A PHYSICALLY-MOTIVATED REGRESSION APPROACH
TO
FORECASTING LAKE POWELL INFLOW

by

Samuel Potteiger

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As members of the Master's Committee, we certify that we have read the thesis prepared by Samuel Edwin Potteiger, titled "A Physically-Motivated Regression Approach To Forecasting Lake Powell Inflow" and recommend that it be accepted as fulfilling the dissertation requirement for the Master's Degree.

____ Date: ___6/4/2020__
Xubin Zeng

____ Date: ___6/5/20_____
Hoshin V. Gupta

____ Date: 6/5/20
Peter A. Troch

Final approval and acceptance of this thesis is contingent upon the candidate's submission of the final copies of the thesis to the Graduate College.

I hereby certify that I have read this thesis prepared under my direction and recommend that it be accepted as fulfilling the Master's requirement.

Date: ___6/5/20_____

____
Xubin Zeng
Master's Thesis Committee Chair
Hydrology and Atmospheric Sciences

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Abstract

The Colorado River provides water for a growing population in seven U.S. states and Mexico, making it undoubtedly one of the most important rivers in the entire world. Lake Powell is the second largest reservoir on the river and is responsible for much of the water which enters Lake Mead. Forecasts of the water supply to Lake Powell are relied upon immensely by water users for planning purposes. The UA model was developed in this study to take a physically-motivated regression approach to modelling Lake Powell Inflow.

The UA model has two parts: the water year estimation method and the inflow model. The water year estimation method uses physical observations to make a binary forecast indicating if a given water year is a high-flow year or low-flow year based on the water year's peak monthly inflow or April-July volumetric flow. The water year prediction is first made on December 1st and provides information for a seven-month forecast. This method was able to predict all high-flow years throughout the 1982-2016, whereas the official forecasting center's January 1st forecast predicted less than half. Most flow comes to Lake Powell in the April-July period, and the operational forecast center releases a forecast for this period on April 1st. The UA model forecast made on April 1st has a 29% lower RMSE for the 1982-2016 period. Sensitivity tests indicate that the use of snow water equivalent in our model is an important reason for the UA model's good performance.

The UA model and the operational model do not have a statistically significant difference in performance in the 2013-2016 period at all lead times except for the 4-month lead time. The operational model has statistically significant better performance at the 4-month lead time during this period.

1. Introduction

The water resources of the Colorado River Basin (CRB) have become progressively stressed over the past half-century and demand is projected to increase (U.S. Bureau of Reclamation, 2012). The Colorado River is today responsible with supplying water to 40 million people across the region and 5.5 million acres of irrigated land (U.S. Bureau of Reclamation, 2012). Total population in the CRB increased from 4.56 million in 1985 to 9.44 million in 2010 (Maupin, Ivahnenko, & Bruce, 2018). Population in Arizona alone has increased from 3.3 million in 1985 to an estimated 7.2 million in 2019 (U.S. Census Bureau, 2019). Combined with increased legislation of groundwater resources in the state, this population surge led to an increase in the use of surface water in the state, primarily from the river. Arizona's percentage of water sourced from surface water was 51% in 1985 and nearly 60% in 2010. Municipal use increased from 10% of the state's total water use to 20% over this period (Maupin, Ivahnenko, & Bruce, 2018). The increased reliance on surface water becomes increasingly precarious as the future of streamflow of the Colorado River becomes uncertain due to the effects of climate change.

Various models for the CRB show the effects of climate change having significant effects on the flow of the river. Early scenarios predicted that an increase in mean annual temperature in the Upper Colorado River Basin (UCRB) of up to two degrees Celsius would result in a 33% decrease in mean annual flow, irrespective of an increase in mean annual precipitation of up to 10% (Stockton & Boggess, 1979). More recent predictions such as downscaled Global Climate Model projections show conditions leading to less precipitation and hotter temperatures (U.S. Bureau of Reclamation, 2012). These projections show the mean natural flow at Lee's Ferry, AZ to decrease by approximately nine percent over the next 50 years. They also indicate long drought periods lasting five or more years are projected to occur 50% of the time from now until 2060 (U.S. Bureau of Reclamation, 2012).

Currently, water users rely on the Colorado River Basin River Forecast Center (CBRFC) for up to date water supply predictions for the entirety of the UCRB system. CBRFC is the government authority for releasing operational inflow forecasts for Lake Powell. Since 2005, they have issued forecasts at the beginning of the water year to estimate Lake Powell monthly inflow for each month in the water year. The model was updated in 2013 to provide these forecasts each month instead of just at the beginning of the water year. In addition to monthly forecasts, CBRFC also produces forecasts for volumetric inflow to Lake Powell for the April-July period.

Streamflow in many mountainous basins like the UCRB is dominated by snowpack related processes. April 1st is historically the date when snowpack reaches its maximum in the UCRB, after which, snowmelt rapidly occurs, contributing vast amounts of water to runoff. Lake Powell receives more than 70% of its annual inflow during this period alone in some water years. The CBRFC has issued forecasts for April-July volumetric inflow in January-May every year since 1980. It has released these estimates in January-July every water year since 1992 (G. Smith, personal communication, June 13, 2019). The forecast made on April 1st is the last forecast that is made before the critical April-July flow period.

The CBRFC has a streamflow forecast testbed to find new approaches which improve on aspects of their flow model. The UA model developed in this study is an attempt to address one of the testbed's challenges: "to demonstrate a new approach that improves long lead streamflow forecast skill (Colorado River Basin Forecast Center, 2011)." The UA model forecasts streamflow with up to a 4-month lead time to provide monthly inflow forecasts and forecasts for volumetric April-July inflow. The UA model also predicts the high-flow or low-flow (occurring during April -July), starting from 1 December.

