the varying potential costs. These values indicate the effects for a water manager of their reliance on forecasts.

Our simulation results show that lead time does not uniformly affect forecast skill. Our results do not show any constant structural connection between lead time and correctly predicting water diversions. Instead, it appears in one season the one-month lead may be more consistently accurate and the next season a seven-month lead most accurate. We also conclude from our simulation that higher forecast skill at more advanced lead times could potentially save millions of dollars for water resource decision makers. It is clear that, if attainable, the ability to acquire water during hot dry periods with more advance notice and at a lower price could save water managers millions of dollars over the course of the water supply year. Our simulations show there is not currently a most consistently accurate lead time to use in making decisions that are affected by future temperature and precipitation.

This thesis is organized as follows: Chapter 2 contains a literature review; analyzing past research done in the field of the economics of climate forecasts. Chapter 3 explains the development of a Lower Colorado River Agriculture water consumption model that was developed at The University of Arizona. Chapter 4 then describes the data collection process and methodology used to create our climate forecast database. This chapter also contains the summary statistics of the dataset, to give a better idea of the type of data being analyzed and its key characteristics. Chapter 5 contains the information on the econometric modeling. This chapter details the different models being used, as well as any parameter or data testing that has been done. Chapter 6 presents the results of the econometric models. Chapter 7 shows the process and results of the agriculture water use simulation model. Finally, chapter 8 concludes the paper and makes recommendations for future work.

Chapter 2: Literature Review

This chapter reviews literature that analyzes, both quantitatively and qualitatively, the effects of climate change. Initially, I reviewed general research on climate change and how forecasts are made and evaluated. Then the focus moves to what hydrologists and economists have done. Typically, climate forecasts are analyzed quantitatively, citing more theory than actual mathematical research, although some authors including Katz, Teisberg, and Adams attempt to quantify the value of climate forecasts to various sectors of the economy. Generally, results show a substantial increase in potential profits to different economic sectors with an improvement in climate change forecasts

Section 2.1 reviews basic climate forecast research. These papers discuss the history of climate forecasts with no special regard to any economic sector, but instead only analyze the usefulness of forecasts in general. Section 2.2 describes the Oceanic Nino Index (ONI) and the El Nino Southern Oscillations Index (ENSO). These two phenomena are a key factor in climate forecasts because they directly impact the weather situations throughout the United States. It is important to understand the research on these weather patterns in order to comprehend what techniques other researchers have used when dealing with climate change. Section 2.3 contains research for the hydrology and water supply sector. This research is focused on reservoir performance and stream flow predictions based on climate forecasts.

Section 2.4 discusses the research performed in regards to the energy sector. The authors analyze how the energy supply and demand markets could be affected based on different climate forecasts. Section 2.5 reviews research performed in regards to the agricultural sector. The majority of this research shows how farmers and water managers use climate forecasts to plan for crop planting and water orders. Section 2.6 shows what case studies have been performed regarding different aspects of climate change forecasts. These case studies vary from analyzing the usability of forecasts to determine how useful they are in practice to water managers, while others determine the effects of an incorrect forecast. Case studies allow researchers the opportunity to view actual data and test different scenarios. Finally, section 2.7 describes my contribution to the research field. Literature regarding forecast skill is also discussed in chapter 4, where we describe various methods of determining the skill of a climate forecast.

2.1 Climate Forecast Research and Background

Climate change and climate forecasting have become popular research subjects since the El Nino/La Nina developments in the mid 1990's. Many economists and hydrologists have studied different patterns and forecasting methods to best predict different possible outcomes based on these weather phenomena. Initial research focused on how climate forecasts were conducted and their usefulness in this United States. Pagano and Garen (2004b) found that although climate forecasts did produce benefits to water managers (including farmers, city planners, and energy managers), although hazards were also present. These hazards stemmed from forecasts being incorrect.

Hill and Mjelde (2002) previously analyzed much of the research done on climate forecasting, going through different phases of seasonal forecasting and evaluating the literature that has been provided. They discuss what actually makes a climate forecast valuable, citing four specific reasons:

- The decision set's structure, what the decision maker will do with the information.
- The decision environment's structure, the decision maker's technology, and resources.
- The decision makers initial beliefs about the distribution of certain inputs.
- The information systems characteristics.

All of these characteristics must be observed while the decision maker has a flexible enough operation to make optimal management decisions. The authors also discuss the different types of valuations seen in papers, including field/farm level valuations and aggregate level studies. Field level involves looking at a single farm or group of farms, while aggregate studies attempt to extrapolate the information in order to speak for a much larger population. Finally, they conclude climate forecasts are at their beginning point with a lot being known but even more left to be figured out. They stress the need for valuing climate forecasts to become an interdisciplinary effort and analyze the situation from many different angles.

Katz (2002) analyzed the uncertainty of climate change and the possible techniques in modeling it. Four types of uncertainty are addressed: measurement error, variability, model structure, and scaling/aggregation. Measurement error is simply that, errors made in basic measurements when recording. Variability deals with the unpredictability of weather including temperature and precipitation. Model structure discusses the type of model used to analyze these weather patterns whether it is linear or non-linear. Scaling error involves differences between the spatial and temporal scale.

Three techniques for applying uncertainty analysis are also discussed: sensitivity analysis, scenario analysis, and Monte Carlo simulations. A sensitivity analysis allows us to change the relative input and see the effect on a certain outcome. However, it does not address the possible uncertainty of the given input. A scenario analysis models output based on trial values for input, but it does not aid in determining uncertainty. Finally, the Monte Carlo simulations treat outputs as a distribution and a function of different input distributions. This method does not account for model uncertainty, but it does take a probabilistic approach which is helpful. After testing these different approaches on different climate models, Katz concludes the most effective method of dealing with uncertainty is the probabilistic approach of Monte Carlo simulations. However, he warns against treating uncertainty as "something to be dealt with later," and states these methods must be used while developing a model instead of afterwards.

Meza and Hansen (2008) performed a review of ex-ante assessments analyzing the economic value of seasonal climate forecasts for agriculture. They discovered past research found climate variability imposes problems on decision makers chiefly through two different mechanisms. The first is climate variability and the second is uncertainty. Basically, the climate variability forces decision makers to make choices based in the future when not a lot of information is present. Taking certain climate situations as probabilities can lead to incorrect decision making for risk-averse and risk-neutral farmers. The second problematic mechanism is the uncertainty associated with climate forecasts. This uncertainty forces decision makers to interpret certain impacts of a forecast, which can either be correct or incorrect and can lead to incorrect planning systems.

The methodology behind this study involved a lot of social science techniques including surveys and participatory research. The authors analyzed a series of papers regarding climate change and agriculture and combined all of this data to form overall conclusions about the value of forecasting. While there is no specific model used in this approach, it does take into account differing opinions of other published papers. Conclusions show useful seasonal climate forecasts have positive benefits to the agriculture sector, however, in a modest fashion to the majority of farming communities. The particularly high rain fed forest regions where climate variability is at its highest is where seasonal forecasts are of the greatest use. The authors suggest the focus should simply be on improving the forecasting systems in a couple simple ways:

- Focus the forecasting on those regions with the highest climate variability and those with high agricultural value.
- Combine the qualitative social science methods with a bio-economic modeling approach.
- Incorporate crop types more heavily in prediction, including possible crop production numbers.
- Broaden the measures of forecast value to include environmental benefits and development.

2.2 Oceanic Nino Index and El Nino Southern Oscillations Index

The Oceanic Nino Index (ONI) is a measure of the departure from normal sea surface temperature in the east-central Pacific Ocean. The Climate Prediction Center (CPC) (2010) released a paper focused mainly on the ONI. They defined the ONI as a three month running mean in the Nino 3.4 region. It is used as a measure to compare current events to historical ones and label El Nino and La Nina periods. Based on the ONI:

El Nino: Positive ONI greater than, equal to +.5 degrees Celsius.

La Nina: Negative ONI less than, equal to -.5 degrees Celsius.

In order for either event to be classified as an official El Nino/La Nina, these characteristics must hold for a period of five consecutive three month seasons. There have been 17 El Nino episodes and 13 La Nina episodes since 1949 based on this criterion. The CPC summarizes that El Nino is present across the Pacific Ocean and will be at least through 2010.

El Niño refers to the above-average sea-surface temperatures that periodically develop across the Pacific. It is sometimes referred to as a Pacific warm episode. The Southern Oscillation describes large fluctuations in air pressure between the western and eastern tropical Pacific. The Southern Oscillation Index (SOI) is designed to measure the strength and phase of these fluctuations. During El Niño episodes, the SOI has a large negative value due to lower-than-average air pressure. Combining these two measures, the ONI and SOI, we arrive at the El Nino Southern Oscillations index (ENSO). El Nino periods typically occur every five years, with the strongest periods being between

December and April. This is because sea surface temperatures are typically warmer during this time of the year (Climate Prediction Center, 2010). Scientists use the ENSO index to detect abnormal climate patterns and adjust accordingly when making climate forecasts.

Livezey (2008) tested the effects ENSO periods had on climate forecasts throughout the United States. Using one year's worth of data on precipitation and temperature forecasts on all 102 climate divisions, Livezey analyzed the change in skill scores over ten different seasonal periods based on the presence of ENSO cycles and varying lead times. He found, in terms of precipitation, ENSO is the only source of skill in climate forecasts. He also found when dealing with temperature, ENSO is a strong positive factor in forecast skill and even without the presence of ENSO skill is strong in the southwestern United States. Finally, Livezey found that skill does not vary across different lead times, with the exception of strong ENSO periods during winter seasons.

2.3 Hydrology and Water Supply Research

Pagano and Garen (2004a) analyzed western United States water supply outlooks based on climate forecasts. They compared two different forecasting techniques: the Natural Resources Conservation Service used a statistical regression to forecast, and the National Weather Service used a simulation of stream-flows program. Comparing the outlook of these two forecasts to actual water supply figures, the authors found the NRCS forecast was preferred. A more general finding was that forecasting skill has improved for the January-March time period. They also found it is feasible with our forecasting techniques to conduct pre January forecasts.

Ivanov and Vivoni (2004) conducted a study of surface and rainfall data and used it to analyze its effect on current hydrology modeling efforts. Using a triangular network hydrological model, they analyzed stream flow predictions versus actual observations and modeled land surface water data as well as energy states and fluxes. This technique enabled analysis of the potential for utilizing fully distributed models. The authors found if stream flow predictions can be more accurate, it lends more reason to use and trust the current hydrological models.

Christensen and Wood (2004) studied the effect of climate change on the hydrology of the Colorado River water basin. They compared simulated hydrological and water resources scenarios derived from downscaled climate simulations of the United States Department of Energy versus observed historical climate. The authors analyzed temperature and precipitation as potential climate variables that would affect water resources. Using a water management model with simulated stream flows and possible climate change scenarios, they found that stream flows associated with control and future climate would significantly degrade the performance of the water resource system. Finally, the authors concluded the high sensitivity of the reservoir system performance was a reflection of the system that requires slightly less than the long term inflow prediction.

2.4 Energy Sector

Research has been performed analyzing climate forecasts and how they play a role in the energy sector. Weiss was one of the first to analyze the effects climate could have on the energy sector (Weiss, 1982). He found temperature and precipitation had a resounding effect on natural gas and residential electric markets. The focus was on the process in which decision makers go through when using climate information. The problem Weiss found was seasonal forecasts had a very limited use in managing energy supply, only because decisions were based very short term (hours to day forecast, not monthly.) However, this research was performed in 1982 when forecasts were still very basic. Weiss concluded forecasts can encourage energy efficiency, help consumers plan for energy emergencies, and help low income households deal with increasingly high energy bills. Some years later, Teisberg and Weiher (2005) followed up on Weiss's research by analyzing the possible savings accurate climate forecasts can have on electricity generators. They looked at two years of energy information and compared the savings to energy generators between a persistent, perfect, and estimated forecast. The estimated forecast was the least useful while the persistent forecast was better. Obviously, the perfect forecast was the best, and it was estimated a perfect 24 hour forecast could save producers approximately $166 million per year in lost energy demand. A perfect forecast is of course un-attainable, but it shows the potential value of more accurate forecasts to the energy sectors.

Tanimoto (2008) continued research in the energy sector, focusing on the Southwest United States. He attempted to create models that would forecast short and medium term electricity load and analyze the factors (specifically climate) that affected demand. Tanimoto found temperature to be a very significant determinant of energy demand in both the short and medium time frames. He also suggests that future research should focus more on climate forecasts, due to the previous nature of the National Weather Service forecasts and their shortcoming. The most notable of these problems being that forecasts were not given enough in advance for them to be particularly useful to energy managers.

2.5 Agriculture Sector

Much like the energy sector, climate forecasts can potentially provide large benefits to the agriculture sector, therefore, much research has been conducted in this field. Adams and Bryant (1998) researched the value of climate predictions to the United States agriculture sector and found perfect climate information would be worth approximately $323 million per year. Adams compared the climatology forecast (equal chances for all forecast categories) to a perfect forecast. Adams found a perfect forecast would allow agriculture users to make perfect decisions and maximize profits.

Jones and Hansen (2000) analyzed the potential benefits of climate forecasting with respect to the agriculture sector. They focused on the Southeastern United States, mainly Georgia, during his study. Using historic weather data including temperature and precipitation, they calculated the benefits of knowing the exact temperature and amount of precipitation in terms of decision making. The conclusions were that perfect knowledge leads to a sizeable increase on overall potential profits. The largest problem the authors found dealt with the uncertainty of temperature and precipitation values, which cause incorrect decisions based on forecasts.

Mjelde and Fuller (2000) compared the value of Southern Oscillation Index-based climate forecast methods for Canadian and United States wheat producers. They analyzed thirteen different producers throughout Canada and the United States. The study compared two different forecast methods: a three phase and a five phase method. The three phase method was the ENSO prediction consisting of below, neutral, and above predictions. The five phase method consisted of consistently negative, consistently positive, rapidly falling, rapidly rising, and consistently zero predictions. The authors also used a perfect forecast as the control for the experiment. The economic decision model was based off of the best of the three, five, and perfect forecast methods. They found five of the thirteen producers preferred the three phase method, seven of the thirteen preferred the five phase method, and one producer preferred no forecast at all. When calculating the economic benefits of each of the methods, the authors found, in terms of the seven producers who prefer it, the five phase method approach is approximately seventy times more valuable than the three phase approach. On the other hand, according to the five producers who prefer it, the three phase approach is approximately twice as valuable as the five phase method. With these results, they conclude a single forecast will not suffice for all producers and different forecasts will need to be calculated depending on different regions.

Hansen (2002) laid the groundwork for how climate forecast can be used by the agricultural sector. He set out a list of conditions that must be followed for climate information to be used. Some of these conditions included having accurate climate information, decision makers must utilize forecasts, proper institutions must be established, and finally, communication between researchers and decision makers must be established. With these conditions being satisfied, Hansen found only then would managers be able to maximize the use of climate forecasts.

Katz and Letson (2009) analyzed the value of ENSO information to typical farmers. Using analysis that compares the expected value of a decision made with accurate climate prediction with that of a decision made with no climate information. The area they focused on is a region near Pergamino, Argentina. The authors use expected utility and prospect theory to decide what would be the "optimal" choice for farmers. Empirically, they use crop simulation models to show what amounts of crops are going to be used in the study. A stochastic whole-farm crop and management choice model was used to capture the role of climate forecasts and estimate their value.

Katz and Letson also attempt to analyze different assumptions about different types of farm operations. For example, they look at land tenure (ownership versus short-term leases). They concludes that the two situations analyzed, land tenure versus objective functions (expected utility or prospect theory), and are inversely related. Depending on the risk preference of the farmer, he can use the information "offensively" and attempt to profit more from the climate predictions. Another possibility is he can act "defensively" and attempt to minimize possible losses. Using all of this information, the authors estimate roughly the improved ENSO information would increase a farmers net worth by twenty-five to thirty percent. However that is all the quantitative information he gives. In terms of discussion the authors point out that land tenure type must be taken into account, as well as risk preferences, goals of the farmer, and crop types. Finally, they close with the thought that improved ENSO will be a benefit to agriculture, but only if the decision maker can incorporate all of these things into his analysis and make an "optimal" decision.

2.6 Case Studies

Case studies are a popular method of analyzing climate forecasts. It gives the researchers the opportunity to look at actual data and test different scenarios. Hammer and Holzworth (1996) conducted a study in Australia in a region with very high climate variability. The problems the region faced included choice of planting time, varietal development pattern, and fertilizer strategy. The authors found the solution to all of these problems was a proper seasonal forecast. Using what they called a forecast with 'moderate' skill (no definition is given), forecasting is sufficient to justify use in tactical management of crops. The authors do suggest that future research work should focus on analyzing sensitivity to location, antecedent conditions, and price structure.

Hamlet and Lettenmaier (2000) focused on the Pacific Northwest and mainly analyzed the Columbia River Basin. Using six different forecast scenarios, climate forecasts were obtained and used in modeling of Pacific Northwest possible stream-flows. Two possible methods of forecasting are looked at: the first being the simple meteorological method analyzing past observed climate data and then comparing it to a similar situation in present day. The other involves using regional nested data to develop a more sophisticated model dependent on the specific area being analyzed. The authors show the ability to forecast winter ENSO in one of the three categories previously described (above, neutral, and below) is feasible with a lead time of roughly six months. Using these six month forecasts, accurate summer stream-flow forecasts can be achieved as well. They conclude that with current technology, short term climate prediction should be dealt with using the meteorological model while long term issues can currently be analyzed with the nested model. Currently, the global climate models being used are adequate for regional use, however, for how long is uncertain. As each region continues to change more severely with climate change, these global models become inadequate.

Hamlet and Huppert (2002) performed a case study analyzing the Columbia River and the economic value of long lead forecasts in terms of hydropower. They took six month lead forecasts and used them to predict energy release cycles and demands. In order to predict stream flow amounts, a reservoir simulation model was used. The authors found a high stream flow led to spot market energy sales as well as increases in non-firm energy production. They conclude the use of long-lead forecasts resulted in an increase in hydropower revenue.

