AN OPERATIONS MODEL FOR TEMPERATURE MANAGEMENT OF THE TRUCKEE RIVER

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Abstract: Warm summer stream temperatures in the Truckee River pose a threat to threatened and endangered fish. Through the Water Quality Settlement Agreement (WQSA), the federal government and local agencies have agreed to purchase water rights to be used to help manage water quality in the river. In particular, stream temperature is one of the indicators used to measure water quality. The acquired water will be stored in upstream reservoirs and released to improve downstream water quality. A prototype decision support system (DSS) has been developed to predict when temperature violations will occur, and to make decisions about when and how much to increase flows using the stored WQSA water. The DSS implements an empirical model to predict maximum daily Truckee River water temperatures in June, July and August given predicted maximum daily air temperature and modeled average daily flow. The empirical model is created using a step-wise linear regression selection process using 1993 and 1994 data. The model is validated using historic data and shown to work in a predictive mode. The predictive model includes a prediction confidence interval to quantify the uncertainty. This research, funded by the U.S. Bureau of Reclamation (USBR) uses a prototype set of operational policies in a DSS developed in RiverWare, and develops additional rules that calculate higher releases using stored WQSA water if the predicted water temperature at Reno is above the target value. Releases are determined from the temperature prediction relationship and a user-specified confidence level for meeting the target. Strategies are developed to effectively use the WQSA water throughout the season. These strategies are based on seasonal climate forecasts, the temperature of the river over the previous few days, and the amount of available WQSA water. The DSS model is tested using historical inflows for dry hydrology from 1988 to 1994. Various scenarios are explored that show the effect of changing the confidence level and using seasonal strategies. Results show that there is not enough water to avoid all temperature violations in a drought, however most of the early violations can be avoided with a high degree of certainty.

INTRODUCTION

Low flows threaten fish by deteriorating habitat and/or water quality. One of the most common summer water quality problems associated with low flows is high stream temperatures—low flows warm up more rapidly than higher flows. High stream temperatures reduce cold water fish populations by inhibiting growth and by killing fish at extremely high temperatures. For this reason, the impact of low flows and high stream temperatures on fish is an issue in many operations studies and National Environmental Policy Act (NEPA) Environmental Impact Statement (EIS) analyses.

Management of water temperature by controlling flow in a large, multi-purpose, multi-reservoir basin can effectively be accomplished with the assistance of a model-based decision support system (DSS) that can predict temperature and incorporate temperature objectives into daily operations objectives. A practical DSS for daily use has the following functional requirements:

1. A water temperature prediction model that is quick, accurate, and spatially and temporally consistent with the operations model.
2. Quantification of confidence associated with the temperature prediction.
3. Operations rules that use the stream temperature prediction and its confidence level to release water that benefits fish.
4. Integration of other operating releases.
5. Seasonal strategies incorporated in the operations to trade off meeting one day's targets with the ability to meet seasonal needs.

Two types of models have been developed in the past to predict stream temperatures: empirical or regression models and physical process models. Regression models use data to create relationships to quantify and predict stream temperatures at various time scales. In contrast, physical process models attempt to model the underlying processes that affect stream temperature such as conduction, radiation, advection, and dispersion. Although a mechanistic temperature model could, in theory, give very accurate results, this type of model requires numerous detailed input data, is computationally intensive and is, therefore, difficult to incorporate in a river and reservoir operations model. Empirical models can be computationally less intensive, therefore quick to implement and validate. With regression models it is possible to statistically quantify the uncertainty.

This paper describes a DSS that meets the above requirements and is organized as follows: First we describe the background of the Truckee River and develop and verify an empirically based predictive stream temperature model. Next, we develop confidence levels for the predictive model using standard statistical techniques. Third, we create operations rules to release water to try to meet stream temperature targets with a desired level of confidence. We then modify the rules to incorporate long-term climate forecasts and information about the previous day's stream temperature. Finally, we present and discuss the results.