2. Data and Methods

2.1. Data

The calibration period for the UA model is water years 1982-2006, and the validation period is water years 2007-2016. The observed temperature and precipitation values are from the PRISM dataset (Daly et al., 2000), averaged over the spatial extent of the UCRB as defined by the USGS (U.S. Geological Survey, 2008). Observed snow water equivalent (SWE) is the spatial average of SWE in the UCRB on the first day of each month taken from the UA snow dataset (Broxton et al., 2019; Dawson & Zeng, 2017; Zeng et al., 2018; Broxton et al., 2016). The GTOPO30 digital elevation model (Earth Resources Observation and Science Center, 1997) was used to obtain an elevation model of the UCRB to find the area in the UCRB above 3000 meters. This area was used to create different spatial averages which are used in the water year estimation model.

Forecasted daily SWE on the 1st day of each month, monthly temperature, and monthly precipitation are also inputs to the model. They are from the NCEP Climate Forecast System (CFS) nine-month forecasts. For 1982-2011, the CFS Reforecast was used (NCEP/NOAA, 2011). Forecasts from 2011-2016 use the CFSv2 Operational Forecasts (Saha et al., 2014). Monthly change in SWE was then computed using the spatially averaged SWE values (Ex. November change in SWE would be calculated as December 1st SWE minus November 1st SWE).

Observed monthly Lake Powell inflow data is from the Bureau of Reclamation's historical data website (U.S. Bureau of Reclamation, 2015).

2.2. Methods

The UCRB is a mountainous basin; snowpack builds in the winter months, leading to a delayed response between winter precipitation and streamflow. In spring, the snowpack melts causing the year's peak inflow period. Therefore, it was paramount for the inflow model to incorporate the change in SWE to reflect the contribution of snowmelt to streamflow. Precipitation in non-winter months acts as a direct contribution to streamflow. The temperature term in the model acts as the main outflow, evapotranspiration.

In general, the temporal change of inflow depends on the water input (rainfall and snowmelt), water loss (from evapotranspiration), and movement of groundwater from mountains to the river. Evapotranspiration and the precipitation partitioning into rainfall and snowfall are dependent on temperature. Motivated by these physical processes, we compute the monthly inflow Q [in million acre-feet (MAF)] at month m from:

$$Q(m) = K_1(m) * P(m) + K_2(m) * \Delta SWE(m) + K_3(m) * T(m) + K_4(m) + Q(m-1) \qquad (1)$$

where P is the monthly precipitation (in millimeters), T is the monthly temperature (in degrees Celsius), and ΔSWE is the change in month m [computed from predicted SWE on the 1st day of month (m+1) minus the observed (for 1-month forecasting) or predicted SWE on the 1st day of month m]. They are all from CFS after adjustment in Eq. 2. Q(m-1) is the observed (for 1-month forecasting) or predicted inflow to the Lake Powell in month (m-1). K_1, K_2, K_3, K_4 are unbounded month-specific fitting parameters, K_4 represents processes not considered in the model such as movement of groundwater from mountains to the river. These month-specific parameters are the same for all lead-times. Inflow for a given month is further constrained by a minimum value that is set as the 10th percentile from April-July and as the 30th percentile for other months. The UA model forecasts inflow with a 1-4 month lead time (with the lead time of 1 month representing the current month prediction issued at the beginning of the month). The April-July period is the critical period of inflow in the UCRB, so our 4-month forecasting issued in early April for the period is considered a priority to compare with the operational center's forecast. This is why we issue forecasts with a lead time of 1-4 months (rather than, say 1-3 months). We will also issue the forecasting in early December of the high-flow or low-flow water year (representing a 7- or 8-month forecast).

The unadjusted CFS forecast values are found to underestimate SWE, overestimate temperature, and overestimate precipitation in both the calibration and validation periods (Table 1). Therefore, they are adjusted to fit the observed calibration climatology from:

$$P(m) = B_1(m,t) * P_{CFS}(m) + B_2(m,t) \tag{2}$$

where coefficients B_1 and B_2 should depend on the forecasted month m and the forecast lead time. Similar equations are used to fit SWE and temperature forecasts to the observed average calibration climatology. Table 1 shows that for the CFS forecast with a lead time of 4 months, the adjustment from Equation 2 reduces the temperature root mean square error (RMSE) by about 50%, the precipitation error by 65%, and the SWE error by 60%. In the UA model, Equation 2 is first used to calibrate P, T, and ΔSWE. The calibrated values are then used in

Equation 1 to predict the monthly inflow. During the validation period, the coefficients in Equations 1 and 2 are re-calibrated each year using data from all preceding years.

Table 1: RMSE of Adjusted and Unadjusted Forecasts

		Temperature [˚C]	Precipitation [mm]	SWE [mm]
Calibration (1982-2006)	Unadjusted	4.34	41.59	34.07
	Adjusted	2.11	14.50	13.35
Validation (2007-2016)	Unadjusted	4.34	51.57	34.13
	Adjusted	2.29	16.67	14.10

Table 1. RMSE of the CFS 4-month forecasts with respect to observations before and after the adjustment in equation 2.

2.3. High-flow and Low-flow Years

In addition to the prediction of inflow with 1-4 month lead time, the UA model also predicts high-flow and low-flow years. As seen in Figure 1, there is a stark difference in the flow regime between years with a peak monthly inflow above 4 MAF and years when the peak monthly inflow is below 4 MAF. "High-flow" years were defined as having a peak monthly inflow above 4 MAF, and "low-flow" years had a peak monthly inflow below 4 MAF.