Ni and Cavazos (2002) studied the history of seasonal precipitation over the last century in Arizona and New Mexico. Using a thousand year reconstruction of precipitation cycles, they constructed linear regression models to ‘predict,’ or analyze, precipitation patterns. The authors found the model performed better in dryer years, although without knowing what explanatory variables went into the model, it is hard to say how accurate the parameters are, especially with just a linear model. Finally, they also found dryer years had a larger impact on forecast error than the wetter years.

Pagano and Hartmann (2001b) looked at the Arizona water supply during the 1997-98 El Nino season. They interviewed different agencies about their experiences and usage with climate forecast. The authors found seasonal precipitation and temperature is being under-utilized. Pagano and Hartmann concluded there is a need for a stronger relationship between forecasters and water managers, most likely in the form of monthly or yearly forums between these groups. They also note an implementation of policies that allow a certain amount of flexibility when using forecasts would immediately encourage water managers to pay more attention to forecasts.

Pagano and Hartmann (2002) continued their previous research (2001) interviewing agencies and studying the El Nino episode of 1997-98. They found the agencies used the climate forecasts as ‘warnings’ of extreme events instead of a modeling tool. Some agencies claimed to be insensitive to climate variability citing a lack of short term flexibility or possible legal barriers. The authors conclude in order for climate information to be useful to actual users of the forecasts, accuracy was a key factor. The more accurate the forecasts, the more reliable and useful they are to decision makers. Yao and Georgakakos (2001) performed a case study on Folsom Lake. Their study analyzed the response of the area to historic climate variability. By testing the sensitivity of the reservoir to different forecast schemes, they conclude more reliable inflow forecasts immensely benefit reservoir performance.

The misinterpretation of forecasts is also a key component not quantitatively analyzed. Hulme (2009) performed a case study in Victoria, Australia, in which decision makers used a climate forecast to develop a water model for the next fifteen years. In this example, the climate changed dramatically and the state was left in a critical condition. Hulme suggests climate forecasts be used to predict what cannot happen, or at the very most, predict what is the worst that can happen. Instead of using forecasts to model probable events, use them to look at improbable events.

2.7 Contribution

In the research conducted to date, no one has made a direct link between forecast skill and the economic aspects of potential improvements in water management that forecasts may facilitate. This linkage between forecast skill and water-related economic benefits is addressed here. This thesis presents a direct link between the skill level of a forecast and the corresponding economic value of forecast skill in water management decisions. The thesis uses econometric techniques to model skill of forecasts based on lead times, as well as a model that simulates water demand for the lower Colorado River, to identify and analyze economic values related to forecast skill.

3. Lower Colorado River Agriculture Water Use Model

A model used in this paper is our Colorado River agriculture water consumptive use model. For the remained of the thesis, we will refer to this model as the agriculture water use model. This model was developed to predict the amount of water a specific irrigation district will consume in any given month based on a variety of climate and planting factors.

3.1 Background and Data

The Colorado River is a major source of water to the southwestern part of the United States providing irrigation and drinking water for California, Nevada, and Arizona. A number of dams have been built to divert water from the river to cities and irrigation districts. Irrigation districts order monthly water diversions from these dams. Over 100 Irrigation Districts use water taken from the Colorado River and these farms fall into different irrigation districts. Many times a farm will order too much water, and the leftover water must be re-diverted back to the river much further downstream. Similarly, farms often time underestimate the amount of water needed in a given month, and therefore, order too little water. This leads to a fall in crop production and an eventual loss in profit to the farm. The Bureau of Reclamation (BOR) reports the amount of water diversions ordered by a certain irrigation district. Using this value, the BOR then calculates how much of the water was used by other sources, as well as how much water was returned downstream. The difference between overall water diversions and the amount used by other sources and also what was returned downstream is the consumptive use by an irrigation district. An example of this accounting method is presented in Appendix A. Our model shows the amount of water consumed by an irrigation district as a function of acres planted, crop shares, precipitation, and temperature. Fourteen irrigation districts were used in the composition of this model. The fourteen chosen were based on their proximity to the river and the amount of water used from the river. They were also chosen in accordance with their history of accurately reporting crop data. Each of the districts has data going back to at least 1995, and not simply total acreage, but data on which type of crop is being planted. Of these fourteen districts, eleven are located in Arizona while three are California based. While some of them span both states, these are categorized based on which state the majority of their crops are grown. A list of the irrigation districts can be found in Table 3.1.

The variables used in this model represent the basic factors that affect how much water is used monthly by irrigation districts. The key dependent variable analyzed is amount of monthly water consumptive use, as reported by the Bureau of Reclamation; the amount of water consumed by districts each month. This acts as our dependent variable in the model. The unit of measure of water consumption is acre-feet per month, and an acre-foot is equivalent to 326,000 gallons of water. The amount of acre-feet used varies widely in regards to the size of the district. The largest district being Imperial Irrigation District with 377,934 acre-feet in July of 1998 and the smallest being Cocopah Irrigation District with18 acre-feet in April of 1996. The explanatory variables were chosen based on factors which are hypothesized to affect agricultural water consumption. The largest factor is clearly the number of acres planted by the district. It is expected that the larger the area of production the more water consumed. The data on total acreage planted came in two forms. Some districts reported only monthly totals of acreage while others only reported their yearly totals. In the case of monthly totals given, those were summed throughout the year and then inputted directly into the data set. The yearly totals were used without modification. There is a wide range of total acres planted across the districts. One of the variables used in this study is the share of different crop groups; cotton, grains, corn, forage, tree, fruits/vegetables (Fruit and vegetable are grouped together), and ‘other’. The share of a certain crop group can be zero representing a district that planted none of the specified crops. These values were inputted into the data set in the same manner as total acreage with equal weight given to each month to represent a total amount per year. All of this data: water consumption, total acreage, and crop shares, were taken from the Bureau of Reclamation annual reports on the lower Colorado River (Lower Colorado River Water Accounting, 2010).

To account for the change in time when comparing monthly water consumptive use to yearly acreage planted, monthly dummy variables were employed. Since different crop types are planted at different times throughout the year, these monthly variables can help to identify which crops are in the ground when different amounts of water are being used. These monthly variables, in conjunction with the different shares of crops, can enable us to see which crop groups are the most water dependent and can be accounted for when calculating total water consumptive use. The water price data was provided by the Imperial Irrigation District news archives. Of all the fourteen districts in this study, only Imperial Irrigation District charges a significant marginal cost per acre-foot of water used. The logarithm of price is taken so a percent change can be analyzed as marginal cost is changing. The marginal cost charged for Imperial Irrigation District is shown in the chart below.

Table 3.2 Marginal Cost of Water

Year	**Ln(Marginal Cost)**
1995	$2.76
1996	$2.56
1997	$2.58
1998	$2.64
1999	$2.66
2000	$2.68
2001	$2.68
2002	$2.70
2003	$2.71

The other thirteen districts charge a marginal cost per irrigated acre, but only if the farm reaches a certain level of consumption. However, growers in these districts do not exceed this cap. Imperial Irrigation District growers do exceed the cap in their district on a monthly basis. The consumption cap per acre is set by a board of directors comprised of members from each irrigation district. Since Imperial Irrigation District growers do pay a per unit marginal cost for water, that cost has been included in this model.

The other explanatory variables used were climate variables: temperature, precipitation, and price. Temperature and precipitation are used to capture the effect variations in current regional climate change potentially have on the amount of water being consumed. These values were taken from the Arizona Meteorological Network (AzMet) and the California Irrigation Management Information System (Cimis). Both of these sources use weather stations placed in different locations throughout the state to monitor different weather variables. AzMet provided weather data for eleven of the irrigation districts, all based in Arizona, while CIMIS provided data for the three

California Irrigation districts. The temperature and precipitation data were recorded daily. The monthly average of temperature was employed in the model, as is the total amount of precipitation in a month.

In order to better understand some of the parameters, certain transformations were applied to the data. Since the size of the districts varies so much from Imperial Irrigation District (500,000 acres/year) to the Cocopah Irrigation District (1300 acres/year), percentage changes are more applicable than net changes. A 1000 acre change means much less to Imperial than it does to Cocopah, but a 10% change in acres is significant throughout all the districts. Therefore, to enable us to look at the percentage changes, we apply a logarithmic transformation to certain variables such as water consumptive use, total acreage, temperature, and price. This transformation allows us to analyze a percentage change in acreage planted, temperature, or price and see the overall percentage change in water consumption. The temperature value was lagged two months in the model developed. In order to analyze the effect of temperature, the previous monthly temperatures are expected to affect water consumption more heavily than the current monthly average temperature. This is because of the need to schedule water deliveries in advance. The lagged temperature variable may also capture cumulative changes in soil temperature and moisture that will affect crop water needs. The model also includes an interaction variable between the lagged temperature and precipitation, which was formed to incorporate the effect on water diversions of extreme climate scenarios. The other variables were not transformed because many had zero values so taking the log would be undefined. Hence, we can only analyze a net change in these explanatory variables and see the corresponding percentage change in water diversions. These variables include all of the monthly dummy variables. The share of certain crop types were not transformed either because some shares are zero when a grower does not plant a certain type of crop. Finally, the precipitation value was not transformed because it is commonly a zero value for certain Irrigation Districts. The summary statistics for our dataset can be found in table 3.3, while a list of the variables, definitions, and expected signs can be found in table 3.4.

3.2 Data Testing

In order to detect specific econometric characteristics in the data, certain tests must be performed. The dataset takes the form of panel data, which refers to a dataset that contains both time series and cross section elements. In our case, there is a time series element within each cross section unit. The cross sectional units are the fourteen irrigation districts. Each irrigation district also has a time series element, which are the separate months that data is collected. Since the dataset is constructed in the form of panel data, there are three possible sources of misspecification. These are contemporaneous correlation, autocorrelation, and heteroscedasticity, all of which must be accounted for.

Our first test performed will be for contemporaneous correlation. This specification tests whether the errors between separate panels (irrigation districts) are correlated with one another. Our hypothesis will be that the errors are correlated. We will use a Breusch-Pagan Lagrange multiplier test statistic that is distributed as a Chi-squared.

The second test performed was a test for autocorrelation to account for the possibility of there being a time correlation between different monthly or yearly periods. A Durbin Watson statistic was generated. Our hypothesis is that there is no autocorrelation present. The last test performed was for heteroscedasticity. In the case of cross sectional data, it is possible that the variances of the estimates may not be constant. In order to run ordinary least squares, constant variance is assumed. If the variance is not constant, this leads to an estimator which is still unbiased and consistent; however the standard errors are incorrect. This can lead to a misinterpretation of the significance of parameter estimates. In order to test for heteroscedasticity, we will use a Lagrange multiplier test that is distributed as a Chi-squared. Our hypothesis will be that the data is homoscedastic (heteroscedasticity is not present). The distributions and test statistics for these specification tests were taken from Greene (2008).

In order to test for all three possible sources of misspecification, the statistical software program ‘SHAZAM’ was used. This program enables us to test for all three errors at the same time, eliminating any source of bias when determining testing order. The program uses the tests we have listed above. The table below shows the results and corresponding test statistics calculated by SHAZAM for each of the tests described above.

Table 3.5 Test Statistics

Potential Problem	**Test**	**Degrees of Freedom**	**Test Stat**	**Correction Needed?**
Contemporaneous Correlation	Breusch-Pagan	91	X^2 =880	Yes
Autocorrelation	Durbin Watson	1,512 X 23	DW =2.082	Yes
Heteroscedasticity	Lagrange Multiplier	13	X^2= 1402.5	Yes

To summarize the findings of the three tests, all three sources of misspecification are present in the data and must be accounted for.

3.3 Model

Since we found misspecification errors in our dataset they must be corrected for. In order to correct for these errors the 'SHAZAM' statistical package was used. This package enables us to automatically correct for the potential econometric errors associated with the data. Using an OLS procedure that has accounted for contemporaneous correlation, autocorrelation, and heteroscedasticity, we arrive at our augmented model. The parameter estimates and standard errors are shown in Table 3.5. The R-squared value for the model is a very good, 0.9312, implying the explanatory variables are rather accurately predicting water consumptive use. As the table shows, all of the variables proved to be significant factors in determining water consumptive use with the exception of the share of forage, share of cotton, and the share of 'other'. The lack of significance with the crop groupings forage, cotton, and "other" are not problematic either since these crop groups are not relatively large water users.

We also tested another model in which none of the independent variables were transformed. Our goal with this model was to determine what improvement in our original model was due to the presence of logarithmic transformations. This model removed transformations from the dependent variable; water consumptive use, as well as our previously transformed independent variables which included temperature, price, and acres planted. We found this model to have an R-squared of 0.801. This implies that the logarithmic transformations do enhance our model, although both models still perform quite well. The ability to compare our model to other models also required us to perform a regression analysis using the same dependent variable in both models. Since the Bureau of Reclamation has developed its own method of analyzing the amount of water consumptive use for each irrigation district, we needed a model that did not transform water diversions so we had the ability to compare across the two models of agricultural water use.

3.3 Evapotranspiration Model

The Bureau of Reclamation (BOR) has developed its own method of determining water usage by various Irrigation Districts. The BOR calculates evapotranspiration (ET) as a measure of water used each month. Evapotranspiration is defined as water lost from both transpiration from plant leaves and evaporation from soil and wet leaves also known as crop water use or consumptive use. ET calculations are not forecasts, but are an accounting method the Bureau of Reclamation Uses to estimate water use by crop in the lower Colorado River Basin. The crop ET can be estimated by calculating the reference

ET for a particular reference crop from weather data and multiplying by a crop coefficient. The reference ET is calculated using an equation developed by the American Society of Civil Engineers (ASCE). This equation varies from crop to crop, however, the general equation takes into account crop type, soil properties, temperature, and precipitation values (Bureau of Reclamation, 2010). Using the reference ET values along with crop data, the crop ET is calculated. Finally, using the different crop ETs along with knowledge of planting decisions, a monthly ET is calculated by the Bureau of Reclamation for each Irrigation District. This monthly ET is representative of how much water an Irrigation District is thought to use each month for agriculture use.

The BOR's method of calculating monthly ET values attempts to model the same dependent variable, water consumptive use, as our agriculture water use model. Therefore, a comparison is needed to ensure our agriculture water use model performs at least as well as the ET model if not better. In order to do this, ET values were gathered from the BOR for ten of the fourteen irrigation districts analyzed in our Colorado River model. (Data on four of the irrigation districts were not available for all of the years, and therefore, were omitted from the study). An ordinary least squares regression was run with the natural log of water consumptive use as the dependent variable and the natural log of monthly ET values as the independent variable. The natural log was used so we were able to compare the BOR model and our agriculture water use model. The R-squared value for this regression was 0.923. In order to further investigate the connection between water consumptive use and ET other regressions were ran using variations of the original model. The next model we ran also included dummy variable for the Irrigation

Districts to determine if the model was more accurate when dealing with certain districts. This model had the form of Log of water diversions as a function of Log of ET and dummy variables for the irrigation districts with an intercept included. The R^2 of this model was .927. The final model run removed the logarithmic transformations from both water consumptive use and ET but maintained the dummy variables for each of the irrigation districts. This model had an R^2 of .956.A comparison can only be made between models in which the dependent variable is in the same form. In our analysis two comparisons can be made, the first in which there is a logarithmic transformation is applied (models 1 and 2 below). The second comparison is between models 3 and 4, in which the water consumptive use variable is not transformed.

Table 3.6 Comparison of Water Consumptive Models

Model	**N**	**R^2 Value**
Agriculture water use model	1,080	0.931
Log(Diversions) = Log(ET) + Irrigation District Dummy Variables	1,080	0.927
Agriculture water use model without logarithmic transformations	1,080	0.801
Diversions = ET + Irrigation District Dummy Variables	1,080	0.956

Comparing these results with our Agriculture water use model we find our model performs slightly better in predicting water diversions than the ET models with a logarithmic transformation. However, our model performs slightly worse than the model where no logarithmic transformation was applied to ET or water diversions. These R-squared values may be slightly skewed because the Agriculture water use model contains more observations than the BOR ET model. However, at the worst, our model performs comparable to the BOR model and can be used with confidence.

3.4 Model Implications

This model yields a critical tool for later simulating a water manager's decision based on climate forecasts (see Chapter 7). By substituting forecasted values for precipitation and temperature into this water consumptive use model, we use the model presented here to calculate the amount of water most likely used by irrigation districts. Using this information enables us to decide what course of action will be taken by city water managers when deciding on diversion amounts. This model will be used later in the thesis to simulate decision by city managers and determine the economic effects of both high and low skilled forecasts.

