Dewberry

Seasonal Forecasting of Lake McClure Inflow: Preliminary Feasibility Study

TECHNICAL MEMO

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Submitted by:

Dewberry
1760 Creekside Oaks Drive, Suite 280
Sacramento, CA 95833

Submitted to:

Mr. Marco Bell
Merced Irrigation District
744 W. 20th Street
Merced, CA 95340

Contributors

Sam Crampton, PE
Principle-in-Charge
scrampton@dewberry.com
678.537.8622

Dmitry Smirnov, PhD
Project Meteorologist
dsmirnov@dewberry.com
303.951.0644

Dana McGlone
Staff Meteorologist
dmcglone@dewberry.com
720.943.5923

Ted Cassidy, PE, PH
Water Resources Engineer/Hydrologist
tcassidy@dewberry.com
916.380.3775

Bibek Joshi, PE
Water Resources Engineer
bjoshi@dewberry.com
916.380.3772

Table of Contents

INTRODUCTION **1**

DATA COLLECTION: PREDICTAND & PREDICTORS **6**

RELATIONSHIP BETWEEN INFLOW AND THE ATMOSPHERE **10**

MODEL DEVELOPMENT & PERFORMANCE **16**

CONCLUSION **19**

RECOMMENDATIONS **20**

REFERENCES **21**

INTRODUCTION

Objective

The objective of this research is to conduct a preliminary analysis into the feasibility of long-range forecasts of Lake McClure April-July inflow. The California Department of Water Resources (DWR) releases a seasonal forecast, called Bulletin 120[1], predicting spring/summer inflow into the state's major reservoirs, including Lake McClure. Bulletin 120 is updated four times a year, during the second week of February, March, April and May.

Table 1 shows a summary of Bulletin 120 February, March and April forecasts for Lake McClure inflow and their performance over the 1990-2017 period. Lake McClure inflow is strongly correlated to maximum basin snowpack, making the latter a key input variable into the Bulletin 120 forecast. As the estimates of maximum snowpack become more certain in time, as expected, the average absolute error of the forecast drops from 195,000 acre-feet in February's forecast to 165,000 in March and then 79,000 in April. Overall, Bulletin 120 forecasts have a weak negative (underestimate) bias of about 35,000 acre-feet in February decreasing to 20,000 acre-feet in April. However, the bias has a dependence on the forecast flow, with high forecast values underestimating the actual flow and vice versa. For example, focusing on the April forecast, when inflow is forecasted above 600,000 acre-feet, B120 underestimates flows by 89,000 acre-feet; when inflow is forecasted below 600,000 acre-feet, B120 overestimates by 20,000 acre-feet.

Bulletin 120 is used by many end-users and the forecasts developed herein will be compared to Bulletin 120. **The goal is to provide a recommendation to MID and DWR to enhance the snow water equivalent forecast for the Merced Basin.** It is noted that this research is part of the scope outlined by the US Bureau of Reclamation's (USBR) Smart Water program. Thus, funding through USBR is one possible mechanism for further investigation.

[1] https://cdec.water.ca.gov/snow/bulletin120/index2.html

Table 1: Summary of CDWR Bulletin 120 February, March and April forecasts and absolute error for April-July inflow into Lake McClure. Note that May 1 forecasts are not shown because validation begins in April. All units are 1000s of acre-feet.

	Forecast Inflow				Absolute Error		
Water Year	**February**	**March**	**April**	**Observed**	**February**	**March**	**April**
1990	360	360	250	249	111	111	1
1991	230	155	410	407	177	252	3
1992	340	410	370	284	56	126	86
1993	850	1,000	960	928	78	72	32
1994	340	390	290	237	103	153	53
1995	900	760	1,180	1,376	476	616	196
1996	560	680	710	694	134	14	16
1997	1,050	900	700	580	470	320	120
1998	620	950	980	1,192	572	242	212
1999	560	630	560	585	25	45	25
2000	480	710	610	581	101	129	29
2001	390	440	360	356	34	84	4
2002	590	470	470	427	163	43	43
2003	540	430	380	561	21	131	181
2004	550	590	450	319	231	271	131
2005	870	870	980	1,057	187	187	77
2006	715	650	830	1,244	529	594	414
2007	360	390	260	200	160	190	60
2008	580	610	490	398	182	212	92
2009	430	500	520	540	110	40	20
2010	600	640	640	746	146	106	106
2011	760	770	1,040	1,128	368	358	88
2012	340	220	270	294	46	74	24
2013	550	360	310	257	293	103	53
2014	260	210	185	165	95	45	20
2015	270	155	90	90	180	65	0
2016	620	500	520	484	136	16	36
2017	970	1,230	1,160	1,243	273	13	83
				Mean Error	**195**	**165**	**79**