TRUCKEE RIVER BACKGROUND

The methodology developed is applied to the Truckee River in California and Nevada. The Truckee River flows 187 km from Lake Tahoe in California's Sierra Nevada Mountains through an arid desert before terminating in Nevada's Lake Pyramid. The upstream reservoirs, shown in Figure 1, are operated to meet the Floriston Rates, a legal flow target measured at the Farad Gage near the California and Nevada border. The flow target, which dictates many of the release decisions in the basin, varies between 300-500 cfs depending on the time of year and the reservoir levels. At certain times of the year, river flows are lower than natural flows because water is stored in reservoirs and/or diverted for irrigation, municipal, and industrial use. During the summer months the low flows result in temperatures in the lower river that are too warm for endangered and threatened cold water fish. In accordance with the Water Quality Settlement Agreement (WQSA, 1996), the federal and local government will purchase water rights that will be used to improve the water quality of the Truckee River. The water acquired by the WQSA will be stored in upstream reservoirs as Water Quality Credit Water (WQCW) and released as necessary to mitigate downstream water quality problems. This study aims to improve the stream temperature at Reno. Below Reno, wastewater effluent and irrigation return flows enter the river, making accurate temperature predictions more complex and uncertain.

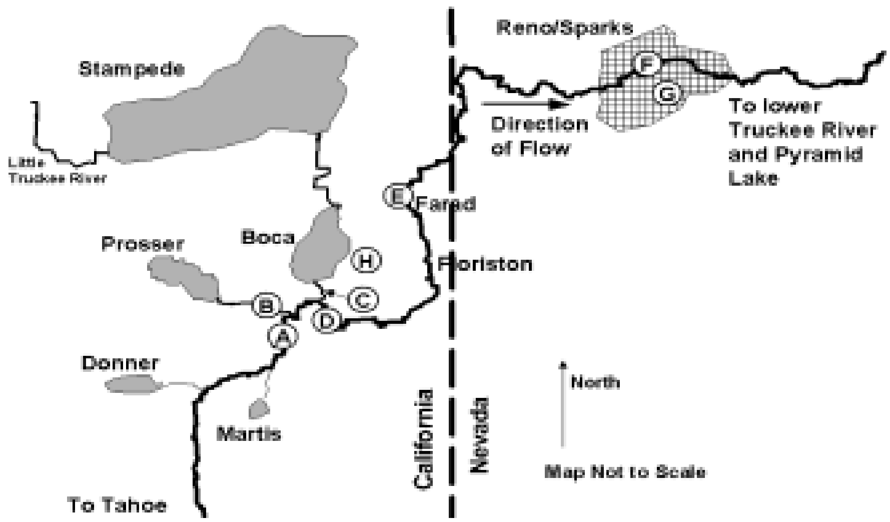

Figure 1: Study section

Fish tolerance levels: Stream temperature targets for fish are the maximum water temperature fish can tolerate for a given duration. The levels used in this paper are based on a summary of Nevada standards given by Brock and Caupp (1996) in which the maximum temperature for juvenile Lahontan cutthroat trout in summer is 24 ºC. Bender (2001) suggested modifying the targets to include four-day maximum limits and allowable one-day maximum temperatures. The resulting targets, shown in Table 1, are realistic, however not official. If the temperature on any given day occurs for more than the specified number of days, the fish are adversely affected. In this paper, that day is defined as a *violation.*

Table 1: Truckee River target temperatures

Target (ºC)	Description	Time Period
$T \leq 22$	Preferred Maximum	> 4days
$22 < T \leq 23$	Chronic Maximum	≤ 4days
$23 < T \leq 24$	Acute Maximum	≤ 1day
$24 < T$	Absolute Maximum	0 days

Baseline operations model using RiverWare: The USBR is currently creating a daily time-step rule-based model of the Truckee and Carson Rivers using RiverWare, a general purpose river and reservoir operations policy modeling software (Zagona et al, 2001). The rules attempt to model the current operations in the basin but are still under development; currently they do not represent all of the policies in the basin. We refer to this set of rules as the *baseline operations*. The baseline operations differ from both historical and current operations; therefore, the model cannot be calibrated or verified against historical observations.

STREAM TEMPERATURE MODEL

The goal of regression models is to fit a set of data with an equation, the simplest being a linear equation. The linear regression model takes the form:

$$\hat{T} = a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_n x_n \qquad \textbf{Equation 1}$$

where $\hat{T}$ is the stream temperature, a_0, a_1, a_2, ..., a_n are coefficients, and x_1,x_2, ..., x_n are independent predictors. The available data on the Truckee River include flows, stream temperatures, and air temperatures at various timesteps and locations. Most of the temperature data was collected after 1993. The most appropriate years to use in the empirical relationships are 1993 and 1994 since these were dry years with low flows and high river temperatures. In addition, only data from June, July, and August is used. September is not included because the river cools in the latter half of the month. We chose to look at data for which the flow at Farad is less than 500 cfs because at flows above this threshold, there is rarely a temperature problem in the study reach.