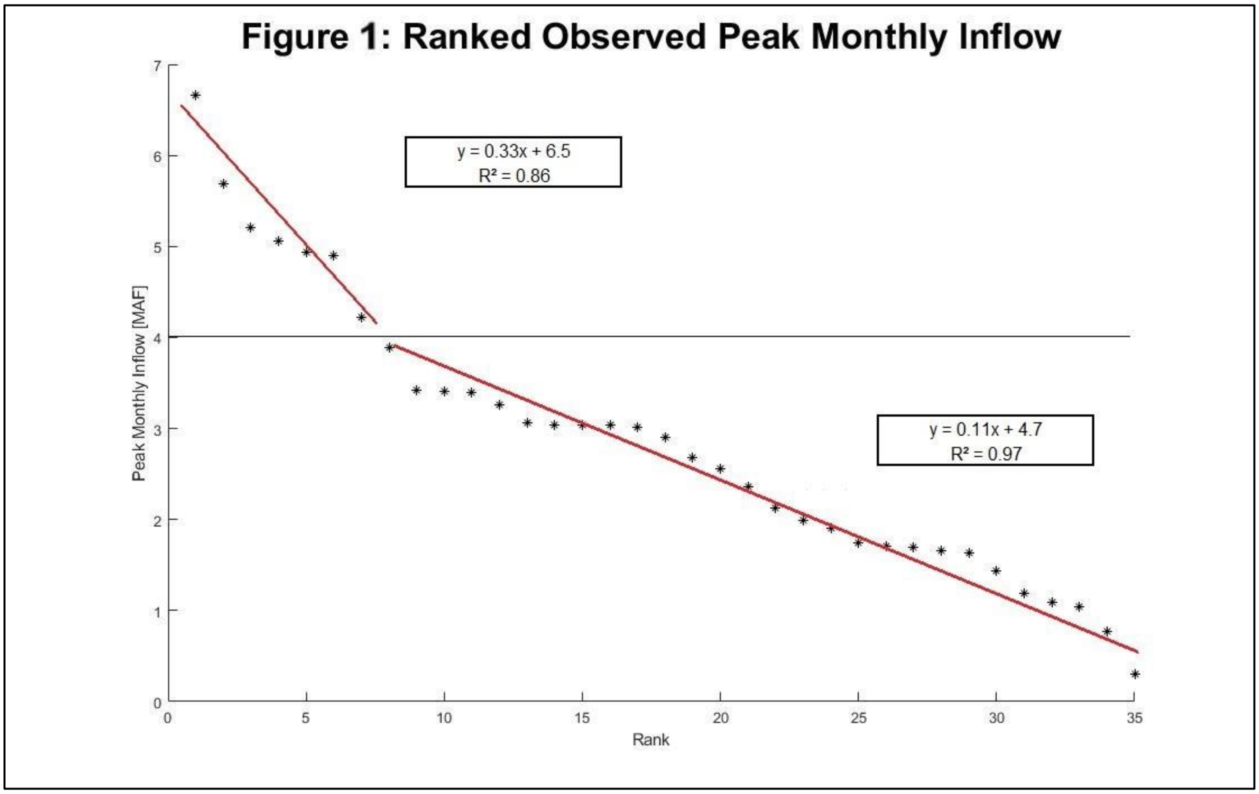

Figure 1. Peak monthly inflow of each year ranked in order from highest to lowest inflow in the calibration and validation periods. Red lines represent the fit to the data for the high-flow and low-flow years.

Figure 1 shows that the slope of the line for high-flow years is three times the value for low-flow years. We hypothesize that there must exist a distinct climate regime in those years to force that difference in the hydrologic response of the system, and hence we will attempt to predict the high-flow versus low-flow years below. The high-flow years during the calibration (1982-2006) period are 1983, 1984, 1985, 1986, 1995, and 1997 (Figure 2). The only high-flow year during the validation (2007-2016) period is in 2011. There are seven high-flow years in the 35-year period and 28 low-flow years. Figure 2 shows the difference in climatic regimes between high-flow and low-flow years. There is greater precipitation early in the water year during high-flow years, leading to greater accumulation of SWE. The larger SWE translates into greater inflow when snowmelt occurs in the spring.