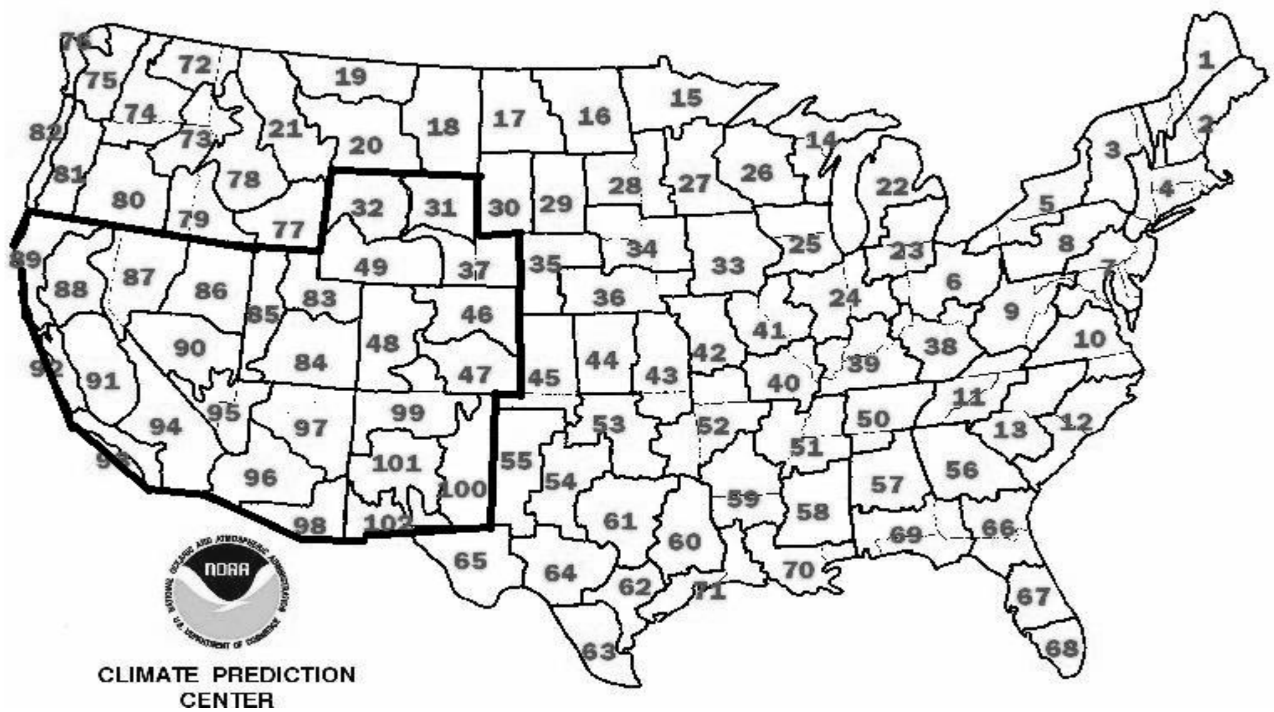
4. Climate Forecast Data

Climate forecasting is thought to have extraordinary benefits to the agriculture sector, a sector that is vulnerable to changes in temperature and precipitation. If future climate can be predicted with relatively good accuracy, the agriculture sector can see the benefits in the form of correct planting decisions and water orders. Forecasting contains many different elements. The elements we are interested in are the forecasting of seasonal temperature and precipitation as it relates to various climate divisions.

4.1 Climate Forecasts

The United States has been separated into 102 climate mega divisions. These divisions are based on groups of weather stations varying in a similar manner from year to year and are thought to reflect similar regional climate processes. Using data from the Climate Prediction Center, we have data on 102 separate climate divisions over twelve years. Our study focuses on the Western United States and the effect climate forecasts will have on this geographical sector. A list of the twenty-seven climate divisions analyzed can be found in Table 4.1. A map showing the different climate divisions is shown below (the area outlined in black show the climate divisions included.)

Figure 4.1 Climate Divisions Map



*Map is from Climate Prediction Center, *www. cpc.noaa.gov*

Each separate data point is given with respect to one climate forecast. Each forecast is made predicting either temperature or precipitation and is made with differing lead times. The lead time describes the difference between when a forecast is issued and when it is issued for. For example, if a forecast is made in April 2003, and it is for May 2003, then it would be a one month lead time. If a forecast is made in April 2003, and it is for May 2004, then it would have a 13 month lead time. The forecasts being analyzed have different lead times ranging from 1 to 13 months. The final descriptive variables included in our dataset are seasons. In terms of climate variability, seasons are described as a three month block. Blocks begin with January-February-March as the first season and end with

December-January-February as the twelfth season. Seasons are used instead of months to represent the longer time perspectives inherit in climate forecasts. Forecasts have historically been aimed at seasons instead of months because the variability month to month is much higher than from season to season. Therefore, we follow the nature of past climatology research and continue to use seasons in our analysis.

4.2 Skill Scores

Skill scores are a method researchers have developed to test the accuracy of different types of forecasts. There are a multitude of different skill scores (Pagano, 2001a). These skill scores are imperfect as there are infinite ways to classify forecast skill. However, the skill scores have become accepted as a national measure of the accuracy of climate forecasts. They are used by the Climate Prediction Center, as well as many Universities dedicated to researching climate change. The method forecasts are used by decision makers differ from case to case and not all forecasts are the same, therefore, different forms of skill scores are needed. Some scores measure how well a forecast captures the event (surprise rate, and false alarm rate are prime examples). Frank Woodcock (1976) was one of the first to layout an evaluation method for forecasts. He analyzed only yes/no forecasts and provided groundwork for evaluation methods that the surprise and false alarm rates we are using stem from. Other forecasts attempt a probabilistic method of how likely an event is and to what degree (i.e. likelihood it will rain and how much). The Brier and Ranked Probability skill scores judge these types of forecasts performance. The Brier score was developed by Brier (1950) while the Ranked

Probability score was suggested by Epstein (1969). These skill scores were not developed by Tom Pagano. However, he was a major contributor towards describing and evaluating them. These scores have been used by climatologist in recent years to evaluate the accuracy of climate forecasts.

The forecasts we are analyzing use a probabilistic method and forecast for one of three categories: Above, normal, or below. A percent weight is given to each of the categories based upon which is most likely to occur. For example, if it is most likely to rain more next month but highly unlikely it will rain less; the forecast would be presented in the following fashion: .15 chance of below, .35 chance of normal, and .5 chance of above. The forecasts probabilities will always sum to one. The table below shows an example of how the CPC seasonal forecasts are provided on their website.

Table 4.2 Climate Forecast Example

Climate Division	Target Year	Climate Variable	Forecast Category	Lower Boundary	Upper Boundary	% prob Lower	% prob Normal	% prob Above
94	1999	1	3	79.9	85.5	.25	.35	.40
95	2002	1	2	78.5	83.1	.333	.334	.333
97	2001	2	1	.05	1.02	.398	.342	.26
98	2000	2	0	0	0.89	.333	.333	.334

This table shows the format in which forecasts are provided by the CPC. The climate variable refers to either precipitation or temperature, in which temperature is coded with a 1 and precipitation with a 2. The forecast category represents the type of forecast being given. A zero represents equal chances, in which there is no skill involved.

One represents a higher probability that the outcome will below, two estimates the outcome will be normal, and three expects an outcome of above. The lower and upper boundaries represent the range in which the possible forecast values can fall. If a forecast is expected to be ‘below’, then it is expected to fall beneath the lower boundary. If a forecast is estimated to be ‘above’ then the observation value is thought to be above the upper boundary. Finally, a forecast with a ‘normal’ expectancy is expected to fall in between the upper and lower boundary. The probability percent represents how likely the forecast is. These forecasts are given as probabilities, and are not expected to be taken as exact. Obviously a higher probability of an outcome represents a higher likelihood of that event occurring. Understanding that, the skill scores we are using associated with these forecasts are as follows:

Brier: The mean squared error of the probability forecasts. It sums up the probability of the forecast less the observed outcome. Basically, if there is a .6 chance of above and above occurs, the Brier Score would be;

BS = (0.6-1) ^2 = 0.16.

Ranked Probability: This score is similar to the Brier score except it takes into account all of the probabilities of each category. For example, if there is a forecast of .2 below, .23 normal, and .57 for above, and above is observed, the Ranked Probability Score would be;

RPS = (.2-0) ^2 + (.43 -0) ^2 + (1-1) ^2= 0.1

Typically, these skill scores by themselves do not mean much, so researchers will usually compare them to a baseline climatology skill and convert them into skill scores. The climatology skill is given as an equal chances prediction in which all three categories: above, normal, and below have the same likelihood (.3333) chance of occurring. The skill score is then calculated by dividing the probabilistic forecast derived above by the climatology forecast and subtracting it from 1. For example, looking at the RPS above, the climatology score would be:

RPSC = (.33-0) ^2 + (.66-0) ^2 + (1-1) ^2= 0.55.

Then in order to calculate the skill score we have 1- 0.1/0.55 = 0.818, a perfect skill score will be equal to 1.

The second group of skill scores is usually applied to a specific group of forecasts (in our case one skill score applies to one season). When evaluating these, the score depends on the observed outcome and whether it is classified as ‘above’, ‘normal’, or ‘below’. Therefore, there will be three skill scores associated with each category (surprise rate, false alarm rate.) One represents the observed ‘above’ outcomes, then the observed ‘normal’, and finally the observed ‘below’. The equations for these descriptive skill scores are as follows:

Surprise rate: One - probability of detection. How often was an event not forecasted?

False alarm: Of all the times an event was forecasted to either occur or not occur. How often did the opposite happen?

As stated previously, all of these score equation and descriptions, brier, ranked probability, surprise rate, and false alarm rate, were taken from Pagano (2001). These scores were not invented, but described and analyzed by Pagano.

In order to calculate these skill scores we must first describe how to tell if they are ‘correct’ or not. The forecasts are given in a probabilistic fashion with probabilities assigned to each of three categories. These categories are also related to an upper and lower boundary on observation values. If the true observation value falls below the lower boundary then the observed outcome is classified as ‘below’. If the true observation falls above the lower boundary and below the upper boundary then the observed is classified as ‘normal’. Finally, if the true observation value is higher than the upper boundary the observed is classified as ‘above’. These lower and upper boundary values are determined by the CPC based on a fixed thirty year mean of historical data. These values are updated once every ten years and a new thirty year mean is calculated (Hartmann, 2010).

Due to the nature of the Ranked Probability and Brier Skill scores each separate forecast can be given a skill score. With a specific climate division, lead time, and observation (temperature or precipitation value) a corresponding skill score can be assigned. Therefore, for each seasonal data set in which we have 4,212 forecasts we also have 4,212 skill scores. However, when analyzing the surprise and false alarm rates the same characteristics do not hold true. These skill scores describe how often an event is captured and not how accurate a forecast is. Therefore, when dealing with these scores, we must analyze them over a period of time and look at the sums of correct forecasts versus incorrect ones. Our decided method is to analyze the scores on a season to season basis. We calculate the surprise and false alarm rates over the course of a season and compare which season's forecasts perform the best.

All of the skill scores were coded and calculated in SAS using equations taken from Pagano. To ensure accuracy, these calculated skill scores were randomly checked against the Forecast Evaluation Tool, which is a website provided by NASA, NOAA, CLIMAS, as well as other parties, that analyzes climate forecast skill. This website uses climate data to calculate various skill scores and report them in a similar fashion as we do to. Therefore, to ensure our forecast skill score coding was correct, comparisons were made between the two methods.

4.3 Data Cleaning

Our original database contained information for twelve years over all 102 climate divisions in the United States. However, our research focused on the agriculture sector and how climate variability would affect decision makers mainly in the Western United States. With this in mind, there is a need to manipulate the dataset to be more representative of our area of interest. The first change needed is to condense the climate divisions being analyzed to only represent those located in the Western United States. Therefore, only twenty-seven climate divisions are included in our study. Also, since seasonality is a large factor affecting climate forecasts, we need to look at the data as it is separated by seasons. Therefore, I have separated the dataset into twelve different subsets with each one representing a separate season. With all of this cleaning, each dataset (representing a single season and single climate variable, and either temperature or precipitation) contains approximately 4,212 observations. Each of these observations represents a separate lead time and issue month with respect to a certain climate forecast.

4.4 Summary Statistics

These summary statistics show the background of the entire data set constructed. Table 4.2 table shows the descriptive statistics in regards to temperature while the table 4.3 describes the precipitation data set. These statistics are representative of all twelve seasons for each climate variable. Lead time describes the monthly difference between when a forecast is issued and its intended season. ONI is an index developed to describe sea surface temperature in the Pacific and is an indicator of the El Nino and La Nina phenomenon. Lower and upper boundaries indicate the approximate bounds that the temperature or precipitation values can be. If a forecast is given as above, then it is assumed to be above the ‘upper boundary’. These statistics are shown to describe how low and high forecasts are typically given. The observation value is the actual temperature or precipitation value observed during the season. Finally the ranked probability and brier score are different measures of forecast accuracy. Both range from negative infinity to one, with zero representing no skill and 1 representing perfect skill.

Table 4.3 Precipitation Summary Statistics:

Variable Name	*N	Minimum	Mean	Maximum
Lead Time	50,544	1	7	13
ONI	50,544	-1.6	0.07	2.5
Lower Boundary (Inches)	50,544	0.09	2.97	17.57
Upper Boundary (Inches)	50,544	0.25	4.33	24.6
Observation Value (Inches)	50,544	0	3.73	39.23
Ranked Probability Score	50,544	-1.514	-0.01	0.94
Brier Score	50,544	-1.106	-0.0003	0.93

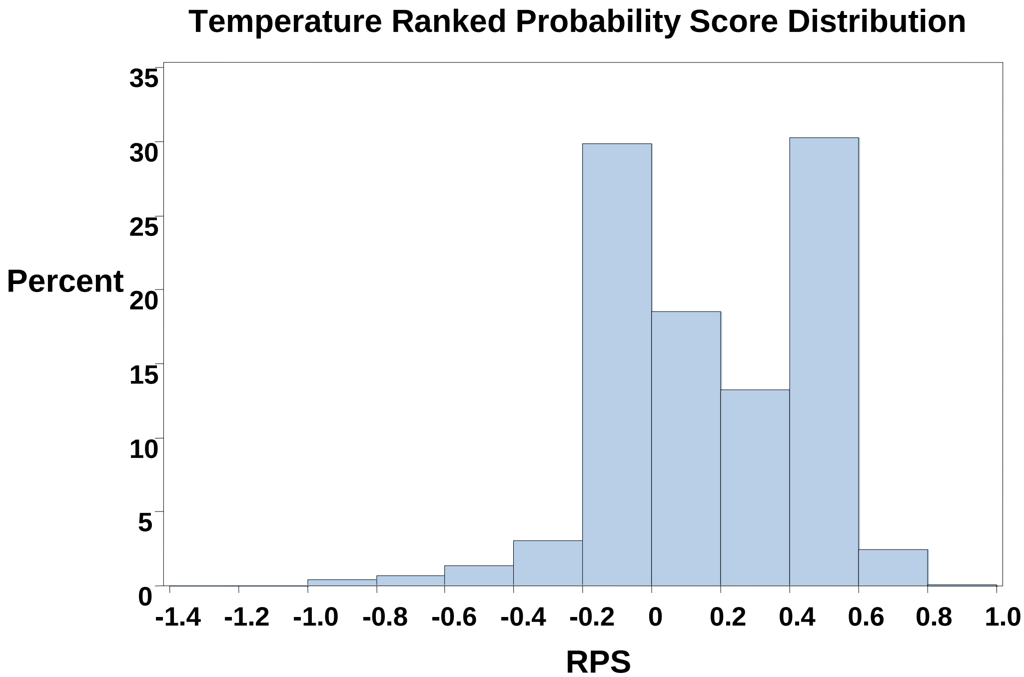
- *50,544 is represented by each of the 12 seasons containing 4,212 observations

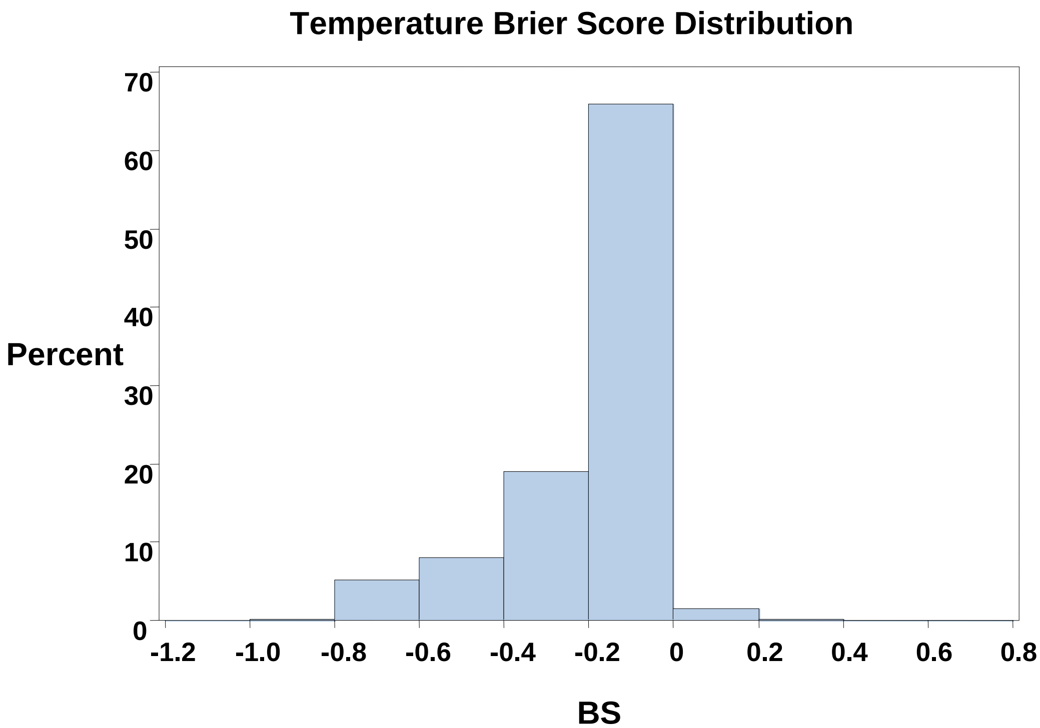
Table 4.4 Temperature Summary Statistics:

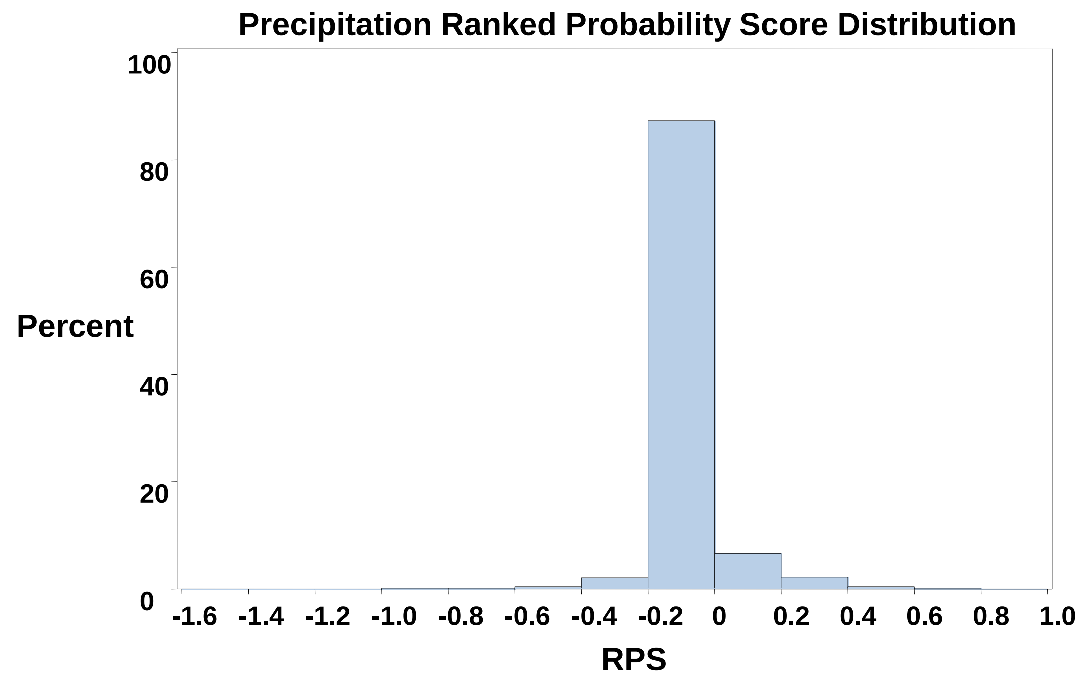
Variable Name	*N	Minimum	Mean	Maximum
Lead Time	50,544	1	7	13
ONI	50,544	-1.6	0.07	2.5
Lower Boundary (Fahrenheit)	50,544	17.7	51.44	84.97
Upper Boundary (Fahrenheit)	50,544	20.33	52.99	86.05
Observation Value (Fahrenheit)	50,544	15.39	53.45	88.97
Ranked Probability Score	50,544	-1.65	-0.21	0.79
Brier Score	50,544	-1.01	-0.16	0.74

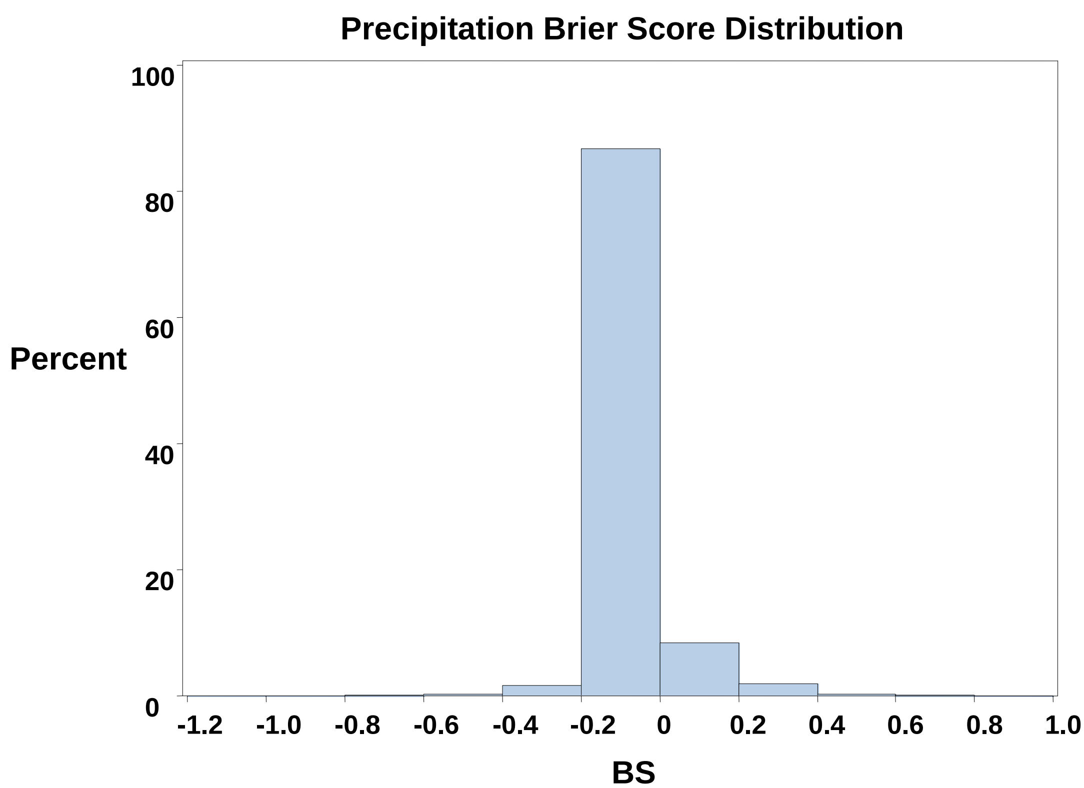
- *50,544 is represented by each of the 12 seasons containing 4,212 observations

Table 4.5 Temperature and Precipitation Histogram






Precipitation Ranked Probability Score Distribution
Percent
100
80
60
40
20
0
-1.6 -1.4 -1.2 -1.0 -0.8 -0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1.0
RPS


Precipitation Brier Score Distribution
Percent
100
80
60
40
20
0
-1.2 -1.0 -0.8 -0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1.0
BS

The histograms above can give us a general idea of the distribution of our chosen skill scores. These graphs show us that the majority of the skills are around the zero value, indicating ‘no skill’. However, the ranked probability score for temperature has a very wide distribution which tells us that there is a variety of skill associated with forecasting temperature. Some of the skill is highly positive indicating ‘high skill’ while a fair amount is negative indicating ‘low skill’. The other histograms all show us the same general distribution in which there are outliers of positive and negative skill, but the majority of the forecasts are located around ‘no skill’. A ‘no skill’ forecast can be interpreted as a forecast where an equal chances (of ‘above’, ‘normal’, and ‘below’) forecast was just as good.

5. Econometrics and Variable Description

5.1 Ranked Probability and Brier Skill Scores Model

The Ranked Probability and Brier Skill scores were first analyzed using a basic Ordinary Least Squares (OLS) model. This model showed questionable results due to the presence of numerous dummy variables, categorical variables, and count variables. The OLS model was run for all twelve seasons on both the temperature and precipitation data sets. The results were ambiguous when analyzing sign and significance of lead time and issue year. No pattern was recognized from one season to another or between temperature and precipitation forecasts. Although the OLS results are useful in determining properties of the data set, its estimates are not consistent enough to use in our simulation models since parameters are often insignificant and change sign far too often. One reason behind this phenomenon is the characteristics of the data set. Our regression models do not contain any continuous variables, for we use categorical variables. Dummy variables were included for each climate division (27). Lead time and issue year are count variables with limited range. Due to these properties, a more sophisticated model is needed.

The most popular panel regression models are the fixed and random effects models. These models correct for the possible presence of autocorrelation and heteroscedasticity. A fixed effects model was chosen, as opposed to a random effects model, based on the nature of climate divisions. A fixed effects model assumes a direct link between each of the cross sectional variables, which in this case are the climate divisions. The climate divisions we are analyzing are all based in the Western United

States and have the same base characteristics in terms of climate forecasts. A fixed effects model does recognize there are differences in each of the cross sectional units and creates a ‘dummy variable’ for each before analyzing the effects the independent variables have on the dependent variable. This method accounts for the differences between each climate division without the assumption they are not similar in any known way. A random effects model assumes the cross sectional units follow an unknown distribution. In our specific case, this is not likely as each climate division behaves similarly to one another.

5.2 Variable Description and Expected Signs

The following variable descriptions are also located in Table 5.1.

Ranked Probability Score: The Ranked Probability Skill Score (RPS) measures the improvement of the multi-category (3) probabilistic forecast relative to an equal chance forecast. It ranges from negative infinity to one where zero represents no skill and one represents perfect skill. Negative values represent ‘bad’ skill while positives represent ‘good’ skill in reference to a no skill forecast. RPS is one of the two dependent variables.

Brier Score: The Brier Skill Score (BS) measures the improvement of the dichotomous probabilistic (2) forecast relative to an equal chance forecast. It ranges from negative infinity to one where zero represents no skill and one represents perfect skill. Negative values represent ‘bad’ skill while positives represent ‘good’ skill in reference to a no skill forecast. BS is one of the two dependent variables.

Lead Time: The lead time variable depicts the amount of time between when a forecast is given and what time period the forecast represents. For example, if a forecast is given in March 2003 and is for April 2003, the lead time would be one. If a forecast is given in March 2003 and is for April 2004, the lead time would be thirteen. The range of lead times varies from one to thirteen months and only given for odd months (1, 3, 5, 7, 9, 11, and 13). We expect the lead time variable to be negatively correlated with skill score, and as lead time increases, the skill of the forecast should decrease.

Oceanic Nino Index: The Oceanic Nino Index (ONI) variable is a measure of the departure from normal sea surface temperature in the east-central Pacific Ocean. It represents the presence of extreme climate scenarios depicted as El Nino or La Nina. The range of the ONI is from -1.6 to 2.5 with large negative numbers representing La Nina periods and large positive numbers citing El Nino periods. These phenomenons are thought to have a positive effect on climate forecasts. However, as Livezey (2008) found, the effect of ONI on skill scores is expected to be larger on temperature than it is on precipitation. The ONI is a variable where sign expectation is not as clear as with other variables. Since weather phenomenon such as El Nino and La Nina behave as fluctuations observed only at the extremes of the ONI; therefore the parameter estimates will fluctuate as well.

Issue Year: The issue year variable represents the year the forecast was made. It serves as a time depiction in our regression model signifying if forecasts have improved over the last twelve years. The issue year spans twelve years and ranges from 1997 to 2008. Our expectations are this variable will be positively correlated with skill score due to anticipated increases in climatology knowledge and ability with forecasting.

6. Forecast Skill Results

Our results are presented in a way that first analyzes the usefulness of forecasts and then the factors that affect forecasts. In order to decide how useful forecasts are we will use our surprise and false alarm rates calculations. These results describe whether a forecast is correct or incorrect. The next section describes our regression results analyzing the factors that affect the Ranked Probability and Brier Skill scores. Our model analyzes and describes the effects of the ONI, lead time, and issue year. Finally we discuss the implications of location. We use our results to infer how climate divisions differ, if at all.

6.1 Surprise Rate and False Alarm Rate

The surprise and false alarm rates were calculated on a season to season basis. In the tables the seasons are represented numerically. The table below shows which Roman numeral corresponds to which season.

Table 6.1 Seasons

January-March	I
February-April	II
March-May	III
April-June	IV
May-July	V

June-August	VI
July-September	VII
August-October	VIII
September-November	IX

October-December	X
November-January	XI
December-February	XII

The climate forecasts we are analyzing, provided by the Center for Climate Prediction (CPC), are given with three separate categories and probabilities. Above, normal and below are the three forecast categories, and each one is assigned a probability between 0 and 1. These three probabilities will sum to 1, and whichever of the three categories is deemed the most likely is be given the highest probability. “Above” refers to higher temperature or amount of precipitation than historically (historically refers to a 30 year average). “Normal” is used to describe what is considered the historic norm, while “below” is defined as colder or less wet than the historic mean. In the tables on the upcoming pages, the skill scores are classified in above, normal, and below whenever the observed outcome is above, normal, and below. The corresponding skill scores are calculated after the actual observed temperature or precipitation is known and can be compared to the forecast.

Using the results for surprise and false alarm rates, we will be able to measure the skill of forecast in terms of accuracy. The surprise rate describes how often an event occurs but was not forecasted. The false alarm rate describes how often an event was forecasted to occur but did not occur. Basically, the false alarm rate tells us how often a forecast predicted an ‘event’ (above, below) was going to happen and instead something else occurred. In terms of water management, both of these scores tell us how often managers might need to change previous actions they took based on a forecast in order to adapt to incorrect forecasts. The precipitation and temperature skill scores can be seen in Tables 6.2 and 6.3 (pages 97 and 98). These tables show skill scores that are broken down based on which condition actually occurred. For instance, table 6.2 tells us that when ‘above’ occurs for precipitation in season I, the surprise rate is 0.846 and the false alarm rate is 0.561. These skill scores are calculated using all of the observations in a given season; a skill score is not available on a forecast to forecast basis.

In order to analyze these scores, we have calculated the percentage of seasons in which the surprise or false alarm rate is above 50%. In other words, how many seasons is it more common to get an incorrect forecast than it is to receive a correct one? The table below shows the percentage of seasons where the surprise or false alarm rate is above 50%.

Table 6.4 Summary of Surprise and False Alarm Rates

	Precipitation	**Temperature**
Surprise Rate Above	41.7%	100%
Surprise Rate Normal	83.3%	0%
Surprise Rate Below	83.3%	100%
False Alarm Rate Above	41.7%	83.3%
False Alarm Rate Normal	41.7%	100%
False Alarm Rate Below	91.7%	58.3%

We will discuss these results in two sections. The first section will analyze precipitation and the second will deal with temperature results. In terms of precipitation, these results show the forecasts do a relatively good job of predicting above and normal, especially when it concerns not incorrectly predicting an outcome (false alarm rate). However, forecasts do a very poor job when analyzing ‘below’ forecasts and constantly predict the incorrect outcome which could lead to water managers having to scramble for water. Again, “above” refers to an outcome in which the precipitation or temperature is higher than the historic norm. “Normal” forecasts refer to an observed outcome that is consistent with previous years, while ‘below’ observes outcomes that are dryer or colder than typically seen. When analyzing the temperature results, we find forecasts are typically incorrect throughout all seasons with the exception of predicting normal outcomes. The 0% surprise rate with a normal forecast indicates forecasts rarely tell us it will be above or below when in fact normal conditions occur. However, very often forecasts will point to normal as most probable when in fact it will not be (this is indicated by the false alarm rate = 100% in the above table). These results show us that although climate forecasts can be used effectively by water managers, they cannot be the only planning method. Since forecasts can very often be incorrect, contingency plans must be in place for when the forecasts are misleading.

Another way to look at these skill scores is to analyze which seasons the forecasts are most accurate. The table below shows overall accuracy of the forecasts per season. Accuracy is determined by analyzing all six skill scores (Surprise and False alarm rates for ‘above’, ‘normal’, and ‘below’) and calculating the percentages of the scores that are below 50%. Below 50% indicates that more than half of the forecasts are incorrect. We can conclude that overall the forecasts are not as accurate as would be desirable.

Table 6.5 Accurate Forecasts by Season

Season	I	II	III	IV	V	VI
% Accurate	8.3%	41.7%	50%	33.4%	25%	33.4%
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
% Accurate	33.4%	25%	41.7%	33.4%	25%	16.7%

These results show us the forecast season in which accuracy is highest is 'March, April, May' where the surprise and false alarm rates are typically lowest. February-March-April and September-October-November are two seasons in which forecast skill is also typically higher. This is key for water managers for two reasons: the first being that key decisions can be made using forecasts for these seasons with more confidence then with forecasts for other seasons. The second reasoning is that a lot of crop mix decisions occur around these three particular seasons (March-April-May, February-March-April, and September-October-November), and therefore it is important that temperature and precipitation forecasts are accurate during these seasons. The worst season for forecasting is January, February, and March where the surprise and false alarm rates are at their highest. The other seasons show accurate forecasts between 17% and 42% of the time. This fact speaks to climate forecasting and the need for improvements before water managers can use them on a consistent basis.

Table 6.6 Accurate Forecasts by Lead Time

Lead Time (Months)	1	3	5	7	9	11	13
% Accurate	33.4%	36.3%	24.6%	11.4%	9.8%	11.4%	7.8%

Finally, the results in Table 6.6 show the effect lead time has on the number of accurate forecasts. Past literature has shown lead times longer than a seven month lead time will typically lead to an incorrect forecast. It has also been shown that lead time is not a significant determinant of forecast skill. The results here would oppose those findings, showing there is a significant difference between a thirteen and a one month lead time. However, our results show that the majority of forecasts are incorrect, and therefore, we can conclude our results confirm that any lead time longer than seven months typically leads to an incorrect forecast. We can also conclude that while lead time may not be a significant determinant of skill score, there are differences between lead times.

6.2 Ranked Probability and Brier Skill Scores

In the econometric analysis of skill scores, two main dependent variables are the Ranked Probability and Brier skill scores. These scores analyze the accuracy of forecasts with respect to the observed outcome. Our table below shows the average scores given a particular season and climate variable. These averages allow us to analyze which seasons typically have the most forecast skill and which seasons are generally lacking. The

Ranked Probability and Brier skill scores range from negative infinity to one, where zero represents no skill and one represents perfect skill. Negative values represent 'bad' skill while positives represent 'good' skill in reference to an equal chances forecast.

Table 6.7 Seasonal Skill Scores

Ranked Probability	Season											
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
Temperature	0.188	0.251	0.222	0.242	0.171	0.215	0.252	0.254	0.244	0.168	0.195	0.164
Precipitation	-0.017	-0.024	-0.018	-0.012	-0.013	-0.022	-0.008	0.008	0.006	-0.004	-0.006	-0.007

Brier	Season											
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
Temperature	-0.099	-0.244	-0.217	-0.146	-0.140	-0.209	-0.164	-0.209	-0.223	-0.081	-0.054	-0.089
Precipitation	-0.007	-0.011	-0.005	-0.002	-0.003	-0.011	0	0.014	0.013	0.004	0.003	0.002

These tables show us the differences between temperature and precipitation skills in each season. As we can see, the temperature forecasts are relatively more accurate throughout the year when dealing with a probabilistic forecast (Ranked Probability score). However, when the forecast is given dichotomously (Brier Score), the forecast skill is typically negative. Temperature forecasts appear to be relatively more accurate during the late summer seasons, including June-July-August through September-October-

November. Precipitation forecasts, unlike temperature, never seem to do significantly well regardless of season or forecast type. Even in the later months when forecast skill is not negative, it is still close to zero indicating no skill.