Figure 2 shows scatter plots of the candidate predictors and the maximum daily stream temperature at Reno along with a locally weighted regression fit (Loader, 1999).

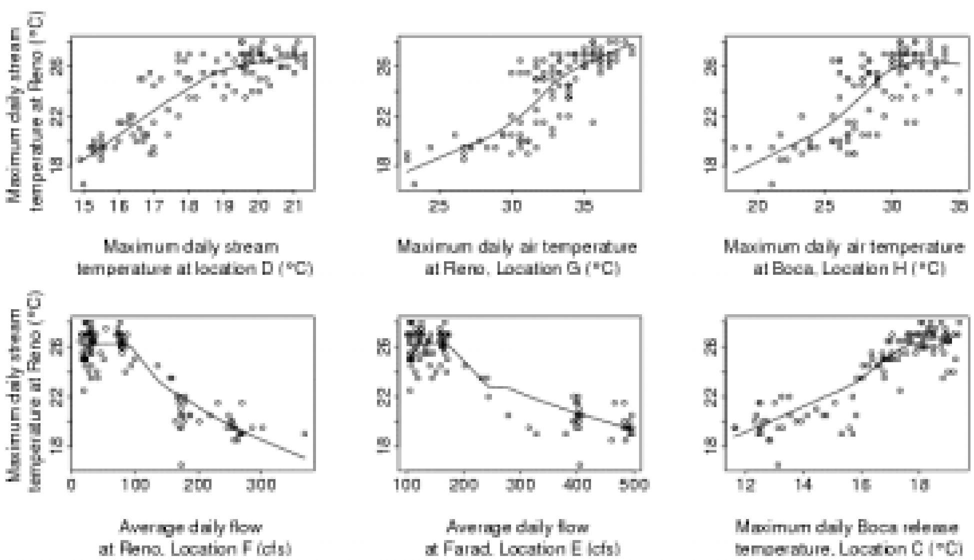

Figure 2: Data used in regression relationship

Since it appears that all of these predictors are related to Reno water temperature, a stepwise regression procedure is used to select the best subset of predictors from the candidate predictors. The stepwise procedure selects the subset of predictors optimizing on one the following indicator statistics: Mallow's Cp, Akaike's Information Criteria (AIC), R^2, or adjusted R^2. The AIC and Cp statistics are widely used because they try to achieve a good compromise between the desire to explain as much variance in the predictor variable as possible (minimize bias) by including all relevant predictor variables, and to minimize the variance of the resulting estimates (minimize the standard error) by keeping the number of coefficients small. The stepwise regression procedure fits all possible combinations of predictors and selects the model that results in the most optimal indicator statistic. We performed a stepwise procedure on the set of predictor variables listed above, optimizing on AIC. The stepwise procedure indicates that air temperature at Reno and flow at Farad are the significant predictors. A linear regression using the predictors selected has the following equation:

$$\hat{T} = a_0 + a_1 T_{Air} + a_2 Q \qquad \textbf{Equation 2}$$

where T_{Air} is the air temperature at Reno and Q is the flow at Farad. The regression coefficients are a_0 = 14.4 ºC, a_1 = 0.40, and a_2 = -0.014 ºC/cfs. The adjusted R^2 for this regression is 0.915. Figure 3 shows the estimated values of maximum daily Truckee River temperature at Reno from the regression equation plotted against the historical observations.

A local non-linear regression model (Loader, 1999) was also fit to the data using the predictors selected in the linear stepwise procedure. The local non-linear regression R^2 is very similar to the R^2 found from the linear model. Because the linear model is simpler and allows for easy uncertainty computations, we used the linear model. For other basins or predictors, a non-linear local regression fit may produce a reasonable fit.