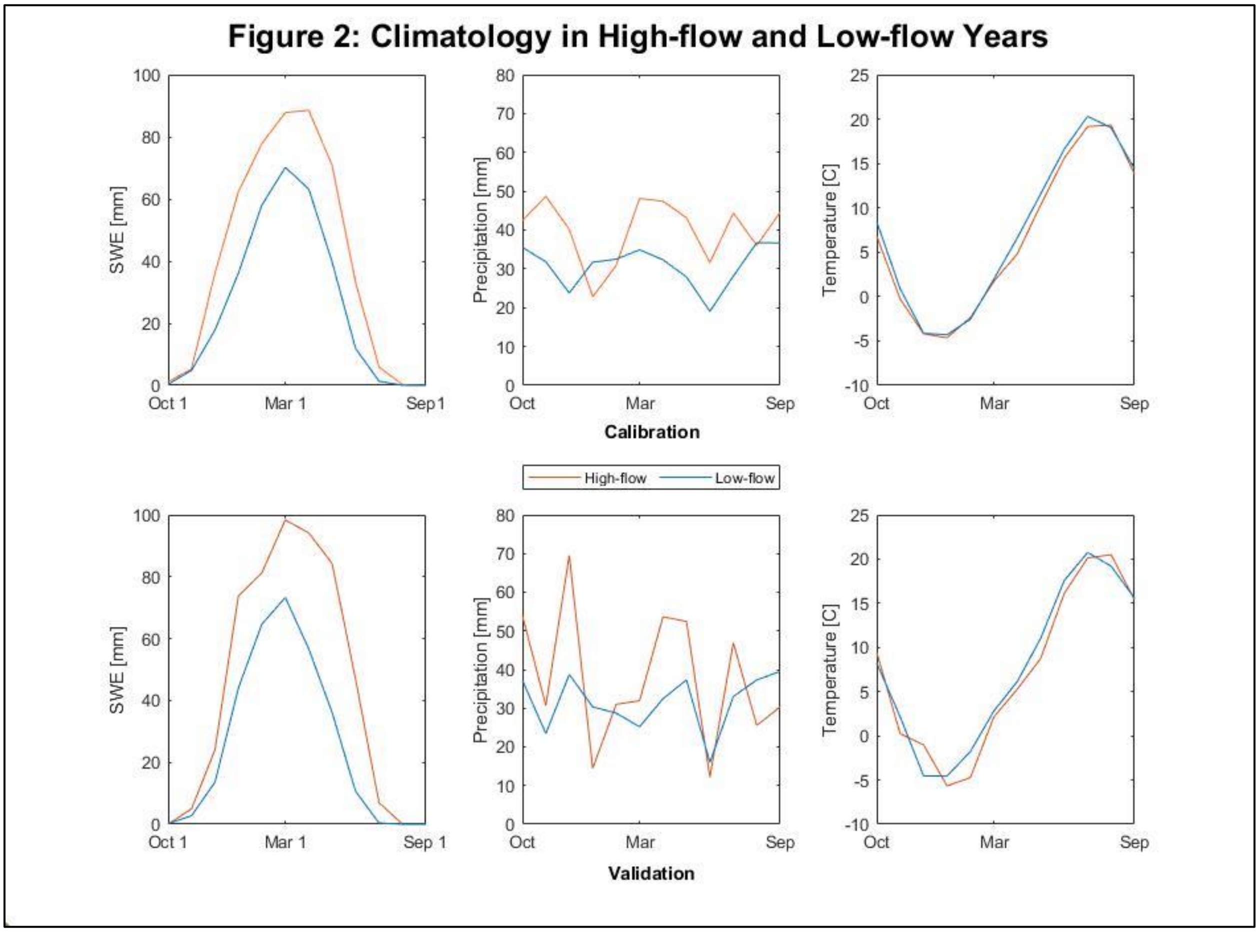

Figure 2. Average annual cycle for high-flow and low-flow years in calibration and validation periods. The high-flow in validation is the climatology of one year (2011).

3. Results

In our first attempt, we considered all years together (without separately considering high-flow versus low-flow years), yielding poor results. The CFS forecasts adjusted to fit the climatology struggles to predict high-flow inflow months (highlighted by orange circles) accurately. Therefore, we decide to calibrate the coefficients in equations 1 and 2 for high-flow and low-flow years separately.

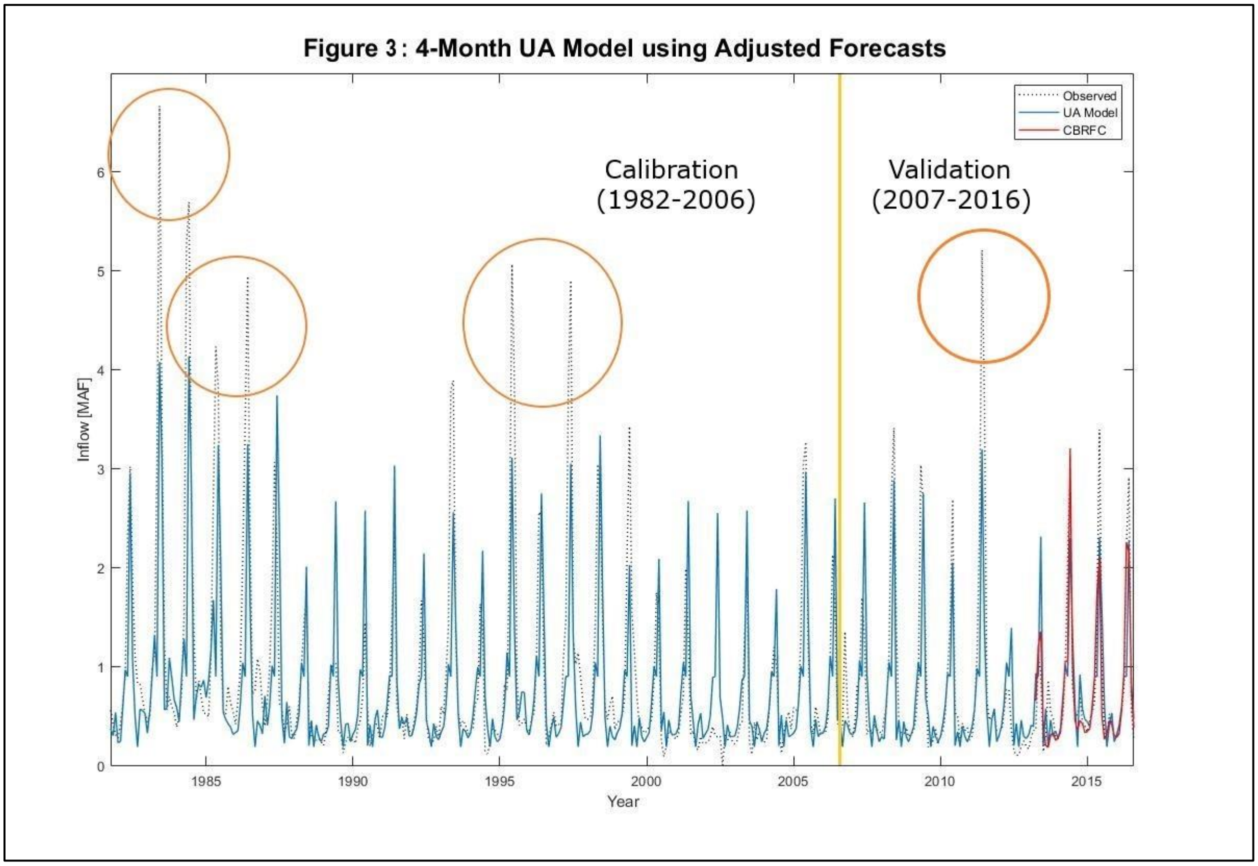

Figure 3. Timeseries of the 4-month lead time UA inflow prediction in comparison with observations and the CBRFC prediction. Coefficients in equations 1 and 2 are determined using all years without considering high-flow versus low-flow years. The orange circles show high-flow months which exhibit very high errors.