The Ranked Probability and Brier skill scores were analyzed using a variety of fixed effects regression models. Twelve regressions were run for each climate variable, temperature and precipitation. Each regression represents one separate three month seasonal block. As part of the fixed effects model, the climate divisions are dummied out as the cross sectional units before the regression is run and will be analyzed using another method at the end of this chapter. The tables below show the regression results for each climate variable data set as well as each independent variable; the Ranked Probability and Brier skill scores as a function of lead time, ONI, and issue year.

Table 6.12 shows the summary statistics for our three independent variables: which are the Oceanic Nino Index, lead time, and issue year. Full regressions results for all seasons, skill scores, and climate variables can be found in tables 6.8 through 6.11. These results are presented to show how often a variable is significant as well as how often it follows the expected sign. These tables are calculated analyzing all seasons and both the Ranked Probability and Brier skill score regressions. We will discuss individual effects on particular skill scores and seasons in the next section of this chapter. Precipitation and temperature statistics have been separated to show how skill scores are affected depending on which climate variable forecasts are made for. Although independent variables may have a positive effect on skill scores for temperature, they may negatively affect a forecast on precipitation.

Table 6.12 Summary of Regression Results

Oceanic Nino Index		
	Precipitation	**Temperature**
% Significant	**91.7%**	**100%**
% Positive	**29.2%**	**91.7%**

Lead Time		
	Precipitation	**Temperature**
% Significant	**79.2%**	**70.8%**
% Negative	**62.5%**	**37.5%**

Issue Year		
	Precipitation	**Temperature**
% Significant	**83.3%**	**100%**
% Positive	**58.3%**	**33.3%**

These results allow us to analyze each of the independent variable's significant effect on climate forecast. We will first discuss the results found regarding the ONI. According to our regressions, the ONI is almost always significant when forecasting precipitation and it is always significant when forecasting temperature. This basically shows us that the climate phenomenon El Nino and La Nina (reflective of the ONI) do, in fact, affect climate forecast skill. How they affect climate forecasts can be seen by analyzing the sign of this variable. As stated previously, the ONI is a limited continuous variable since it only ranges from -1.6 to 2.5. However, from month to month it fluctuates between these values and a continuous period of high or low values signals an El Nino or La Nina period. Therefore, the sign of this parameter can be misleading. When its value is not at an extreme, the ONI will have little or no effect on forecast skill because there are no extreme climate scenarios being observed.

According to our results, the ONI is positively correlated with forecast skill in precipitation in only 29% of the seasons. This can be interpreted in two ways. The first being in some seasons the ONI can have a positive effect on forecast skill, but only during prolonged periods of high or low ONI. During the seasons in which the ONI is fluctuating often or always stays at relatively low values, the forecast skill will not be high. The second interpretation is although the ONI is only positively correlated in 29% of the seasons, during these seasons it can be highly correlated and have a large effect on skill scores. Previous research has shown during ENSO periods, skill is typically higher in the western United States. When dealing with temperature, the ONI is almost always positive and always significant. These results confirm what Livezey (2008) found during his one year limited study, that the ONI is a strong presence in temperature forecasts.

The results of the regression analysis when dealing with lead time are not exactly what we hypothesized. The initial thought was as lead time increases skill should decrease, consistently giving the parameter a negative sign. However, we found the lead time parameter is negative in terms of precipitation only 62% of the time, and it is negative 38% of the time with temperature. Although these results are not what we expected, they are still informative. They tell us despite the improvements in technology and forecasting methods, the ability to predict further into the future has not followed suit. By looking at how often our lead time parameter is significant, we can develop a better picture of lead times overall effect on skill scores. For precipitation, lead time is significant 80% of the time, and temperature it is significant only 70%. These values are not definitive enough to conclude that lead time is always a factor or that it is never important. We can, however, conclude lead time is not a distinct negative factor in terms of forecast skill score for precipitation or temperature. Livezey (2008) also had similar findings; Livezey concluded that, for precipitation, forecast lead time had no effect on forecast skill. He was unable to conclude definitively on lead times effect for temperature forecasts.

The final independent variable analyzed was the year the forecast was issued. This parameter was expected to be positive, which would indicate the skill in conducting forecasts has improved over the last twelve years. Our results show the issue year parameter is significant almost all of the time, with a slight exception in precipitation forecasts. However, our results also show the estimate for temperature is usually negative, which signifies that temperature forecast skill has declined over time. Although the parameter estimate for precipitation is significant and positive more often, it is not at a high enough rate to conclude forecast skill is increasing each year. The best conclusion we can reach is that over the years forecast skills have improved in some aspects but still have room to improve.

6.3 Climate Division Effects

The fixed effects model used to analyze the forecast skill scores created dummy variables for each of the cross sectional units in our data set, and in our case, these cross sectional units are climate divisions. In order to analyze the effect location has on forecast skill score, we must look at the individual effects of each climate division. A full list of tables with the individual effect of each climate division with regards to various skill scores and climate variables is available in Appendix A. In our analysis, effects are recorded for twenty-six climate divisions. The base climate division, that all others are compared too, is division #102, Southern New Mexico. The base attributes of this climate division are important to ensure other climate divisions can be accurately compared. Livezey found the entire western United States had superior skill in climate forecasting compared to the rest of the United States, but he also noted the skill in the Southwest was typically higher than the rest of the west. Based on this it is assumed Climate Division #102 is one of the higher skilled divisions. With these base attributes known, the remaining climate divisions can be analyzed.

We examine a climate division's effect on forecast skill throughout all seasons. The first important aspect is significance, or how often a climate division is any different from our base division. The second factor to be analyzed is whether a climate division has a more positive impact on skill score than our base. This would signify forecast predictions are more accurate in certain regions than in others. The tables below show the percentage of climate division effects that are significant as well as the percent that are positive. These percents are calculated using all three of the skill scores, both climate variables, and all twelve seasons.

Table 6.13 Climate Divisions Temperature Forecast Skill Summary Statistics

Climate Division	% Significant Temp	% Positive Temp
31	100%	66.7%
32	83.3%	62.5%
37	83.3%	70.8%
46	95.8%	66.7%
47	75%	70.8%
48	79.2%	58.3%
49	83.3%	58.3%
83	83.3%	54.2%
84	79.2%	54.2%
85	83.3%	54.2%
86	79.2%	58.3%
87	75%	54.2%
88	75%	58.3%

Climate Division	% Significant Temp	% Positive Temp
89	75%	66.7%
90	87.5%	50%
91	79.2%	54.2%
92	87.5%	62.5%
93	75%	66.7%
94	75%	50%
95	83.3%	45.8%
96	87.5%	37.5%
97	70.8%	41.7%
98	95.8%	41.7%
99	87.5%	58.3%
100	75%	62.5%
101	66.7%	66.7%

Table 6.14 Summary of Effects

Temperature	**Significant Positive Effect**	**Significant Negative Effect**
# of Climate Divisions	**20**	**4**

From these tables (6.13 and 6.14) we can see that the climate division effect is very strong when forecasting temperature. The fact that all of the climate divisions are significantly different than our base climate divisions allows us to conclude that climate division is an important component in understanding forecast skill. When analyzing the climate division effects on a state to state basis, compared to our New Mexico base climate division the results are typical. Climate divisions located in the same state commonly exhibit the same characteristics and have the same marginal effect on forecast skill. For example, all three of the Utah climate divisions have a positive affect 54.2 % of the time.

Twenty of the twenty-six climate divisions have a significant positive effect on skill scores compared to the base division. The four climate divisions that typically have lower skill scores include the Las Vegas region and climate divisions in Arizona. A significant negative effect in these four climate divisions allows us to conclude that forecast skill the average is slightly weaker in Arizona and Las Vegas compared to Southern New Mexico.

Table 6.15 Climate Divisions Precipitation Forecast Skill Summary Statistics

Climate Division	% Significant Precip	% Positive Precip
31	45.8%	62.5%
32	37.5%	70.8%
37	54.2%	62.5%
46	33.3%	70.8%
47	33.3%	62.5%
48	50%	70.8%
49	41.7%	54.2%
83	50%	62.5%
84	50%	66.7%
85	45.8%	58.3%
86	45.8%	66.7%
87	62.5%	58.3%
88	54.2%	62.5%

Climate Division	% Significant Precip	% Positive Precip
89	50%	45.8%
90	50%	70.8%
91	33.3%	62.5%
92	41.7%	54.2%
93	37.5%	58.3%
94	54.2%	70.8%
95	45.8%	79.2%
96	37.5%	70.8%
97	41.7%	79.2%
98	45.8%	79.2%
99	29.2%	62.5%
100	50%	45.8%
101	25%	45.8%

Table 6.16 Summary of Effects

Precipitation	Significant Positive Effect	Significant Negative Effect
# of Climate Divisions	8	2

Moving from the effect of climate division on temperature to effects on precipitation, tables 6.15 and 6.16 indicate that unlike temperature, precipitation skill does not change as much depending on climate division. Only eight of the twenty-six climate divisions are significantly different from our New Mexico base division. This is most likely due to the generally low amounts of precipitation that are seen in the western United States. Since only eight divisions have a positive effect and two have a negative effect, the majority of the climate divisions behave very similarly. In terms of climate forecasting, unlike temperature, different precipitation forecasts are most likely not needed based on geographic region. The two climate divisions that exhibit a significant negative effect are the Northern California Coast and Eastern New Mexico divisions. Conclusions cannot be accurately drawn because these two divisions do not have many characteristics in common. The Northern California Coast is a high precipitation area, while Eastern New Mexico is typically dry. These results are consistent with what past research, including Livezey and Katz, has found. The interpretation that forecast skill for precipitation is typically weak in the western United States holds true with our results.

7. Water Diversions Simulation

In order to develop some practical insights from both our agricultural water use and skill scores regression models, we created a series of simulation models. These models use seasonal climate forecasts for temperature and precipitation with differing skill levels and insert the forecasted temperature and precipitation into the water diversions model in order to understand the potential implications of varying forecast skills for decision makers. Our simulation considers the decisions of an urban water manager whose water supplies are a lower priority than agricultural water supplies and thus affected by the quantity that senior agriculture uses, a common situation in the western US. In order to explore the potential effects of forecast skill and interpretation, we create the following representative decision situation. An urban water manager must consider whether nearby agriculture is likely to use a larger or smaller amount of water than average in the summer season, knowing that urban water supplies are the residual (leftover) after agricultural diversions. If the agricultural sector is expected to use more than an average amount of water, then the urban water manager must contract to purchase additional summer supplies for their upcoming June, July, and August water delivery season. The table below shows a simplified hypothetical decision facing an urban water manager.

Table 7.1 Water Managers Decision Simulation

	Forecasted Agricultural Water Use		
	Higher than Average	Average	Lower than Average
Water Managers Action	Arrange to lease water	No action	No action

In this hypothetical situation, a water manager seeks to estimate the amount of water that the agriculture sector will need in the upcoming June-July-August season using seasonal forecasts. Using these predictions, if it is expected to need more water than usual, the manager must arrange to lease water to counter the smaller amount available for urban use. If agriculture is expected to use the same or less water than normal, no action is required by the water manager because enough water is expected to be available. The average amount of water used by agriculture is calculated by averaging the total amount used over the years we have data for (1998-2003).

Our simulation analyzes the differences in amounts of water ordered based on different methods for incorporating climate and weather, ranging from naïve to more sophisticated. Using the agriculture water use values we have calculated from our simulation model, we simulate how much an urban water manager might need to pay depending on a how far in advance the water leases are arranged. These methods range from the most naïve to the scientific. Using our diversion amounts we are able to simulate the cost to a manager if he must pay the standard price for water versus an emergency price.

7.1 Choosing the forecasts

Two different approaches are used when choosing possible temperature and precipitation values to use in estimating summer season agriculture use. The first method incorporates historic data to predict summer season agriculture use. When climate forecasts are not available or viewed as too unreliable, decision makers will often use historic weather patterns to make water decisions. The most naïve planning approach we model for using climate and weather information is to use last year's temperature and precipitation information.

In the second planning method the urban water manager is assumed to calculate a three year running mean of the previous years temperature and precipitation. We average out the previous three years temperature and precipitations values, and use those as our current time periods. These values will only come from the corresponding season we are addressing. For example, to simulate a decision made for the June-July-August season in 2002, we will take the average temperature and precipitation value from the June-July-August season in 2001, 2000, and 1999. This planning method will be referred to as the "three year mean" approach. The final method is used as a control or baseline value. It represents perfect foresight. This method is unattainable in actual terms, however very useful for our simulations. We use actual temperature and precipitation values from specific summer seasons to estimate how much water is used by agriculture. These agriculture water use values serve as a baseline (perfect foresight, no uncertainty) planning methods.

A second set of simulations for agriculture water use allows us to analyze the effect of using forecasts with different lead times. We use climate forecasts given with a one, seven, and thirteen month lead time. These forecasts are obtained using the two climate divisions which contain the specific Lower Colorado River Basin irrigation districts being analyzed. Based on the regression analysis reported in chapter 6, lead time is not expected to have a significant impact on the amount of water diversions ordered. We do not expect to identify an overall preferred lead time when simulating water consumptive use.

The table below shows a summary of possible planning methods that will be used in our simulations.

Table 7.2 Urban Water Manager Planning Methods Simulated

Planning Method	Assumptions
Perfect Foresight	Actual temperature and precipitation values for the given season
Previous Year	Upcoming temperature and precipitation values will be identical to the previous years
3 Year Mean	Upcoming temperature and precipitation values will be the same as the mean of the past 3 years
1 Month Lead Time	Temperature and precipitation values taken from forecast with 1 month lead time
7 Month Lead Time	Temperature and precipitation values taken from forecast with 7 month lead time
13 Month Lead Time	Temperature and precipitation values taken from forecast with 13 month lead time

7.2 Model

In order to simulate the decision facing an urban water manager needing to predict the upcoming summer, we use our agriculture water use model and the parameters we estimated in Table 3.5. When we combine our agriculture water use data and the climate forecast dataset, we have a six year overlapping period. From 1998-2003, we have data on irrigation districts as well as corresponding climate forecasts. Therefore, using these six years, we simulate how much water agriculture would order based on historic data and climate forecasting. Four specific irrigation districts have been chosen for our simulations. Those four are: Imperial Irrigation District, Palo Verde Irrigation District, Wellton Mohawk Irrigation District, and the Colorado River Indian Tribe (CRIT) Irrigation District. These four were chosen based on the proximity to the Colorado River as well as the size of the irrigation districts. Imperial and Palo Verde are located in California, while Wellton Mohawk and CRIT are Arizona irrigation districts.

The parameter estimates from our agriculture water use model are used along with known values for acres planted, crop shares, and price. These values allow us to calculate the amount of consumptive water use for each irrigation district based on different planning methods. The values for acres planted, price, and crop shares change from month to month and season to season but are the same regardless of planning method. The only variables changing will be temperature and precipitation. Since our base model analyzes the log of consumptive water use, we must also re-transform our dependent variable back to the untransformed consumptive water use variable. After all of this, we arrive at our desired calculation; consumptive water use by a specific irrigation district in a given season and year based off different planning methods.

7.3 Results

A complete description of the results from our simulations is presented in Appendix C. The tables are separated into the four different Irrigation Districts and six years used in this experiment, resulting in twenty-four tables in all. Each table shows a different planning method for incorporating temperature and precipitation along with the potential cost to a water manger based on the difference between the estimated and average water use from an irrigation district. Using these calculations for the quantity of water used, prices are applied per each acre foot. We have three possible prices that correspond to the time period in which the urban water manager is acquiring additional water supplies. The lowest price is set at $90, which reflects a water manager acquiring water through a voluntary lease transaction more than seven months in advance. The second potential price shows the cost when a decision maker arranges a water lease more than one month in advance, but less than seven months in advance. The cost per acre foot in this instance is $120. These figures are an estimate based on recent pilot water leasing agreements between the Bureau of Reclamation and an Arizona irrigation district (Bureau of Reclamation, 2008 and 2009). The highest potential price paid is $210 per acre foot. This price reflects an urgent situation in which the water lease is negotiated only one month in advance of need. O’Donnell (2010) found this price to be an average paid for water leases in California.

It is important to note when viewing the tables in Appendix C, that according to our decision model, if an irrigation district is expected to use the average or less than the average amount of water, no water lease needs to be arranged by the urban water manage. The table below shows an example of how our simulations were conducted:

Table 7.3 Simulation Example

Palo Verde	Average Consumptive Use (Acre/Feet)	1 Month Lead Time Estimated Consumptive Use (Acre/Feet)	Difference (Acre/feet)	Cost @$210 ($)
1998	116,350	94,214	-22,136	-$4,648,512
1999	116,350	84,759	-31,591	-$6,634,196
2000	116,350	75,242	-41,108	-$8,632,745
2001	116,350	90,063	-26,288	-$5,520,375
2002	116,350	93,259	-23,091	-$4,849,188
2003	116,350	91,761	-24,589	-$5,163,732

- Negative values indicate that no water lease is anticipated

The average water consumptive use over our six year course for each irrigation district was calculated. Then using various planning methods (in this example the method is a forecast with a one month lead time) we calculated the expected consumptive water use by an irrigation district. The next step was to determine if the estimated water use means an urban water manager must arrange to lease water or do nothing, this is determined by subtracting the estimated water use by the average water use. Our example shows that the agriculture sector is expected to use less water than average, which means water will be available for urban use and the water manager does not need to take action. These simulations were done for the six possible planning methods described above for all four irrigation districts.