Model Diagnostics: To investigate the performance of the regression model, we looked at the following diagnostics: normality of the residuals, auto correlation of the residuals, and a cross validation of the data. Linear regression theory assumes residuals are normally distributed and symmetric about the mean. To formally test for normality, a correlation is computed between the residual and normal quantiles. For the distribution to be normal, the correlation must be greater than or equal to the 95% confidence level, critical probability plot correlation coefficient from Helsel and Hirsch (1992). The correlation for our data is 0.987 and the critical value for a 95% confidence level and 108 observations is 0.987. Therefore, the residuals are significantly normal. One of the assumptions of linear regression theory is that the residuals are not auto-correlated. An analysis of the auto-correlation shows that there is some serial correlation between the residuals at lag 1 but shows no clear trends. Finally, a cross validation technique is used in which one historical observation is dropped from the fitting process and is predicted using the regression fit based on the remaining observations. This is repeated for all observations. The R^2 value between the cross-validated estimates and observed values is 0.91, which is quite good. This further shows that the relationship fits the data well.

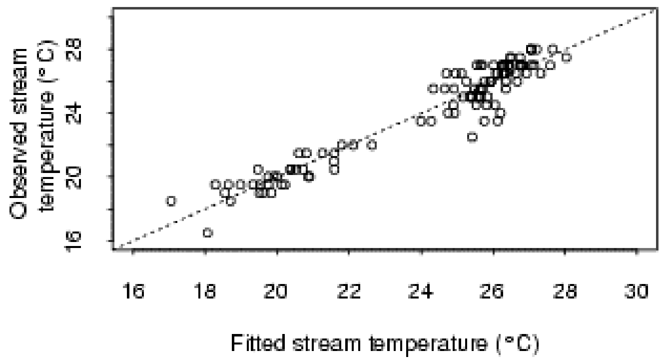

Figure 3: Estimated versus observed daily maximum stream temperature for the Truckee River at Reno, NV. Dotted line represents best fit.

Model Verification: An empirically developed multiple linear regression model may fit the data used to estimate the regression coefficients very well, but its ability to predict new data is not certain. We validate the model using observations not used in fitting the regression to assess the ability of the model to predict future events. Figure 4 shows the predicted and observed maximum daily stream temperature at Reno for June, July, and August of 1991. The predicted temperatures are from Equation 2.

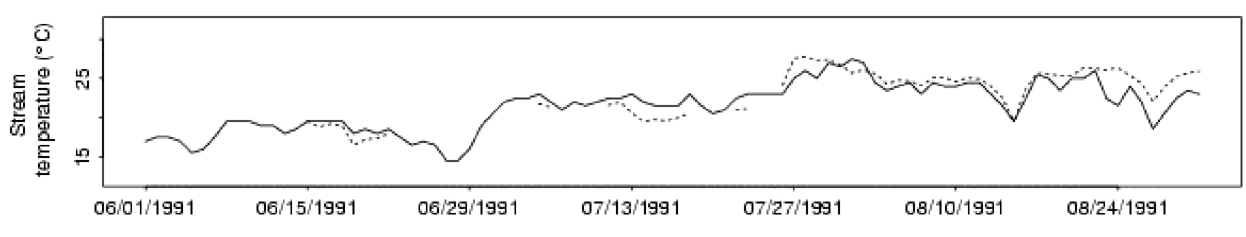

Figure 4: June-August 1991, validation of maximum daily stream temperatures

Missing predictions indicate that the Farad flow was greater than 500 cfs. The R^2 value for this validation process, 0.74, is lower than the fitting procedure, which is consistent with linear regression theory. Figure 3 shows that there are two regions in the fitting procedure, the range above 23ºC has more scatter than the range below 23ºC. In other words, the regression is better at explaining variance below 23ºC than above. As a result, the skill in predicting temperatures above 23ºC is not as good.

Uncertainty of Predicted Temperatures: To quantify the uncertainty of the regression, Helsel and Hirsch (1992, p. 300) define the *confidence interval* as the range (+/- the mean) of values in which the mean of estimates by regression will lie. For example, the 95% confidence interval indicates that 95% of the time, the mean estimated response variable will be within the interval. A similar concept called the *prediction interval* is used in a predictive mode. The prediction interval is defined as "the confidence interval for prediction of an estimate of an individual response variable." For example, the 95% prediction interval indicates that 95% of the time the predicted value will be within the interval. Linear regression theory provides the upper prediction interval to be approximated by (Helsel and Hirsch 1992, p. 300):

$$\text{Prediction Interval} = \hat{y} + t(\alpha, n-p)\sigma \qquad \textbf{Equation 3}$$

where $t(\alpha, n-p)$ is the quantile given by the 100(α) percentile on the student's t-distribution having n-p degrees of freedom (Ang and Tang, 1975, p. 237).