Seasonal Forecasting

The goal of seasonal forecasting is to use a range of atmospheric and oceanic predictors to provide long-range forecasts of sensible variables such as temperature, precipitation, streamflow or snowpack. The most notable of the vast array of predictors is the El Nino-Southern Oscillation (ENSO) phenomenon, which is measured by many indices including but not limited to the Southern Oscillation Index, the NINO3.4 index and the Multivariate ENSO Index. Due to the large amount of uncertainty involved, seasonal forecasts are typically probabilistic (e.g. “60% chance of above normal precipitation”) versus deterministic (e.g. “total precipitation will be 30 inches this winter”). Forecasts of temperature are almost always more skillful than their precipitation-related counterparts. For example, the National Oceanic and Atmospheric Administration’s Climate Prediction Center releases a

monthly precipitation forecast, but it is frequently no more accurate than using simple climatology even at a one-month lead time (e.g. Gottschalck and Halpert, 2016; see their slide 38).

In the context of hydrology, forecast lead time plays an important role that can impact a forecast's utility. Because of the complexity and involvement of many stakeholders, several weeks or even months of lead time are ideal to allow for water supply operators to discuss options and implement high-stakes decisions. However, conventionally, forecasts with such lead time have showed that skill drops of with lead time. For example, the average error in the Bulletin 120 March forecast (effectively three weeks of lead time) is 165,000 acre-feet (see **Table 1**). This is about 50% lower than using the climatological average flow, providing this forecast possible utility for operations. However, the mean error for the February increases to 195,000 acre-feet. In short, there is a delicate trade-off between forecast skill and lead time.

Recently, Dewberry (2016) developed a seasonal forecast model for streamflow and reservoir inflow on the North Platte River. Despite the presence of numerous large water control structures, high forecast skill was shown with forecast correlation exceeding 0.8 and mean error of about 50% less than that of climatology. Notably, results were markedly better than previous research in the North Platte River basin such as Kalra et al. (2009) and AMEC (2013), who showed little useful skill. A key difference in the work by Dewberry was the inclusion of the Palmer Drought Severity Index (PDSI) as a predictive variable. The PDSI accounted for a large portion of the overall forecast skill. The goal of this research is to extend the results of Dewberry (2016) into the Merced River basin, and specifically Lake McClure inflow.

Figure 1 shows a schematic of the reduction in forecast uncertainty, relative to climatology, that can be provided using two forecast methods. The first, here called the "initial condition" method, is currently being used by Dewberry in seasonal forecasts as part of the MIDH2O project. In this method, the current state of the snowpack is used to constrain the possible range of April-July runoff based on historical 10th, 50th and 90th percentiles of precipitation. The memory of the current condition will yield a better forecast than using climatology, but with limited lead time. The method proposed herein, and used by Bulletin 120 is termed the "statistical/dynamical forecast" based not only on the current condition, but also the predictive value of various predictors such as conventional Hydro-Climate Indices (HCIs) such as ENSO and the Pacific Decadal Oscillation, but also other predictors such as the PDSI and dynamical models such as the NOAA Climate Forecast System.
From **Figure 1**, it should be noted that there are several methods of developing a seasonal forecast. Conventionally, a common method is termed "deterministic" and involves forecasting a single value, typically analogous to the "most likely" outcome or the 50th percentile in **Figure 1** and **Figure 2**. For example, the April-July inflow at Lake McClure will be 600,000 acre-feet. Due to the relatively large uncertainty involved with seasonal forecasting (even for the short-lead April forecast as seen in **Table 1**), it is very unlikely that such a forecast will be exactly correct. For example, even though it has clear value, the Bulletin 120 April forecast is within 10,000 acre-feet of the observed value only four times during its 28 year record. Thus, an alternate method of presenting the forecast is using the probabilities. For example, the probability of inflow exceeding average to imply a need to increase storage capacity or being below the 25th percentile to imply a need to aggressively store water. The main benefit of a probabilistic approach is that it shifts the focus away from an exact number to a more comprehensive, impact-driven measure. Due to the preliminary nature of this study, we focus on the deterministic approach, which if successful, can be relatively easily extended to a probabilistic approach.