A summary of the possible decisions a water manager may make based on different planning methods and the economic ramifications of those decisions are presented below.

Table 7.3 Simulations Summary

		1 Month Lead	**7 Month Lead**	**13 Month Lead**	**Perfect Foresight**	**Last Year**	**3 Year Mean**
Cost	**Average Water Cons.**	**$210/acre foot**	**$120/acre foot**	**$90/ acre foot**	**$120/ acre foot**	**$120/ acre foot**	**$120/ acre foot**
1998 CRIT	75,443	-$6,624,395	-$3,778,516	-$2,828,741	$1,095,798	$3,120,960	$4,200,960
1999 Well	46,535	-$3,418,979	-$,1094,246	-$896,072	$226,6386	$4,647,041	$8,441,700
2000 IID	355,611	-$43,251,558	-$16,966,308	-$8,539,515	$5,449,742	$29,500,800	$31,106,520
2001 PV	116,350	-$5,520,375	-$3,140,441	-$2,943,960	$5,076,241	$2,344,800	$10,216,440

- Note: Negative values indicate that no water lease is anticipated

The table above shows us that shows us that all of the lead time methods (1, 7, and 13 month leads) provide the urban water manager with underestimations of water diversions. This results in water managers deciding not to negotiate water leases on the assumption that agriculture use less than average. However, this use of forecast temperature and precipitation will leave the urban water manager in shortage of accrual water needed. While we do not assign a monetary cost to this predicament, we can conclude that the decision to not negotiate water leases in advance of need could cost the city a lot of money because the city will be in shortage and may be forced to pay a higher price for short turnaround water acquisitions or incur significant costs due to cutbacks.

However, the 'more naïve' approaches of using historical data (last year and three year average temperature and precipitation values) produce the opposite result. We find that these planning methods predict that agriculture will use more water than the average and therefore water managers must negotiate water leases for the upcoming summer season.

Our results also show that there is not a constant preferred lead time in terms of decision making for the urban water manager. At some points a one month lead time will cost the least, but at others a seven or thirteen month may. This result confirms the findings of Livezey (2008), who found that lead time was not a significant factor in the skill of forecasts. Our results also do not show any consistently preferred method of planning, whether it is using climate forecasts or historical data.

8. Conclusions and Recommendations

The scope of this thesis was to investigate the factors that affect climate forecast skill. We also wanted to make a connection between climate forecast skill and the economic ramifications of application and interpretations of those forecasts. In order to determine the factors affecting climate forecasts, we analyzed the surprise and false alarm rates along with the Ranked Probability and Brier Skill scores. Then, to investigate the economic implications, we ran simulations depicting hypothetical decisions that an urban water manager could make based on various uses of forecasts compared to using information about past years climate variables.

8.1 Skill Scores

These four descriptive skill scores each told us something different regarding forecast performance. The surprise and false alarm rates indicate forecasts are not currently accurate enough to be used on a consistent basis by water managers. The forecasts made are not consistently accurate, and they can, therefore, lead to incorrect decisions.

The Ranked Probability and Brier Skill scores give us a better understanding of what measurable factors affect forecast skill. Using our fixed effects model, we were able to measure how ONI, lead time, issue year, and location determine forecast skill. Although our results were spread out over different seasons, we can still draw general conclusions in regards to climate forecasting. Our results show the ONI only affects forecast skill when extreme values are observed. Extreme values lead to El Nino and La Nina climate periods, and these periods typically lead to better forecast skill. When the

ONI does not reach extreme values, it is typically insignificant in forecast skill. Our results show the ONI plays a large role in temperature forecasts than in precipitation, however, it can still play a large role in both. The interpretation is basically that climate forecasters find the El Nino and La Nina weather phenomenon present better climate conditions in terms of prediction.

Using the results from our skill score analysis, we were able to analyze the time effect of forecast skill. Both the lead time and issue year dependent variables were analyzed and found to be insignificant or have a negative effect on overall forecast skill. Our interpretation is that technology has not been developed well enough to account for the ever changing climate scenarios. Additional research and development is needed to ensure future climate forecasting can be done more than six months in advance and that each year forecast skill improves. The final independent variable analyzed was the geographic location of the target forecast. Our climate division dummy variables allowed us to analyze each climate division individually with respect to forecast skill. Our results showed with respect to precipitation, location was not a key factor in determining forecast skill. Each climate division showed typically the same forecast skill. However, when analyzing temperature, we found forecast skill differed depending on the region forecasted. This infers there is a need for separate temperature forecast methods depending on the target location.

8.2 Simulations

Our simulation model allowed us to estimate a monetary ‘stake’ associated with the use of different planning methods. We found that because Imperial Irrigation District is such a large water user, that accurate estimates of their consumptive water use can provide the largest benefits to urban water managers. Our model has also shown there is not a significant difference in accuracy and economic benefits between the various lead times for seasonal forecasts. In some situations, the simplest planning method of using the previous year’s temperature and precipitation values performs as well as using the seasonal forecast methods we have analyzed. However, simply using historic weather data is not a recommended method due to the long term changes in regional climate.

8.3 Recommendations and Future Work

Our analysis has led us to conclude current climate forecasts are not as skillful as decision makers' need. The realistic use of climate forecasts for decision makers must be as a planning tool. Managers cannot use climate forecasts (regardless of lead time) as their only source of information for the upcoming planning season. If this were the method a decision maker chose, then one incorrect forecast would create devastating results. Instead, it is suggested that climate forecasts are used to prepare for the worst and help eliminate the possible scenarios most likely not to occur. If managers can use forecasts to limit their scopes of what is most likely to happen, but still plan for other possibilities, then climate forecasts can be useful.

Of course it is important for a decision maker to consider the various location factors affecting climate and their possible water supply. Water managers need to not only focus on their own climate divisions forecast, but also on those divisions that play critical parts in supplying their water. An example can be taken from a water manager in the Lower Colorado River Basin. It is not only critical what the climate forecasts are in his geographical area, but also further upstream along the Colorado River, because the higher elevation portions of the basin are where the majority of his water supply comes from.

Future work can be performed in both the climatology and economic sectors. There is a need for better methods of forecasting throughout the Western United States. The high surprise and false alarm rates imply forecasts are rarely useful and cannot be trusted by managers as a legitimate planning tool. This is the basic fault of climate forecasts and with further research and development can be accounted for. Economic research should attempt to find and quantify other factors that play a role in forecast skill. Our research analyzed four of the base factors (ONI, lead time, issue year, and location), however, many more factors exist and can play key roles in forecasts. These include, but are not limited to, other climate phenomenon such as the Pacific Decadal Oscillation. Future research could also focus on the rest of the United States since our analysis only covered the western United States. Although the western United States contains much of the agricultural sector, the energy sector is also a primary user of climate forecasts and has implications throughout the United States.

More work is needed to analyze exactly how decision makers use climate forecasts on a day to day basis. Our simulation model assumes urban water managers have adequate planning time and information; however, this may not be the case for all managers. A unique decision and simulation model would be very useful in determining the exact economic benefits and losses due to climate forecasts.

Figure 3.1 Irrigation District Map

*Photo from metropolitan Water District of Southern California

Table 3.1 Irrigation Districts:

1. North Gila, Arizona

2. Unit “B” division, Arizona

3. Wellton Mohawk, Arizona

4. Yuma, Arizona

5. Yuma County Water Users Associates (YCWUA), Arizona

6. Yuma-Mesa, Arizona

7. Imperial, California

8. Palo Verde, California

9. Fort Mohave, Arizona

10. Mohave Valley, Arizona

11. Colorado River Indian Tribe, Arizona

12. Cocopah, Arizona

13. Sturges Gila Farms, Arizona

14. Fort Yuma Indian Reservation - Bard Unit, California

Table 3.3 Descriptive Statistics Colorado River

Variable Name	N	Minimum	Mean	Maximum
Ln (Water Diversions)	1,512	2.89	8.97	12.84
Precipitation	1,512	0	0.211	5.37
Ln (Price)	1,512	0	0.189	2.71
Lag [Ln (Temp)]	1,512	3.85	4.26	4.57
Lag [Ln(temp)]*precipitation	1,512	0	0.89	24.34
Ln (Acres)	1,512	7.16	9.84	13.23
Share Cotton	1,512	0	0.13	0.52
Share Grain	1,512	0	0.12	0.39
Share Forage	1,512	0.05	0.38	0.85
Share Corn	1,512	0	0.19	0.2
Share Tree	1,512	0	0.09	0.74
Share Fruits and Vegetables	1,512	0	0.22	0.58
Share Other	1,512	0	0.01	0.1
Ln (Evapotranspiration)	1080*	6.12	9.21	11.1

Table 3.4 Colorado River Variable List:

Variable	Definition	Units of Measure	Expected Sign
Ln (Water Diversions)	Total Amount of water diversions used by a specific Irrigation District	Acre/Feet	Dependent Variable
Precipitation	Total amount of precipitation in a given month	Inches	-
Ln (Price)	The natural log of price per acre/foot of water paid by the Irrigation District	Dollars	-
Lag [Ln (Temp)]	Two month lagged average monthly temperature value	Degrees Fahrenheit	+
Lag [Ln(temp)]*rain	Interaction variable between lagged temperature value and total precipitation	Degrees Fahrenheit*Inches	+
Ln (Acres)	Natural Log of total acres planted in a specific Irrigation District	Acres	+
Share Cotton	The amount of acres planted for Cotton divided by the total number of acres planted	% Acres	-
Share Grain	The amount of acres planted for Grains divided by the total number of acres planted	% Acres	-
Share Forage	The amount of acres planted for Forage divided by the total number of acres planted	% Acres	-
Share Corn	The amount of acres planted for Corn divided by the total number of acres planted	% Acres	-
Share Tree	The amount of acres planted for Tree crops divided by the total number of acres planted	% Acres	+
Share Fruits and Vegetables	The amount of acres planted for Fruits and Vegetables divided by the total number of acres planted	% Acres	-
Share Other	The amount of total acres planted subtracted by the sum of acres planted for Cotton, Grain, Forage, Corn, Tree, Fruits and Vegetables divided by the total amount of acres planted.	% Acres	+

Table 3.5 Colorado River Parameter Estimates; Dependent Variable: Ln Water Diversions

Variable	Estimate	Standard Error	P Value
Intercept	-1.544	0.325	-4.750
Precipitation	-2.553	0.338	-7.560
Ln(price)	-0.193	0.127	-1.520
Lag(temp)	-0.013	0.003	-4.540
Lag(lntemp)*precip	0.555	0.079	7.050
Ln(acres)	1.154	0.021	55.310
Sharefruit/vegetable	-0.531	0.164	-3.230
Share tree	1.215	0.256	4.760
Share forage	0.071	0.261	0.270
Share cotton	-0.408	0.366	-1.110
Share grain	-2.770	0.703	-3.940
Share corn	-1.487	0.757	-1.960

Variable	Estimate	Standard Error	P Value
Share other	1.123	4.079	0.280
fjan	-0.231	0.036	-6.430
ffeb	0.448	0.041	10.890
fmar	0.605	0.052	11.600
fapr	0.799	0.061	13.180
fmay	0.896	0.074	12.040
fjun	1.032	0.089	11.570
fjul	0.953	0.103	9.280
faug	0.890	0.105	8.500
fsep	0.817	0.091	8.940
foct	0.349	0.058	6.060
fnov	-2.553	0.338	-7.560

Table 4.1 Climate Divisions:

	89: Northern California Coast
31: Northeastern Wyoming	90: Central Nevada
32: Northwestern Wyoming	91: Fresno Region, California
37: Western Nebraska/Cheyenne	92: Central California Coast
46: Northeastern Colorado	93: Southern California Coast
47: Southeastern Colorado	94: Southeastern California
48: Western Colorado	95: Las Vegas Region, Nevada
49: Southwestern Wyoming	96: Southwestern Arizona
83: Northeastern Utah	97: Northeastern Arizona
84: Southeastern Utah	98: Southeastern Arizona
85: Western Utah	99: Northern New Mexico
86: Northeastern Nevada	100: Eastern New Mexico
87: Northwestern Nevada	101: Central New Mexico
88: Sacramento Region, California	102: Southern New Mexico

Table 5.1 Climate Variable List:

Variable	Definition	Expected Sign
Ranked Probability Score	Score which measures the skill of a climate forecast with three possibilities; below, normal or above.	Dependent Variable
Brier Score	Score which measures the skill of a climate forecast with two possibilities; above or not above	Dependent Variable
Lead Time	The amount of time between when a forecast is made and what time period it is intended for, between 1 and 13 months	-
Oceanic Nino Index	Three month running mean of deviations from typical sea surface temperatures. Used as a measure to compare current events to historical ones	+
Issue Year	The year in which the forecast was made. Ranges from 1997 through 2008	+

Table 6.2 Precipitation Skill Scores

Variable	Season					
	I	II	III	IV	V	VI
Surprise Rate Above	0.846	0.742	0.771	0.822	0.941	0.853
Surprise Rate Normal	0.280	0.288	0.292	0.274	0.133	0.144
Surprise Rate Below	0.860	0.871	0.882	0.897	0.947	0.958
False Alarm Rate Above	0.561	0.489	0.437	0.630	0.778	0.663
False Alarm Rate Normal	0.727	0.723	0.700	0.704	0.741	0.766
False Alarm Rate Below	0.546	0.560	0.689	0.641	0.629	0.502

Variable	Season					
	VII	VIII	IX	X	XI	XII
Surprise Rate Above	0.974	0.973	0.94	0.918	0.937	0.913
Surprise Rate Normal	0.127	0.239	0.231	0.130	0.153	0.209
Surprise Rate Below	0.918	0.660	0.734	0.872	0.897	0.844
False Alarm Rate Above	0.813	0.825	0.554	0.579	0.75	0.761
False Alarm Rate Normal	0.707	0.677	0.695	0.623	0.631	0.636
False Alarm Rate Below	0.448	0.365	0.485	0.468	0.576	0.466

Table 6.3 Temperature Skill Scores

Variable	Season					
	I	II	III	IV	V	VI
Surprise Rate Above	0.594	0.272	0.138	0.135	0.045	0.302
Surprise Rate Normal	0.582	0.893	0.807	0.794	0.593	0.497
Surprise Rate Below	0.998	0.988	0.972	0.981	0.996	0.957
False Alarm Rate Above	0.591	0.437	0.452	0.382	0.365	0.249
False Alarm Rate Normal	0.721	0.141	0.405	0.370	0.709	0.692
False Alarm Rate Below	0.955	0.75	0.36	0.771	0.897	0.591

Variable	Season					
	VII	VIII	IX	X	XI	XII
Surprise Rate Above	0.231	0.769	0.172	0.538	0.64	0.581
Surprise Rate Normal	0.739	0.727	0.171	0.538	0.639	0.581
Surprise Rate Below	0.950	0.993	0.815	0.474	0.386	0.544
False Alarm Rate Above	0.260	0.273	0.998	0.998	0.959	0.996
False Alarm Rate Normal	0.704	0.792	0.433	0.400	0.440	0.541
False Alarm Rate Below	0.914	0.988	0.662	0.761	0.707	0.778

Table 6.8
Precipitation Model Dependent Variable = Ranked Probability Score

Variable	Season					
	I	II	III	IV	V	VI
Intercept	18.43	12.12	-0.20	33.94	-20.29	7.55
ONI	0.005 (0.004)	-0.03** (0.005)	0.04** (0.006)	-0.06** (0.008)	0.03** (0.009)	-0.02** (0.007)
Lead Time	-0.003** (0.001)	-0.004** (0.001)	-0.002* (0.002)	-0.002* (0.001)	0.003** (0.001)	-0.001** (0.001)
Issue Year	-0.01** (0.001)	-0.01** (0.001)	0.0002 (0.001)	-0.02** (0.001)	0.01** (0.001)	-0.004** (0.001)

Variable	Season					
	VII	VIII	IX	X	XI	XII
Intercept	-3.61	-8.50	-1.2	-22.1	-33.7	13.57
ONI	-0.04** (0.006)	-0.05** (0.005)	-0.02** (0.005)	0.03** (0.004)	0.05** (0.004)	-0.01** (0.004)
Lead Time	-0.0004 (0.001)	0.002 (0.001)	0.001 (0.001)	0.002* (0.001)	0.003** (0.001)	-0.003** (0.001)
Issue Year	0.002 (0.001)	0.004** (0.001)	0.001 (0.001)	0.01** (0.001)	0.02** (0.001)	-0.01** (0.001)

*Standard Errors are in parenthesis.

Significance Levels: *.05 **.01

Table 6.9 Precipitation Model Dependent Variable = Brier Score

Variable	Season					
	I	**II**	**III**	**IV**	**V**	**VI**
Intercept	-3.62	-2.67	12.06	6.55	0.58	-2.69
ONI	-0.03** (.001)	-0.06** (0.002)	-0.09** (0.003)	-0.11** (0.003)	-0.027** (0.002)	-0.003** (0.001)
Lead Time	0.002** (.0004)	0.002** (0.0005)	0.001* (0.0006)	-0.001 (0.0006)	-0.001** (0.0003)	-0.001** (0.0002)
Issue Year	0.002** (0.0004)	0.001* (0.0005)	-0.01** (0.0006)	-0.003** (0.0005)	-0.001 (0.0003)	0.001** (0.0003)

Variable	Season					
	VII	**VIII**	**IX**	**X**	**XI**	**XII**
Intercept	-2.58	-6.67	-3.1	2.49	1.98	-3.3
ONI	0.0003 (0.008)	0.006** (0.001)	-0.003** (0.002)	-0.01** (0.0009)	-0.01** (0.001)	-0.01** (0.001)
Lead Time	-0.0002 (0.0002)	0.001** (0.002)	-0.001** (0.003)	-0.002** (0.0002)	-0.002** (0.0003)	-0.001** (0.0003)
Issue Year	0.001** (0.0002)	0.003** (0.003)	0.002** (0.0003)	-0.001** (0.001)	-0.001** (0.0003)	0.002** (0.0004)

*Standard Errors are in parenthesis.