At large degrees of freedom, (n-p), the students t-distribution is identical to a Gaussian distribution. The desired confidence level is 1-α and the data has a standard deviation σ. There are n observations used to create the regression and p explanatory variables plus one (for the intercept term). This means that with 100(α) percent confidence, Equation 3 is the upper limit for the predicted value. Figure 5 shows the regression line from Equation 2 and the 95% confidence upper prediction interval line. The upper prediction interval is approximately 1.5ºC from the dotted, best fit line. Lowering the prediction confidence below 95% would move the upper prediction interval closer to the fitted regression line (i.e. the dotted line).

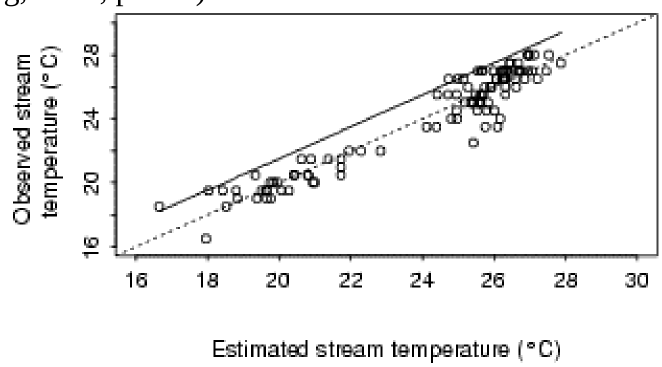

Figure 5: Estimated versus observed daily maximum stream temperature for the Truckee River at Reno, NV with 95% prediction interval upper limit

Prediction Confidence Distance: As the stream temperature model in Equation 2 includes flow as a predictor, we can release additional water to cool stream temperatures. The operations approach is as follows: determine reservoir releases based on baseline operating policies and predict the stream temperature using Equation 2. If the predicted stream temperature is above the target, release additional water to meet a target temperature. The regression and the prediction upper interval can be used to determine a strategy to determine how much additional water to release.

Using the regression model, Equation 2, we predict a stream temperature, and its associated Gaussian distribution denoted by curve A. This is too warm and may adversely affect fish. By releasing more water, we can shift the distribution to the left. If the expected value of the distribution is shifted to the target temperature, T_{Target}, as shown by curve B, the probability of exceeding that target is 0.5. Shifting the distribution to the left of the target temperature, a distance defined as PCD, gives a specified probability of exceeding the target temperature. Curve C shows the distribution that results by shifting the distribution to $T_{Necessary}$, which is the target minus the PCD such that the distribution gives 0.05 probability of exceeding T_{Target}. The PCD is defined as:

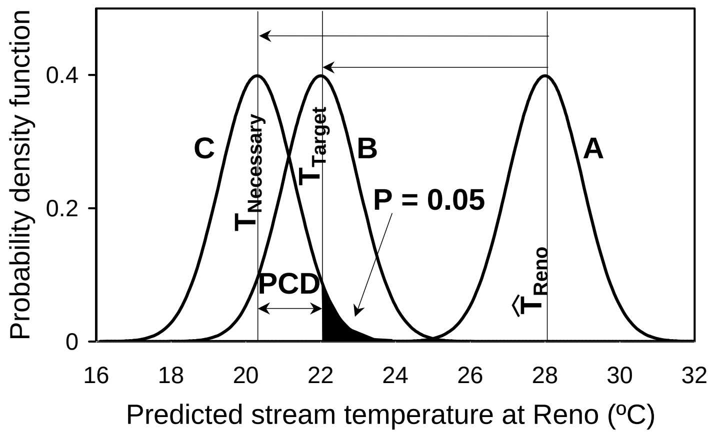

Figure 6: Temperature reduction to meet desired exceedance probability

$$\mathrm{PCD} = t(\alpha, n-p)\sigma \qquad \textbf{Equation 4}$$

The empirical regression formula to predict stream temperature from flow and air temperature, Equation 2, is used to determine how much additional water is required to lower the temperature such that the probability of exceeding the target is as specified. Evaluating Equation 2 with $T_{Necessary}$ as $\hat{T}$ and rearranging to solve for Q, we get the required flow at Farad:

$$Q_{\text{Required}} = \frac{T_{\text{Necessary}} - a_1 T_{Air} - a_0}{a_2} \qquad \textbf{Equation 5}$$