3.1. Prediction of High-flow and Low-flow Years

A water year's (October 1st to September 30th) status as a high-flow year or low year was predicted based on observations. These binary (high-flow or low-flow) predictions were made every month starting on December 1st. The observations at elevations above 3000 in the UCRB over 3000 m are emphasized because the UCRB is a mountainous basin and streamflow is particularly sensitive to high-elevation conditions. This method was able to predict 92% (23/25) of water years correctly in the calibration period and all 10 of the water years in the validation period. For October and November, high-flow or low-flow year in the following summer is not relevant, all years were used for the calibration.

From December 1st to April 1st, we predict the high-flow versus low-flow year each month, with the parameters provided in Table 2 for the December 1st forecast and in Appendix A for later months.

Table 2: Threshold Values for Water Year Prediction

	Percentile Threshold	Value
Oct 1st SWE above 3000 m	0.90	15 mm
Nov 1st SWE above 3000 m	0.80	50 mm
Dec 1st SWE above 3000 m	0.60	100 mm
October Inflow	0.30	0.3 MAF
November Inflow	0.70	0.6 MAF
Nov Precip above 3000 m	0.55	85 mm

Table 2. Parameters and their percentile thresholds and absolute values used to estimate high-flow (if at least three values are above the threshold) versus low-flow water year. This prediction is made on December 1st.

The predictions made in months after December are used to update the prediction-

- The January 1st prediction does not update a water year's classification to avoid oscillations in the prediction of high-flow versus low-flow years;
- After the February 1st prediction, the majority among the three predictions made on the 1st of December, January, and February will be the new prediction.
- The March 1st prediction does not update a water year's classification.
- After the April 1st prediction, the majority among the five predictions made on the 1st of December-April will be the final prediction for the high-flow versus low-flow year.
- The same prediction is used for remaining months (May to September).

CBRFC issued the prediction of inflow for April-July on January 1st. To compare our binary prediction with the CBRFC prediction, we first determine the corresponding high-flow versus low-flow years using the April-July inflow. The observed inflow data analysis indicates that the peak monthly inflow above 4 MAF is greater than the 75th percentile of peak monthly inflow in the calibration period. The corresponding value to this percentile threshold for April-July volumetric inflow is 11 MAF. Therefore, high-flow (or low-flow) year can be defined for April-July inflow greater (or less) than 11 MAF. The operational center's official forecast of the 50% exceedance probability made on January 1st was converted to this binary representation. Table 3 shows that our approach on December 1st can predict the high-flow versus low-flow year (with a 7-8 month lead time) much better than the CBRFC method on January 1st. In particular, CBRFC missed four of the seven high-flow years, while our method would correctly predict all seven.

Table 3: High-Flow versus Low-Flow Water Year Prediction

		High-flow %	Low-flow %
UA Model	Calibration (1982-2006)	100	89
	Validation (2007-2016)	100	100
	35-Year Period (1982-2016)	100	93
CBRFC	Calibration (1982-2006)	50	100
	Validation (2007-2016)	0	100
	35-Year Period (1982-2016)	43	100

Table 3. Performance of the UA model in predicting high-flow versus low-flow year on December 1st versus the CBRFC prediction on January 1st. "High-flow %" (or "Low-flow %") refers to the percentage of correctly predicted high-flow (or low-flow) years.

3.2. UA Inflow Prediction

As mentioned earlier, two sets of coefficients are calibrated in equations 1 and 2 for high-flow and low-flow years, respectively. After the prediction of high- or low-flow year in section 3.1, we can then do the inflow prediction. Compared with the prediction without considering high- versus low-flow year (Figure 1), the 4-month forecast of the UA model in Figure 4 is much better for high-flow years. Indeed, Figure 5 shows that the 4-month forecast of the UA model can reproduce very well the average seasonal cycle of inflow for high- and low-flow years during the calibration and validation periods.

Table 4 shows that the UA model's performance in terms of correlation and Nash-Sutcliffe efficiency (NSE)

$$NSE = 1 - \frac{\sum_{m=1}^{M}(Q_{Est}(m) - Q_{Obs}(m))^2}{\sum_{m=1}^{M}\left(Q_{Obs}(m) - \overline{Q_{Obs}(m)}\right)^2} \tag{3}$$

where the overbar denotes the monthly climatology of inflow based on observations available by that year. A perfect match of modeled streamflow to observed streamflow would have an NSE of 1. A value above 0.65 is considered "good" and above 0.75 is considered "very good" (Moriasi et al., 2007). Table 4 shows that the UA model has similar performance in the calibration and validation period in both correlation and NSE. It also shows that the UA model's forecast skill is the best overall for the 1-month lead time, but the degradation of the skill with the increase of the lead time from 1- to 4-month is small. These results demonstrate the robustness of the UA model for the inflow forecasts of the lead time of 1-4 months.

For the period of 2013-2016 when the CBRFC forecasts are also available, Figure 5 shows that the averaged seasonal cycle from the 4-month forecasts of CBRFC is slightly better than that of the UA model. The differences between the two models can be further examined in Table 4. However, the only statistically significant difference between the two models is in the 4-month lead time. While the UA model shows the slight degradation of forecast skill for the lead time from 1 to 4 months, which is expected, the CBRFC model shows the abnormal behavior of better forecast skills at 1- and 4-month lead times than at 2- and 3-month lead times.