Significance Levels: *.05 **.01

Table 6.10 Temperature Model Dependent Variable = Ranked Probability Score

Variable	**Season**					
	I	**II**	**III**	**IV**	**V**	**VI**
Intercept	36.87	5.73	5.42	-10.63	-53.45	-26.86
ONI	0.03** (0.005)	0.03** (0.005)	0.08** (0.007)	0.02* (0.01)	0.11** (0.008)	0.02** (0.007)
Lead Time	-0.01** (0.002)	-0.003* (0.001)	0.0003 (0.001)	-0.0004 (0.001)	-0.0002 (0.001)	-0.004** (0.001)
Issue Year	-0.02** (0.001)	-0.003* (0.001)	-0.003* (0.002)	0.005** (0.001)	0.027** (0.001)	0.014** (0.001)

Variable	**Season**					
	VII	**VIII**	**IX**	**X**	**XI**	**XII**
Intercept	-7.84	-33.65	21.43	-35.66	-18.91	-28.02
ONI	0.02** (0.006)	-0.04** (0.005)	-0.04** (0.005)	0.04** (0.004)	0.08** (0.003)	0.01** (0.003)
Lead Time	-0.01** (0.001)	-0.001 (0.001)	0.002 (0.001)	0.002* (0.001)	-0.002* (0.001)	-0.0002 (0.001)
Issue Year	0.004** (0.001)	0.02** (0.001)	-0.01** (0.001)	0.02** (0.001)	0.01** (0.001)	0.02** (0.001)

*Standard Errors are in parenthesis.

Significance Levels: *.05 **.01

Table 6.11 Temperature Model Dependent Variable = Brier Score

Variable	Season					
	I	II	III	IV	V	VI
Intercept	27.77	24.6	18.98	5.47	22.92	35.28
ONI	0.01** (0.002)	0.03** (0.003)	0.04** (0.001)	0.04** (0.005)	0.06** (0.004)	0.03** (0.004)
Lead Time	0.01** (0.001)	0.002** (0.001)	0.0002 (0.001)	0.001* (0.001)	0.005** (0.001)	0.007** (0.001)
Issue Year	-0.02** (0.001)	-0.01** (0.001)	-0.01** (0.001)	-0.003** (0.001)	-0.01** (0.001)	-0.02** (0.001)

Variable	Season					
	VII	VIII	IX	X	XI	XII
Intercept	44.72	61.14	27.72	16.2	9.77	22.34
ONI	0.02** (0.003)	0.02** (0.002)	0.007** (0.002)	0.005** (0.001)	0.007** (0.001)	0.006** (0.002)
Lead Time	0.01** (0.001)	0.001* (0.001)	0.002** (0.001)	0.002** (0.0004)	0.006** (0.0004)	0.01** (0.001)
Issue Year	-0.02** (0.001)	-0.03** (0.001)	-0.01** (0.001)	-0.01** (0.0004)	-0.01** (0.0004)	-0.01** (0.001)

*Standard Errors are in parenthesis.
Significance Levels: *.05 **.01

Appendix A: Bureau of Reclamation Water Accounting Method- Example

Table A1

Water User	2001	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Imperial Irrigation District	Diversions Ordered	110000	125000	98000	121000	86400	113000	143000	156000	98700	89000	104000	129000	1373100
	Other use	22000	15000	11000	10000	12000	14000	8000	7000	9000	10000	11000	8000	137000
	Returns	12000	14000	10000	6000	8000	14000	12000	9000	4000	8000	4000	6000	107000
	Consumptive Use	76000	96000	77000	105000	66400	85000	123000	140000	85700	71000	89000	115000	1129100
Palo Verde Irrigation District	Diversions Ordered	65000	54000	60000	55000	42000	39000	52000	47000	51000	50000	46000	53000	614000
	Other use	11000	12000	7000	8000	7000	10000	8000	4000	6000	4000	8000	7000	92000
	Returns	2500	1000	4000	3000	2000	1000	3000	2000	2500	500	1000	2000	24500
	Consumptive Use	51500	41000	49000	44000	33000	28000	41000	41000	42500	45500	37000	44000	497500

Appendix B: Climate Division Effects

Table B1 Climate Division Effects: Division 31

Season	I	II	III	IV	V	VI
RPS Temp	-0.125**	-0.125**	-0.181**	-0.095**	0.051*	-0.064*
BS Temp	0.124**	0.195**	0.171**	0.186**	0.219**	0.235**
RPS Precip	-0.069*	-0.127**	-0.047	0.010	0.239**	0.100**
BS Precip	0.039**	0.014	0.013	0.015	0.005	0.010
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.055*	0.109**	0.086*	-0.077**	-0.139**	-0.121**
BS Temp	0.186**	0.181**	0.269**	0.173**	0.133**	0.146**
RPS Precip	0.092**	0.168**	-0.098**	0.253**	0.212**	-0.071
BS Precip	0.004	0.010	-0.005	-0.005	-0.029**	-0.016

Significance Levels: *.05 **.01

Table B2 Climate Division Effects: Division 32

Season	I	II	III	IV	V	VI
RPS Temp	-0.106**	-0.271**	-0.018	-0.032	-0.004	-0.121**
BS Temp	0.145**	0.196**	0.141**	0.133**	0.210**	0.226**
RPS Precip	0.012	-0.118**	0.141**	-0.041	0.133**	0.004
BS Precip	0.059**	0.026	0.020	0.011	0.001	0.011
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.008**	0.068	0.151**	-0.076*	-0.142**	-0.093*
BS Temp	0.175**	0.150**	0.257**	0.172**	0.133**	0.159**
RPS Precip	0.011	0.172**	-0.152**	0.051	0.204**	0.027
BS Precip	0.009	0.017**	-0.002	0.001	-0.022**	-0.009

Significance Levels: *.05 **.01

Table B3 Climate Division Effects: Division 37

Season	I	II	III	IV	V	VI
RPS Temp	-0.119**	-0.209**	0.073*	-0.081*	-0.098**	-0.014
BS Temp	0.113**	0.192**	0.176**	0.203**	0.219**	0.233**
RPS Precip	-0.027	-0.214**	-0.061*	0.050	0.090**	0.103**
BS Precip	0.025**	0.018	0.021	0.022	0.009	0.011
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.002	0.041**	0.041	-0.132**	0.001	-0.181**
BS Temp	0.201**	0.184**	0.261**	0.173**	0.126**	0.114**
RPS Precip	0.093**	0.170**	-0.243**	0.071*	0.011	-0.023
BS Precip	0.001	0.006*	-0.032**	-0.050**	-0.040**	-0.002

Significance Levels: *.05 **.01

Table B4 Climate Division Effects: Division 46

Season	I	II	III	IV	V	VI
RPS Temp	-0.208**	-0.166**	0.021	0.044*	-0.084**	-0.009**
BS Temp	0.112**	0.157**	0.147**	0.190**	0.207**	0.223**
RPS Precip	0.074*	-0.098**	-0.217**	0.042	0.293**	0.056*
BS Precip	0.022	0.016	0.024	0.033	0.012	0.011
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.047*	0.153**	0.151**	-0.128**	-0.131**	-0.124**
BS Temp	0.198**	0.161**	0.228**	0.171**	0.122**	0.104**
RPS Precip	0.144**	0.018	-0.290**	0.151**	0.004	0.025
BS Precip	0.002	0.004	-0.018	-0.009	-0.010	-0.006

Significance Levels: *.05 **.01

Table B5 Climate Division Effects: Division 47

Season	I	II	III	IV	V	VI
RPS Temp	-0.197**	-0.239**	0.029	0.019	-0.044	-0.102**
BS Temp	0.099**	0.126**	0.127**	0.176**	0.192**	0.209**
RPS Precip	0.027	-0.142**	-0.235**	0.083	0.092**	0.151**
BS Precip	0.019	0.007	0.021	0.030	0.013	0.011
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.032	0.034	0.212**	0.028	-0.161**	-0.165**
BS Temp	0.178**	0.152**	0.211**	0.166**	0.122**	0.102**
RPS Precip	0.093**	0.061*	-0.204**	0.049	-0.048	-0.072*
BS Precip	0.002	0.005	-0.007	-0.002	-0.006	-0.010

Significance Levels: *.05 **.01

Table B6 Climate Division Effects: Division 48

Season	I	II	III	IV	V	VI
RPS Temp	-0.049	-0.230**	-0.020	-0.036	-0.168**	-0.016
BS Temp	0.124**	0.097**	-0.004	0.035*	0.124**	0.151**
RPS Precip	0.022	0.035	0.145**	-0.122**	0.088**	0.102**
BS Precip	0.024*	0.014	0.032	0.036	0.012**	0.010
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.055*	0.208**	0.203**	-0.130**	-0.077**	-0.096**
BS Temp	0.071**	0.029*	0.117**	0.152**	0.116**	0.124**
RPS Precip	0.095**	0.217**	-0.182**	-0.062*	0.151**	-0.122**
BS Precip	0.006	0.005	-0.002	0.003	-0.007	-0.008

Significance Levels: *.05 **.01

Table B7 Climate Division Effects: Division 49

Season	I	II	III	IV	V	VI
RPS Temp	-0.022	-0.070*	-0.042	-0.056	-0.159**	-0.094**
BS Temp	0.153**	0.191**	0.111**	0.122**	0.203**	0.226**
RPS Precip	-0.019	-0.021	-0.105**	0.059*	0.188**	0.158**
BS Precip	0.027**	0.011	0.014	0.015	0.006	0.013
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.062*	0.121**	0.274**	-0.077**	-0.038	-0.050*
BS Temp	0.158**	0.120**	0.218**	0.168**	0.131**	0.155**
RPS Precip	-0.053*	0.086**	-0.301**	-0.003	0.162**	-0.183**
BS Precip	0.009	0.014	-0.005	0.000	-0.017	-0.016

Significance Levels: *.05 **.01

Table B8 Climate Division Effects: Division 83

Season	I	II	III	IV	V	VI
RPS Temp	-0.072*	-0.217**	-0.037	0.060*	-0.224**	-0.033
BS Temp	0.150**	0.127**	-0.043*	-0.049*	0.121**	0.154**
RPS Precip	-0.126**	-0.169**	-0.119**	-0.150**	0.142**	0.007
BS Precip	0.024	0.014	0.031	0.024	0.009	0.012
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.064*	0.184**	0.236**	-0.075*	-0.082**	-0.046
BS Temp	0.058**	-0.019	0.069**	0.149**	0.121**	0.149**
RPS Precip	0.149**	0.270**	-0.247**	-0.001	0.214**	-0.104**
BS Precip	0.013**	0.015**	0.007	0.007	-0.013	-0.010

Significance Levels: *.05 **.01

Table B9 Climate Division Effects: Division 84

Season	I	II	III	IV	V	VI
RPS Temp	-0.119**	-0.171**	-0.013	-0.001	-0.209**	-0.083**
BS Temp	0.108**	0.038*	-0.102**	-0.069**	0.065**	0.095**
RPS Precip	-0.014	-0.053**	-0.123**	0.132**	0.180**	0.119**
BS Precip	0.026	0.016	0.036	0.036**	0.013	0.009
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.115**	0.258**	0.201**	-0.062*	0.023	-0.079**
BS Temp	0.001	-0.051**	0.024	0.131**	0.107**	0.111**
RPS Precip	0.094**	0.108**	-0.261**	-0.117**	0.151**	-0.072*
BS Precip	0.006	0.007	0.002	0.010	-0.002	-0.005

Significance Levels: *.05 **.01

Table B10 Climate Division Effects: Division 85

Season	I	II	III	IV	V	VI
RPS Temp	-0.195**	-0.184**	0.009	0.093**	-0.165**	-0.021
BS Temp	0.138**	0.077**	-0.101**	-0.121**	0.080**	0.111**
RPS Precip	-0.068*	-0.059*	-0.049	-0.031	0.088**	-0.045
BS Precip	0.023	0.011	0.028	0.022	0.008	0.010
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.185**	0.220**	0.154**	-0.089**	-0.107**	-0.229**
BS Temp	0.018	-0.091**	-0.013	0.132**	0.112**	0.137**
RPS Precip	0.057**	0.037	-0.242**	-0.062*	0.263**	-0.022
BS Precip	0.017**	0.034**	0.032**	0.013*	-0.011	-0.010

Significance Levels: *.05 **.01

Table B11 Climate Division Effects: Division 86

Season	I	II	III	IV	V	VI
RPS Temp	-0.081*	-0.176**	0.020	-0.023	-0.106**	-0.111**
BS Temp	0.160**	0.145**	-0.042*	-0.091**	0.139**	0.142**
RPS Precip	-0.072*	-0.013	0.006	-0.073*	0.187**	-0.047*
BS Precip	0.020	0.008	0.016	0.010	0.003	0.006
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.153**	0.341**	0.010	-0.029	0.006	-0.171**
BS Temp	0.085**	-0.042**	0.045**	0.153**	0.122**	0.156**
RPS Precip	0.187**	0.111**	-0.166**	-0.047	0.212**	0.029
BS Precip	0.039**	0.100**	0.083**	0.016	-0.018	-0.010

Significance Levels: *.05 **.01

Table B12 Climate Division Effects: Division 87

Season	I	II	III	IV	V	VI
RPS Temp	-0.084*	-0.124**	0.035	0.004	-0.072*	-0.146**
BS Temp	0.156**	0.129**	-0.022	-0.080**	0.133**	0.150**
RPS Precip	0.076*	-0.062*	-0.093**	-0.140**	0.079**	-0.079**
BS Precip	0.022	0.004	0.011	0.007	-0.002	-0.018**
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.046**	0.313	0.371**	-0.016	0.000	-0.060*
BS Temp	0.074**	-0.050**	0.063**	0.151**	0.118**	0.158**
RPS Precip	0.013	0.029	-0.203**	-0.170**	0.160**	0.131**
BS Precip	0.030**	0.153**	0.085**	0.021**	-0.020	-0.010

Significance Levels: *.05 **.01

Table B13 Climate Division Effects: Division 88

Season	**I**	**II**	**III**	**IV**	**V**	**VI**
RPS Temp	-0.010	-0.172**	-0.166**	-0.199**	-0.174**	-0.126**
BS Temp	0.147**	0.106**	0.008	-0.031*	0.120**	0.150**
RPS Precip	0.081*	0.047	0.010	-0.131**	0.188**	-0.086**
BS Precip	0.015	-0.010	0.006	0.001	-0.006	-0.083**
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.044	0.199**	0.157**	-0.036	-0.057*	-0.011
BS Temp	0.069**	0.001	0.134**	0.156**	0.116**	0.155**
RPS Precip	0.065*	0.227**	-0.225**	0.007	0.210**	-0.021
BS Precip	0.012**	0.096**	0.039**	0.010	-0.022**	-0.011

Significance Levels: *.05 **.01

Table B14 Climate Division Effects: Division 89

Season	**I**	**II**	**III**	**IV**	**V**	**VI**
RPS Temp	-0.084*	-0.149**	-0.064*	-0.104*	-0.046	-0.205**
BS Temp	0.146**	0.120**	0.033	-0.002	0.099**	0.148**
RPS Precip	0.127**	-0.054*	-0.040	-0.081*	0.081**	-0.101**
BS Precip	0.013	-0.010	0.006	-0.001	-0.024**	-0.125**
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.013	0.249**	0.047	0.029	0.055*	0.065*
BS Temp	0.058**	0.032**	0.184**	0.163**	0.118**	0.148**
RPS Precip	-0.002	0.048	-0.352**	0.011	0.205**	-0.023
BS Precip	0.009	0.066**	0.026**	0.003	-0.027**	-0.017

Significance Levels: *.05 **.01

Table B15 Climate Division Effects: Division 90

Season	**I**	**II**	**III**	**IV**	**V**	**VI**
RPS Temp	-0.003	-0.075*	0.091*	0.121**	-0.064*	-0.059*
BS Temp	0.105**	-0.008	-0.148**	-0.187**	0.016*	0.042**
RPS Precip	-0.023	0.045	-0.094**	-0.018	0.140**	0.101**
BS Precip	0.019	0.002	0.020	0.011	0.005	0.005
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.140**	0.394**	0.333**	-0.089**	0.114**	-0.016
BS Temp	-0.057**	-0.197**	-0.119**	0.068**	0.094**	0.117**
RPS Precip	0.247**	0.222**	-0.288**	-0.001	0.316**	0.080*
BS Precip	0.015**	0.071**	0.043**	0.017**	-0.011	-0.010

Significance Levels: *.05 **.01

Table B16 Climate Division Effects: Division 91

Season	I	II	III	IV	V	VI
RPS Temp	-0.031	-0.139**	-0.131**	-0.073*	-0.147**	-0.162**
BS Temp	0.147**	0.072**	0.005	-0.016	0.100**	0.151**
RPS Precip	0.025	-0.009	-0.039	-0.025	0.139**	0.109**
BS Precip	0.014	-0.014	0.009	-0.004	0.005	-0.021*
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.005	0.227**	0.238**	-0.070*	-0.102**	-0.007
BS Temp	0.068**	0.029*	0.122**	0.154**	0.124**	0.157**
RPS Precip	0.045	0.174**	-0.245**	0.102**	0.115**	0.048
BS Precip	0.007	0.036*	0.003	0.004	-0.014	-0.011

Significance Levels: *.05 **.01

Table B17 Climate Division Effects: Division 92

Season	I	II	III	IV	V	VI
RPS Temp	-0.068*	-0.196**	-0.175**	-0.162**	-0.011	-0.083**
BS Temp	0.154**	0.103**	0.047*	0.024	0.121**	0.168**
RPS Precip	0.028	-0.062*	-0.089**	0.044	0.147**	0.054*
BS Precip	0.016	-0.007	0.003	-0.007	0.006	-0.037*
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.030	0.217**	0.229**	-0.223**	-0.148**	-0.111**
BS Temp	0.094**	0.101**	0.177**	0.165**	0.124**	0.162**
RPS Precip	0.095**	0.171**	-0.300**	0.042	-0.036	-0.120**
BS Precip	0.006	0.024*	-0.001	0.003	-0.015*	-0.011