Subtracting Equation 2 from Equation 5 and rearranging, we get the additional flow required:

$$\left(Q_{\text{Required}} - Q\right) = \frac{\hat{T} - T_{\text{Necessary}}}{-a_2} \qquad \textbf{Equation 6}$$

To generalize, we can also define $T_{Necessary}$ as in Figure 6:

$$T_{\text{Necessary}} = T_{\text{Target}} - PCD \qquad \textbf{Equation 7}$$

We can replace $T_{Necessary}$ in Equation 6 with Equation 7 to get:

$$\Delta Q = \frac{\hat{T} - T_{\text{Target}} + PCD}{-a_2} \qquad \textbf{Equation 8}$$

A lookup table was developed for each target temperature for use in the decision support system. For a target temperature, the table has the initial predicted temperature on one axis and the probability of exceedance on the other axis. The values in the table are the additional flow necessary to reduce the temperature to the target as calculated by Equation 8. Table 2 shows the additional flows needed to reach a target temperature of 22 ºC.

The table works as follows. The water temperature at Reno is predicted using Equation 2. This value is found in the first column, and the additional flow is found in the desired probability of exceedance column. Linear interpolation can be performed between rows if necessary.

Table 2: Additional flow required at Farad to reduce maximum daily river temperature to a target of 22ºC

		Probability of Exceedance						
		0.05	0.10	0.20	0.30	0.40	0.50	0.60
Predicted Temperature (ºC)	22	114	89	58	36	17	0	-17
	23	191	166	135	113	94	77	60
	24	268	243	212	190	171	154	137
	25	345	320	289	267	249	231	214
	26	422	397	366	344	326	308	291
Values in table are additional flow required (cfs)								

DSS DEVELOPMENT

The rules execute the baseline operating policy to determine a flow at Farad. Now, the stream temperature can be predicted and if it is too high, additional flow is released to meet the determined target with the desired level of confidence. Water resources managers have a number of variables that they can use to try different policy and release patterns as follows:

1. Probability of exceedance (confidence level)
2. Fish targets
3. Climate forecasts (probability of above normal occurrence)
4. Average volume of WQCW in storage

Varying the probability of exceedances is a useful variable to determine how much water to release. Water managers might decide that on a given day they must meet the temperature target with a high degree of certainty and will set the probability of exceedance very low. Or, they might decide they only have minimal confidence in the prediction and will, therefore, not release as much water. Water managers can use additional information to determine the target temperature. This allows water managers to make use of information about the previous day's stream temperature and the climate forecasts to try to avoid stream temperature violations. The following sections describe the logic used to determine the stream temperature target.

Seasonal Strategies: To improve the use of the WQCW, seasonal strategies can be developed. The seasonal strategies act to modify the stream target temperature to allow for slightly higher temperatures under certain conditions. The strategy uses the concept of degree-days. Each day of the simulation, a variable called "degree-days" is calculated as the number of degrees above the target for that given day. Degree-days are summed over time; each day has a cumulative sum, which is the current day's degree-days plus the previous day's cumulative degree-days. The degree-days are reset to zero when the stream temperature is less than or equal to the target. The calculation of degree-days is a useful way to keep track of variations in temperature over time. We can use this policy to determine the severity of a temperature violation. If the temperature does not exceed the standard by very much and there were cold temperatures the day before, additional water is not necessary. However, if the standard has been violated for the last four days, a large release may be necessary to reset the system to zero degree-days.

Incorporating seasonal climate forecasts into WQCW release rules: To effectively conserve water throughout a summer, we use a forecast from the Climate Prediction Center of the

National Oceanic and Atmospheric Administration (Climate, 2001) to modify temperature targets. The CPC produces forecasts for both 30 and 90-day periods in the middle of the previous month for the next period and for each subsequent period. The climate forecasts give the probability that the temperature will be above, near, or below normal. For an average year, the following probabilities are predicted: 33.3% above normal, 33.3% near normal, and 33.3% below normal. This paper uses the probability that the temperature will be above normal as the indicator variable. The anomaly probability can be read off the prediction map published by the CPC or in the absence of a map, estimates of the probability anomaly may be provided from other sources.