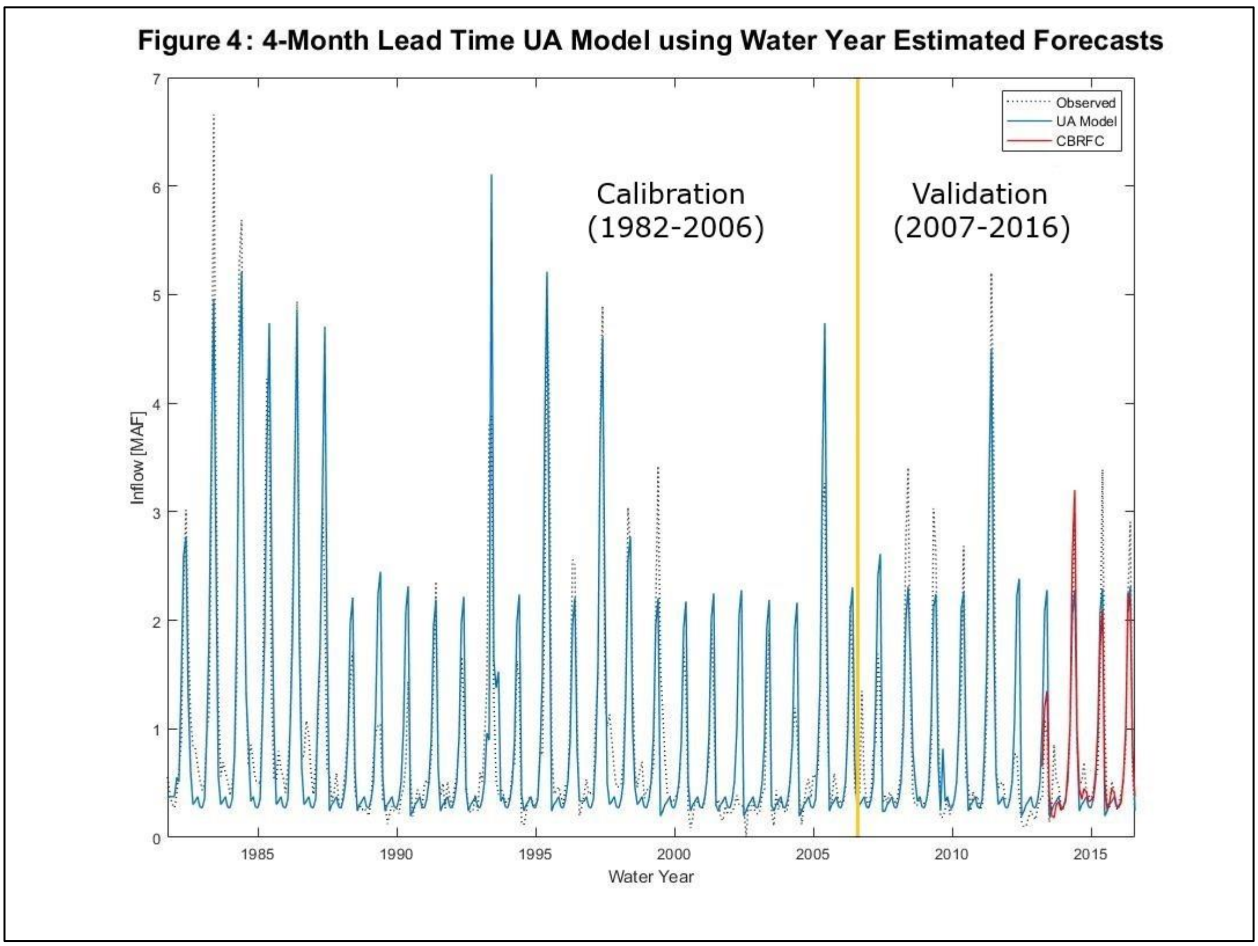

Figure 4. Comparison of the four-month forecast of inflow using the UA model (including the prediction of high-flow versus low-flow year) for the calibration and validation periods. Results from the CBRFC for the last four years are also shown.