Significance Levels: *.05 **.01

Table B18 Climate Division Effects: Division 93

Season	I	II	III	IV	V	VI
RPS Temp	0.024	-0.158**	-0.117**	-0.080*	-0.131**	-0.009
BS Temp	0.132**	0.082**	0.019	0.010	0.081**	0.127**
RPS Precip	-0.021	0.048	-0.075**	0.027	0.090**	-0.053*
BS Precip	0.013	-0.013	-0.001	-0.012	0.005	0.001
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.020	0.216**	0.135**	-0.067*	0.058*	0.000
BS Temp	0.080**	0.090**	0.144**	0.153**	0.132**	0.159**
RPS Precip	0.095**	0.217**	-0.295**	0.154**	0.074*	-0.155**
BS Precip	0.005	0.012	0.001	0.006	-0.011	-0.006

Significance Levels: *.05 **.01

Table B19 Climate Division Effects: Division 94

Season	I	II	III	IV	V	VI
RPS Temp	-0.0568**	0.008	-0.224**	0.032	-0.035	0.018
BS Temp	0.054**	-0.050*	-0.105**	-0.140**	-0.030*	-0.021
RPS Precip	0.085**	0.051*	-0.074*	0.137**	0.192**	0.118**
BS Precip	0.015	-0.013	0.013	-0.001	0.003	0.005
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.119**	0.341**	0.118**	0.043	0.113**	-0.125**
BS Temp	-0.105**	-0.172**	-0.102**	0.032*	0.085**	0.086**
RPS Precip	0.095**	0.135**	-0.195**	0.104**	0.177**	-0.057*
BS Precip	0.006	0.017**	0.008	0.017	-0.004	0.000

Significance Levels: *.05 **.01

Table B20 Climate Division Effects: Division 95

Season	I	II	III	IV	V	VI
RPS Temp	0.003	0.048	0.187**	0.248**	0.081**	0.130**
BS Temp	-0.035*	-0.143**	-0.225**	-0.267**	-0.124**	-0.122**
RPS Precip	-0.019	0.010	-0.134**	0.193**	0.087**	0.050*
BS Precip	0.024	0.002	0.024	0.012	0.004	0.005
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.229**	0.476**	0.460**	0.072*	-0.086**	-0.031
BS Temp	-0.238**	-0.346**	-0.253**	-0.093**	0.021*	-0.014
RPS Precip	0.094**	0.017	-0.244**	0.084*	0.173**	-0.061*
BS Precip	0.005	0.020**	0.016	0.027**	0.005	0.000

Significance Levels: *.05 **.01

Table B21 Climate Division Effects: Division 96

Season	I	II	III	IV	V	VI
RPS Temp	-0.099**	0.061*	0.132**	0.163**	0.077*	0.127**
BS Temp	-0.073**	-0.139**	-0.194**	-0.232**	-0.155**	-0.189**
RPS Precip	-0.043	0.032	-0.011	0.046	0.166**	-0.051*
BS Precip	0.029**	-0.002	0.016	0.012	0.002	0.004
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.256**	0.459**	0.441**	-0.029	0.018	-0.017
BS Temp	-0.255**	-0.328**	-0.250**	-0.187**	-0.058**	-0.072**
RPS Precip	0.145*	0.104**	-0.202**	0.046	0.023	-0.045
BS Precip	0.000	0.003	0.008	0.026**	0.024**	0.030**

Significance Levels: *.05 **.01

Table B22 Climate Division Effects: Division 97

Season	I	II	III	IV	V	VI
RPS Temp	-0.075*	-0.067*	0.109**	0.151**	-0.007	-0.018
BS Temp	0.019	-0.096**	-0.195**	-0.185**	-0.056**	-0.058**
RPS Precip	-0.016	0.024	0.090**	0.122**	0.116**	-0.002
BS Precip	0.027	0.011	0.024	0.021**	0.008	0.005
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.128**	0.317**	0.225**	-0.012	0.063*	-0.005
BS Temp	-0.132**	-0.185**	-0.131**	0.004	0.038**	0.021
RPS Precip	0.042	0.208**	-0.266**	-0.067*	0.193**	-0.159**
BS Precip	0.002	0.002	0.005	0.020**	0.007	0.013

Significance Levels: *.05 **.01

Table B23 Climate Division Effects: Division 98

Season	I	II	III	IV	V	VI
RPS Temp	-0.067*	0.057*	0.124**	0.122**	0.070*	0.202**
BS Temp	-0.056**	-0.109**	-0.168**	-0.207**	-0.136**	-0.189**
RPS Precip	0.066*	0.120**	0.012	-0.019	0.147**	0.052*
BS Precip	0.036**	0.004	0.011	0.014	0.003	0.003
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	0.226**	0.414**	0.425**	0.098**	-0.065*	0.021
BS Temp	-0.225**	-0.296**	-0.245**	-0.228**	-0.101**	-0.074**
RPS Precip	0.054*	0.043	-0.133**	0.070*	0.112**	-0.029
BS Precip	-0.005	-0.002	0.002	0.016	0.028**	0.034**

Significance Levels: *.05 **.01

Table B24 Climate Division Effects: Division 99

Season	I	II	III	IV	V	VI
RPS Temp	-0.163**	-0.227**	-0.095**	0.000	-0.110**	-0.109**
BS Temp	0.074**	0.068**	0.037*	0.081**	0.113**	0.134**
RPS Precip	-0.015	0.040	-0.196**	0.007	0.067**	0.062*
BS Precip	0.016	0.008	0.021	0.021	0.006	0.007
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.031**	0.110**	0.046	-0.064*	-0.014	-0.233**
BS Temp	0.104**	0.076**	0.122**	0.140**	0.097**	0.080**
RPS Precip	0.091**	0.001	-0.208**	-0.002	0.099**	-0.072*
BS Precip	0.003	0.003	-0.006	0.000	-0.004	-0.011

Significance Levels: *.05 **.01

Table B25 Climate Division Effects: Division 100

Season	I	II	III	IV	V	VI
RPS Temp	-0.037	-0.121**	0.045	0.024	-0.152**	-0.074**
BS Temp	0.028*	0.064**	0.092**	0.127**	0.123**	0.138**
RPS Precip	0.127**	-0.174**	-0.179**	-0.207**	0.111**	0.053**
BS Precip	-0.019	-0.013	-0.004	-0.002	0.003	0.006
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.023	-0.061*	0.029	-0.002	-0.086**	-0.136**
BS Temp	0.118**	0.109**	0.135**	0.121**	0.068**	0.042**
RPS Precip	0.042	0.058*	-0.151**	-0.101**	0.101**	-0.097**
BS Precip	0.003	0.006	0.000	0.001	-0.003	-0.027**

Significance Levels: *.05 **.01

Table B26 Climate Division Effects: Division 101

Season	I	II	III	IV	V	VI
RPS Temp	0.020	-0.023	0.068*	-0.010	0.023	-0.049*
BS Temp	0.034*	0.026	-0.005	0.017	0.038*	0.057**
RPS Precip	0.011	-0.004	-0.034	-0.158**	0.093**	-0.003
BS Precip	0.012	0.006	0.014	0.009	0.003	0.005
Season	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
RPS Temp	-0.016	0.070**	0.135**	-0.153**	-0.109**	-0.132**
BS Temp	0.047**	0.025*	0.048**	0.077**	0.047**	0.032*
RPS Precip	0.044	-0.051**	-0.051*	0.101**	0.097**	-0.003
BS Precip	0.000	0.001	-0.006	-0.002	-0.003	-0.006

Significance Levels: *.05 **.01

Appendix C Simulation Results Tables

Variable Notes:

Average: Average number of consumptive water used by a specific irrigation district in the June- July-August season from 1998 through 2003.

1 Month: Water consumption forecasted based on a one month lead time forecast (Acre/feet)

7 Month: Water consumption forecasted based on a seven month lead time forecast (Acre/feet)

13 Month: Water consumption forecasted based on a thirteen month lead time forecast (Acre/feet)

Diff: The difference between the forecasted water consumption amount and the average water consumption amount (Acre/feet)

Cost @ X: The number of diversions times the price per acre foot

($/acre-foot)

*Note: Negative values indicate that no water lease is anticipated

Table C.1 CRIT Simulation

CRIT	Average	1 Month	Diff	Cost @$210
1998	75,443	43898	-31545	-$6,624,395
1999	75,443	40774	-34669	-$7,280,427
2000	75,443	45685	-29758	-$6,249,281
2001	75,443	45606	-29837	-$6,265,873
2002	75,443	49086	-26357	-$5,534,945
2003	75,443	47639	-27804	-$5,838,781

CRIT	Average	7Month	Diff	Cost @ 120
1998	75,443	43955	-31488	-$3,778,516
1999	75,443	40827	-34616	-$4,153,879
2000	75,443	44213	-31230	-$3,747,586
2001	75,443	45665	-29778	-$3,573,379
2002	75,443	45645	-29798	-$3,575,803
2003	75,443	44299	-31144	-$3,737,250

CRIT	Average	13 Month	Diff	Cost @ 90
1998	75,443	44,013	-31,430	-$2,828,741
1999	75,443	41,938	-33,505	-$3,015,490
2000	75,443	50,298	-25,145	-$2,263,021
2001	75,443	42,353	-33,090	-$2,978,103
2002	75,443	47,376	-28,067	-$2,526,028
2003	75,443	43,577	-31,866	-$2,867,908

CRIT	Average	Perfect	Diff	Cost @$120
1998	75,443	84,575	9,132	$1,095,798
1999	75,443	84,269	8,826	$1,059,098
2000	75,443	89,654	14,211	$1,705,345
2001	75,443	91,479	16,036	$1,924,278
2002	75,443	90,544	15,101	$1,812,102
2003	75,443	92,588	17,145	$2,057,358

CRIT	Average	Last Year	Diff	Cost @120
1998	75,443	101,451	26,008	$3,120,960
1999	75,443	103,458	28,015	$3,361,800
2000	75,443	95,784	20,341	$2,440,920
2001	75,443	98,745	23,302	$2,796,240
2002	75,443	99,849	24,406	$2,928,720
2003	75,443	104,578	29,135	$3,496,200

CRIT	Average	3 Year	Diff	Cost @120
1998	75,443	110,451	35,008	$4,200,960
1999	75,443	98,745	23,302	$2,796,240
2000	75,443	85,456	10,013	$1,201,560
2001	75,443	104,510	29,067	$3,488,040
2002	75,443	102,111	26,668	$3,200,160
2003	75,443	94,578	19,135	$2,296,200

Table C.2 Wellton Simulation

WELL	Average	1 Month	Diff	Cost @$210
1998	46,535	35,487	-11,048	-$2,320,040
1999	46,535	30,254	-16,281	-$3,418,979
2000	46,535	30,296	-16,239	-$3,410,257
2001	46,535	28,574	-17,961	-$3,771,743
2002	46,535	36,479	-10,057	-$2,111,865
2003	46,535	30,187	-16,348	-$3,433,028

WELL	Average	7Month	Diff	Cost @ 120
1998	46,535	40,542	-5,993	-$71,9214
1999	46,535	37,416	-9,119	-$,1094,246
2000	46,535	26,579	-19,956	-$2,394,770
2001	46,535	30,126	-16,409	-$1,969,122
2002	46,535	32,459	-14,076	-$1,689,173
2003	46,535	36,241	-10,294	-$1,235,240

WELL	Average	13 Month	Diff	Cost @ 90
1998	46,535	35,451	-11,084	-$997,542
1999	46,535	36,579	-9,956	-$896,072
2000	46,535	37,891	-8,644	-$777,942
2001	46,535	29,841	-16,694	-$1,502,449
2002	46,535	27,485	-19,050	-$1,714,468
2003	46,535	24,581	-21,954	-$1,975,826

WELL	Average	Perfect	Diff	Cost @$120
1998	46,535	79,814	33,279	$399,3440
1999	46,535	65,422	18,887	$226,6386
2000	46,535	58,745	12,210	$146,5225
2001	46,535	48,754	2,219	$26,6318
2002	46,535	58,742	12,207	$146,4798
2003	46,535	101,210	54,675	$656,1030

WELL	Average	Last Year	Diff	Cost @120
1998	46,535	104,376	57,841	$6,940,860
1999	46,535	85,260	38,725	$4,647,041
2000	46,535	84,752	38,217	$4,586,040
2001	46,535	106,541	60,006	$7,200,720
2002	46,535	65,478	18,943	$2,273,160
2003	46,535	73,548	27,013	$3,241,560

WELL	Average	3 Year	Diff	Cost @120
1998	46,535	112,487	65,952	$7,914,240
1999	46,535	116,882	70,348	$8,441,700
2000	46,535	57,487	10,952	$1,314,240
2001	46,535	65,125	18,590	$2,230,800
2002	46,535	107,232	60,697	$7,283,676
2003	46,535	90,381	43,847	$5,261,585

Table C.3 Imperial Simulation

IID	Average	1 Month	Diff	Cost @$210
1998	355,611	226,548	-129,063	-$27,103,167
1999	355,611	253,495	-102,116	-$21,444,276
2000	355,611	149,651	-205,960	-$43,251,558
2001	355,611	247,986	-107,625	-$22,601,166
2002	355,611	250,364	-105,247	-$22,101,849
2003	355,611	232,934	-122,677	-$25,762,191

IID	Average	7Month	Diff	Cost @ 120
1998	355,611	226,843	-128,768	-$15,452,148
1999	355,611	253,825	-101,786	-$12,214,296
2000	355,611	214,225	-141,386	-$16,966,308
2001	355,611	248,309	-107,302	-$12,876,240
2002	355,611	232,811	-122,800	-$14,736,012
2003	355,611	216,603	-139,008	-$16,680,996

IID	Average	13 Month	Diff	Cost @ 90
1998	355,611	227,138	-128,473	-$11,562,561
1999	355,611	260,728	-94,884	-$8,539,515
2000	355,611	243,710	-111,901	-$10,071,126
2001	355,611	230,300	-125,311	-$11,277,963
2002	355,611	241,642	-113,969	-$10,257,228
2003	355,611	213,073	-142,538	-$12,828,420

IID	Average	Perfect	Diff	Cost @$120
1998	355,611	451,453	95,842	$11,500,985
1999	355,611	523,903	168,292	$20,194,992
2000	355,611	401,026	45,415	$5,449,742
2001	355,611	501,742	146,131	$17,535,714
2002	355,611	412,554	56,943	$6,833,160
2003	355,611	1,336,641	981,030	$117,723,600

IID	Average	Last Year	Diff	Cost @120
1998	355,611	547,865	192,254	$23,070,480
1999	355,611	501,254	145,643	$17,477,160
2000	355,611	601,451	245,840	$29,500,800
2001	355,611	458,956	103,345	$12,401,400
2002	355,611	487,621	132,010	$15,841,200
2003	355,611	512,456	156,845	$18,821,400

IID	Average	3 Year	Diff	Cost @120
1998	355,611	587,621	232,010	$27,841,200
1999	355,611	504,189	148,578	$17,829,360
2000	355,611	614,832	259,221	$31,106,520
2001	355,611	602,103	246,492	$29,579,040
2002	355,611	705,412	349,801	$41,976,120
2003	355,611	547,851	192,240	$23,068,800

Table C.4 Palo Verde Simulation

PV	Average	1 Month	Diff	Cost @$210
1998	116,350	94,214	-22,136	-$4,648,512
1999	116,350	84,759	-31,591	-$6,634,196
2000	116,350	75,242	-41,108	-$8,632,745
2001	116,350	90,063	-26,288	-$5,520,375
2002	116,350	93,259	-23,091	-$4,849,188
2003	116,350	91,761	-24,589	-$5,163,732

PV	Average	7Month	Diff	Cost @ 120
1998	116,350	56,221	-60,129	-$7,215,438
1999	116,350	67,004	-49,346	-$5,921,557
2000	116,350	84,357	-31,993	-$3,839,210
2001	116,350	90,180	-26,170	-$3,140,441
2002	116,350	86,720	-29,630	-$3,555,578
2003	116,350	85,327	-31,023	-$3,722,717

PV	Average	13 Month	Diff	Cost @ 90
1998	116,350	56,294	-60,056	-$5,404,997
1999	116,350	68,826	-47,524	-$4,277,184
2000	116,350	95,967	-20,383	-$1,834,484
2001	116,350	83,639	-32,711	-$2,943,960
2002	116,350	85,529	-30,821	-$2,773,881
2003	116,350	86,107	-30,243	-$2,721,836

PV	Average	Perfect	Diff	Cost @$120
1998	116,350	154,126	37,776	$4,533,078
1999	116,350	129,875	13,525	$1,622,953
2000	116,350	136,525	20,175	$2,420,942
2001	116,350	158,652	42,302	$5,076,241
2002	116,350	139,459	23,109	$2,773,038
2003	116,350	124,559	8,209	$985,129

PV	Average	Last Year	Diff	Cost @120
1998	116,350	189,541	73,191	$8,782,920
1999	116,350	145,741	29,391	$3,526,920
2000	116,350	165,847	49,497	$5,939,640
2001	116,350	135,890	19,540	$2,344,800
2002	116,350	157,824	41,474	$4,976,880
2003	116,350	146,982	30,632	$3,675,840

PV	Average	3 Year	Diff	Cost @120
1998	116,350	181,664	65,314	$7,837,632
1999	116,350	227,846	111,496	$13,379,460
2000	116,350	159,119	42,769	$5,132,292
2001	116,350	201,487	85,137	$10,216,440
2002	116,350	154,265	37,915	$4,549,800
2003	116,350	186,465	70,115	$8,413,836

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