Because we know the WQCW volume stored at any given time, we can create a variable called *Storage and Forecast Factor* (SAFF) that combines the available water and the climate forecast.

$$SAFF = \frac{\text{Volume of available WQCW}}{\text{Probability of above normal occurance}} \qquad \textbf{Equation 9}$$

During operations, we will calculate the actual SAFF for each day. A low SAFF indicates little water is available and hot weather is predicted. A high SAFF indicates plenty of WQCW is available and cool weather is forecasted. This variable is useful because it allows the quantification of available water and climate forecast.

It is necessary to be conservative in terms of water use in the beginning of the season no matter what scenario is used. If the actual temperature does not follow the long-term forecasts, it is critical to ensure water is still available to reduce water temperatures. In the middle or end of the season, if the SAFF is above average, we do not need to conserve water; any temperature violation can be eliminated. If the SAFF is below average, we must conserve as much water as possible, only releasing when absolutely necessary to meet the targets. Depending on the month, the predicted river temperature, the SAFF and the number of accumulated degree-days, a different target temperature is used in the DSS. Table 3 shows the logic to select the target. $\hat{T}$ is the predicted maximum daily river temperature at Reno and DD is the degree-days from the previous day. The actual targets are found in Table 1.

Table 3: Temperature target determination

	June	July		August	
		Above average SAFF	Below average SAFF	Above average SAFF	Below average SAFF
$\hat{T}$ >25 ºC and DD ≤ 4	Chronic	Chronic	Chronic	Preferred	Chronic
$\hat{T}$ > 25 ºC and DD > 4	Preferred	Preferred	Preferred	Preferred	Preferred
24 ºC ≤ $\hat{T}$ ≤ 25 ºC and 1 ≤ DD < 4	Chronic	Preferred	Chronic	Preferred	Preferred
24 ºC ≤ $\hat{T}$ ≤ 25 ºC and DD < 1	Acute	Chronic	Acute	Preferred	Chronic
24 ºC ≤ $\hat{T}$ ≤ 25 ºC and DD > 4	Preferred	Preferred	Preferred	Preferred	Preferred
22 ºC ≤ $\hat{T}$ ≤ 24 ºC and DD < 4	Chronic	Preferred	Chronic	Preferred	Chronic
22 ºC ≤ $\hat{T}$ ≤ 24 ºC and DD ≤ 4	Preferred	Preferred	Preferred	Preferred	Preferred

RESULTS

We applied the DSS to the period from 1980-1997. Of those years, 1988-1994 were dry years; the flow target was not always met during the summer. The results presented cannot be compared to observed river temperatures because the policies modeled in the DSS are not comparable to historic operations. The baseline policies in the DSS reflect the current stage of development of the policy rules by the USBR. These rules reflect most of the legal policies, but omit some policies and operations that influence releases like reservoir maintenance, operating errors, or human judgment. We define scenarios simulated by the DSS runs with a particular set of input values and operating policies. Table 4 shows the scenarios that are investigated.

Table 4: DSS scenarios

Scenario	Description
1	Baseline USBR operations policy: ▪ WQCW storage and spill only.
2	Operations with: ▪ WQCW storage and spill ▪ WQCW releases to meet stream temperature target of 22º C ▪ Probability of stream temperature exceedance = **0.1** ▪ No seasonal strategies
3	Operations with: ▪ WQCW storage and spill ▪ WQCW releases to meet stream temperature target of 22º C ▪ Probability of stream temperature exceedance = **0.3** ▪ No seasonal strategies
4	Operations with: ▪ WQCW storage and spill ▪ WQCW releases to meet target calculated in Table 3 ▪ Probability of stream temperature exceedance = **0.3** ▪ Seasonal strategies that include degree-days and climate forecast

We present results from 1994 and the total volume of WQCW used from 1988-1994. Results presented for each run include the maximum daily river temperature at Reno, the number of violations for each scenario, and the amount of water that is used in each scenario. Figure 7 shows the maximum daily stream temperature at Reno for each scenario for 1994. Having a low probability of exceedance in scenario 2, leads to much lower stream temperatures, but, all of the water is used by the end of July. Using a higher probability of exceedance, scenario 3, water lasts through the middle of August. Finally, changing the target based on the climate forecast and the previous day's stream temperature, in scenario 4, leads to higher temperatures but no additional violations with enough water to last until the end of the season.