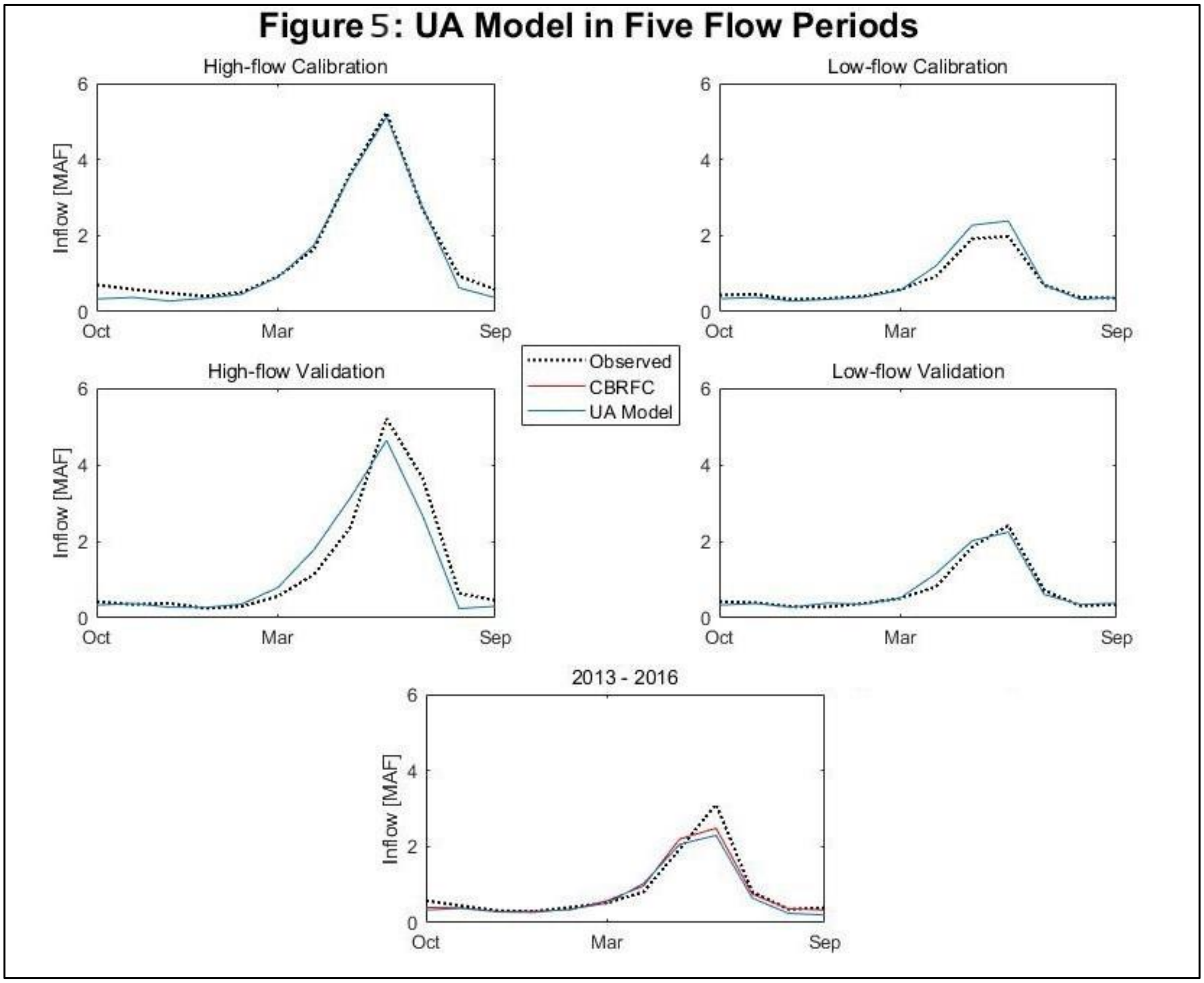

Figure 5. Results in Figure 4 averaged into five different periods.

Table 4: UA Model 1-4 Month Lead Time Performance

	Correlation	NSE
Calibration (1982-2006)	0.92, 0.91, 0.90, 0.89	0.85, 0.81, 0.78, 0.75
Validation (2007-2016)	0.88, 0.89, 0.89, 0.85	0.79, 0.81, 0.79, 0.72
35-Year Period (1982-2016)	0.91, 0.91, 0.90, 0.88	0.83, 0.81, 0.78, 0.75
UA Model (2013-2016)	0.90, 0.86, 0.85, 0.85	0.79, 0.72, 0.73, 0.71
CBRFC (2013-2016)	0.92, 0.83, 0.85, 0.92	0.84, 0.67, 0.71, 0.84

Table 4. UA model performance in different periods at different lead times. In each column (e.g., Correlation), the four values represent the results for the forecasts with lead times from 1 to 4 months. The CBRFC model performance is also shown for 2013-2016.

Table 5 shows the performance of the UA model in the April-July inflow period.

Table 5: Model Performance in April-July Period

		Correlation	NSE	Predict %
UA Model	Calibration (1982-2006)	0.92	0.84	68
	Validation (2007-2016)	0.88	0.80	80
	35-Year Period (1982-2016)	0.91	0.83	**71**
CBRFC	Calibration (1982-2006)	0.84	0.65	48
	Validation (2007-2016)	0.87	0.75	70
	35-Year Period (1982-2016)	0.84	0.67	**54**

Table 5. Comparison of the April 1st forecasts of the April-July inflow from the UA model and the CBRFC model. Prediction percentage is the proportion of years when the observed flow is within the prediction range discussed in the text.

The prediction of the April-July inflow is crucial for water resources and hence CBRFC has a relatively long record of its forecasts (compared with the short period of forecast records for each month in Table 4). Table 5 compares the April 1st forecast of the April-July forecasts using the UA model versus the CBRFC model, with the former consistently performing better. For instance, the NSE of the UA model is 20% greater (0.83) than that of the operational model (0.67). This is a statistically significant difference.

One way to represent the prediction range is to use the 25th and 75th percentiles of the forecast errors, and this range is smaller (by 1.5 MAF) for the UA model than that for the CBRFC model. To have a fair comparison, we use the same prediction range from the CBRFC, and the prediction percentage in Table 5 refers to the proportions of years when the observed flow is within the prediction range. For the 35 year period, the UA model's prediction percentage is 30% better (71) compared with the CBRFC value (54).

3.3. UA Model Robustness

To test the robustness of the UA model, a separate calibration and validation period were defined. The new calibration selected to test for robustness was the 25 years of 1982-1991 and 2002-2016. The new validation period for the test of robustness was the ten year period 1992-2001. Two of the ten years are high-flow years in this period; 20% of the years in the 35-year study period are high-flow years as well. The forecasted climatology was fitted to the high-flow and low-flow climatology of the new calibration period. Results in Table 6 are consistent with those in Table 5, and results in Table 7 are consistent with those in Table 4, demonstrating the robustness of the UA model.

Table 6: Model Performance in April-July Period

		Correlation	NSE	Predict %
UA Model	New Calibration (1982-1991, 2002-2016)	0.87	0.77	64
	New Validation (1992-2001)	0.85	0.68	60
	35-Year Period (1982-2016)	0.88	0.75	**63**
CBRFC	New Calibration (1982-1991, 2002-2016)	0.85	0.69	60
	New Validation (1992-2001)	0.75	0.57	40
	35-Year Period (1982-2016)	0.84	0.66	**54**

Table 6. Comparison of the April 1st forecasts of the April-July inflow from the UA model and the CBRFC model in the new calibration and validation periods. Prediction percentage is the proportion of years when the observed flow is within the prediction range discussed in the text.