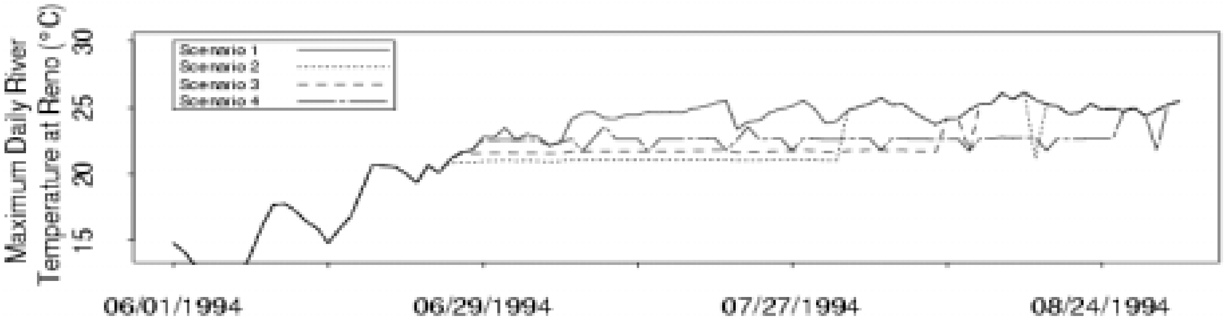

Figure 7: Maximum daily river temperature at Reno, 1994

In addition, it is necessary to look at the number of violations and the volume of water released. To have a valid comparison, we will look at the results from 1988-1994 as shown in Table 5. The number of violations decreases as we increase the probability of exceedance. In addition, using information about the previous day's stream temperature and climate forecast in scenario 4 decreases the number of violations. By effectively managing the water it is possible to reduce the number of violations without using more water.

Table 5: Violations and WQCW released (1988-1994)

	Number of Violation (days)	WQCW Released (acre-feet)
Scenario 1	216	23000 (spill)
Scenario 2	117	63000
Scenario 3	94	62800
Scenario 4	76	62600

DISCUSSION AND SUMMARY

Discussion: The stepwise selection procedure creates a standardized process to select the most relevant predictors. This is useful when there are large amounts of data that appear to be related to the stream temperature. For summer Truckee River stream temperatures, the most significant predictors are flow and air temperature. The stream temperature prediction model fits the historic data well (R^2 = 0.9) and fits the verification period relatively well. A more accurate, less simple model could be developed, particularly for the high temperature range. The relationships in this study were strongly linear therefore linear regression is adequate. In other studies, non-linear techniques that can capture the dependence structure are attractive and should be explored. Further data and monitoring will help to improve the relationship to make it more certain. Less water will be necessary to meet the temperature targets with the desired probability of exceedance allowing water to be saved for the future.

Results were presented that show that large volumes of water are necessary to meet a temperature target with a high degree of certainty and extreme violations may still occur if all of the WQCW is used. A lower degree of certainty uses less water but there is a higher probability that the temperature target will be exceeded. Seasonal strategies to conserve water throughout the summer were then presented that allow minor violations to occur. Even with seasonal strategies, extreme violations still occur when all of the water is used. No matter what policy or strategy is used, not all of the temperature violations can be avoided without additional water. This shows that additional water may need to be purchased.

The framework developed in this paper will perform better in daily operations because of additional observed data. To determine how much water to release on a given day, observed data from previous days is available. In addition, climate forecasts can be updated monthly. Both of these improve the use of the limited supply of water by including additional information. The structure of the prediction model lends itself to relatively easy computation of uncertainties of the prediction. These uncertainties provide useful information in deciding how much water to release. The results of the scenarios illustrate that the efficient use of water is highly dependent on the required confidence level to meet the targets.

Summary: We presented a regression model to predict daily maximum stream temperatures. A stepwise procedure was used to select a parsimonious set of predictors that capture as much variance of the stream temperature as possible. The results show that Truckee River stream temperatures at Reno can be predicted using a simple linear regression relationship based on flow and air temperature. Linear regression theory is used to quantify the prediction uncertainty. A DSS is created that models baseline operating policy and predicts the stream temperature based on these releases. Using the uncertainty calculation, a method is developed to determine the additional flow required to meet a target temperature with a desired level of confidence. Results show that this procedure will reduce the number of temperature violations. In addition, seasonal strategies further decrease the number of violations without using more water.

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