Table 7: UA Model Robustness Test for 1-4 Month Lead Times

	Correlation	NSE
New Calibration (1982-1991, 2002-2016)	0.92, 0.90, 0.89, 0.88	0.84, 0.81, 0.81, 0.78
New Validation (1992-2001)	0.91, 0.89, 0.87, 0.79	0.84, 0.79, 0.76, 0.36
35-Year Period (1982-2016)	0.92, 0.90, 0.89, 0.85	0.84, 0.81, 0.79, 0.67

Table 7. UA model performance in different periods at different lead times with new validation and calibration periods. In each column (e.g., Correlation), the four values represent the results for the forecasts with lead times from 1 to 4 months.

3.4. Additional Analysis

Naturalized flow is a computed variable which estimates the flow in the Colorado River in the absence of human obstructions of the river and artificial withdrawals. This data is available for each gauge along the Colorado River and is used in the Colorado River Simulation System (CRSS) (Prairie & Callejo, 2005). The CRSS is the comprehensive long-term planning model used by the Bureau of Reclamation. The UA model was used to forecast naturalized flow estimates at the Lee's Ferry USGS gauge. Lee's Ferry notably serves as the demarcation point between the upper and lower CRB. Table 8 shows the UA Model forecasts naturalized flow at Lee's Ferry at a similar skill.

Additional analysis was also done to determine how using SWE in Equation 1 improves the efficacy of the model. K_2 was fixed as zero for this analysis and other coefficients were recalibrated. Results can be seen in Table 9. Averaged across all lead times, NSE of the model over the 35-year period is 70% higher when considering SWE in Equation 1.

Table 8: UA Model Naturalized Flow for 1-4 Month Lead Times

	Correlation	NSE
Calibration (1982-2006)	0.93, 0.91, 0.91, 0.92	0.83, 0.81, 0.83, 0.83
Validation (2007-2016)	0.91, 0.91, 0.90, 0.88,	0.76, 0.80, 0.79, 0.77
35-Year Period (1982-2016)	0.92, 0.91, 0.91, 0.91	0.81, 0.81, 0.82, 0.82

Table 8. UA model performance in different periods at different lead times for predicting naturalized flow at Lee's Ferry with validation and calibration periods. In each column (e.g., Correlation), the four values represent the results for the forecasts with lead times from 1 to 4 months.

Table 9: UA Model without SWE for 1-4 Month Lead Times

	Correlation	NSE
Calibration (1982-2006)	0.85, 0.82, 0.84, 0.81	0.68, 0.62, 0.67, 0.69
Validation (2007-2016)	0.75, 0.77, 0.76, 0.71	0.50, 0.46, 0.46, 0.47
35-Year Period (1982-2016)	0.82, 0.80, 0.82, 0.79	0.64, 0.58, 0.62, 0.64

Table 9. UA model performance in different periods at different lead times for predicting Lake Powell inflow with validation and calibration periods when not considering SWE. K_2 is equal to zero in Equation 1.

4. Conclusions

We have developed a hybrid model for the forecasts of the inflow to the Lake Powell. First, observational data are used to predict a high- or low-flow year (with the peak during April-July), starting from December 1^{st} to April 1^{st}. Our prediction on December 1^{st} is much better than the CBRFC's forecast on January 1^{st}. Second, we calibrate the NCEP CFS seasonal forecasts of monthly temperature, monthly precipitation, and snow water equivalent on the first day of each month (in equation 2) and use them to predict monthly inflow through a regression equation (i.e., equation 1), with the coefficients determined for the high- and low-flow year separately. UA model's April 1^{st} forecasts for the critical April-July inflow is better than that of the operational center. Sensitivity tests indicate that the use of snow water equivalent in our model is an important reason for the UA model's good performance. For the 2013-2016 period, the operational model has a statistically significant better performance than the UA model in the 4-month lead time. There is no statistically significant difference between the two models in other lead times.

5. Appendix

A. Water Year Prediction Threshold Tables for Different Months. If three or more observations are above the threshold then it was predicted to be a high-flow year.

December Water Year Prediction (Prediction made Dec 1st)

	Percentile Threshold	Value
Oct 1st SWE above 3000 m	0.90	15 mm
Nov 1st SWE above 3000 m	0.80	50 mm
Dec 1st SWE above 3000 m	0.60	100 mm
October Inflow	0.30	0.3 MAF
November Inflow	0.70	0.6 MAF
Nov Precip above 3000 m	0.55	85 mm

January Water Year Prediction (Prediction made Jan 1st)

	Percentile Threshold	Value
Oct 1st SWE above 3000 m	0.60	1 mm
Nov 1st SWE above 3000 m	0.80	50 mm
Dec 1st SWE above 3000 m	0.60	100 mm
Jan 1st SWE above 3000 m	0.50	165 mm
November Inflow	0.70	0.6 MAF
December Inflow	0.60	0.4 MAF

February Water Year Prediction (Prediction made Feb 1st)

	Percentile Threshold	Value
Nov 1st SWE above 3000 m	0.90	65 mm
Dec 1st SWE above 3000 m	0.50	100 mm
Jan 1st SWE above 3000 m	0.50	165 mm
Feb 1st SWE above 3000 m	0.60	250 mm
December Inflow	0.80	0.5 MAF
January Inflow	0.80	0.5 MAF

March Water Year Prediction (Prediction made Mar 1st)

	Percentile Threshold	Value
Jan 1st SWE above 3000 m	0.50	165 mm
Feb 1st SWE above 3000 m	0.60	250 mm
Mar 1st SWE above 3000 m	0.80	380 mm
January Inflow	0.50	0.35 MAF
February Inflow	0.80	0.5 MAF
Feb Precip above 3000 m	0.50	80 mm

April Water Year Prediction (Prediction made Apr 1st)

	Percentile Threshold	Value
Feb 1st SWE above 3000 m	0.80	300 mm
Mar 1st SWE above 3000 m	0.60	320 mm
Apr 1st SWE above 3000 m	0.60	420 mm
February Inflow	0.50	0.6 MAF
March Inflow	0.80	0.95 MAF
Mar Precip above 3000 m	0.60	100 mm

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