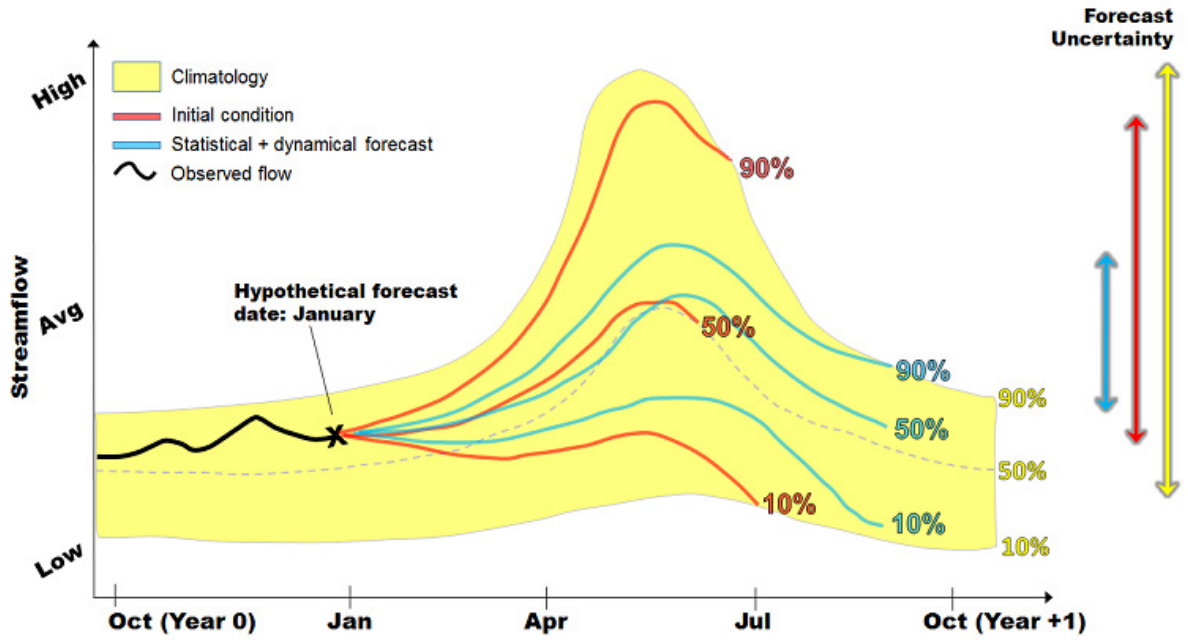

Figure 1: Schematic showing seasonal forecast uncertainty associated with a hypothetical January forecast of spring/summer streamflow. Climatological uncertainty, measured by the 10th and 90th percentiles is shown in yellow, while the red and blue lines show a forecast using initial conditions, and statistical/dynamical model, respectively. Arrows on the right-hand side measure the amount of uncertainty (10th – 90th range).

Merced River Streamflow Variability

In California's Merced River basin, variations in year-to-year precipitation and streamflow are significant, resulting in a need for routine monitoring of atmospheric and hydrologic conditions. **Figure 2** shows April-July volumetric inflow into Lake McClure (operated by the Merced Irrigation District, hereafter MID) over the existence of New Exchequer Dam (1967-present). During times of prolific precipitation such as the early 1980s, the winter high-elevation snowpack is deep, the summer landscape is lush and agricultural productivity is high, though flooding can be a threat. Meanwhile, during times of drought, such as the most recent record-breaking multi-year drought of 2011-2015, water storage and rationing, as well as environmental stewardship to protect sensitive riparian ecosystems, becomes of paramount importance.

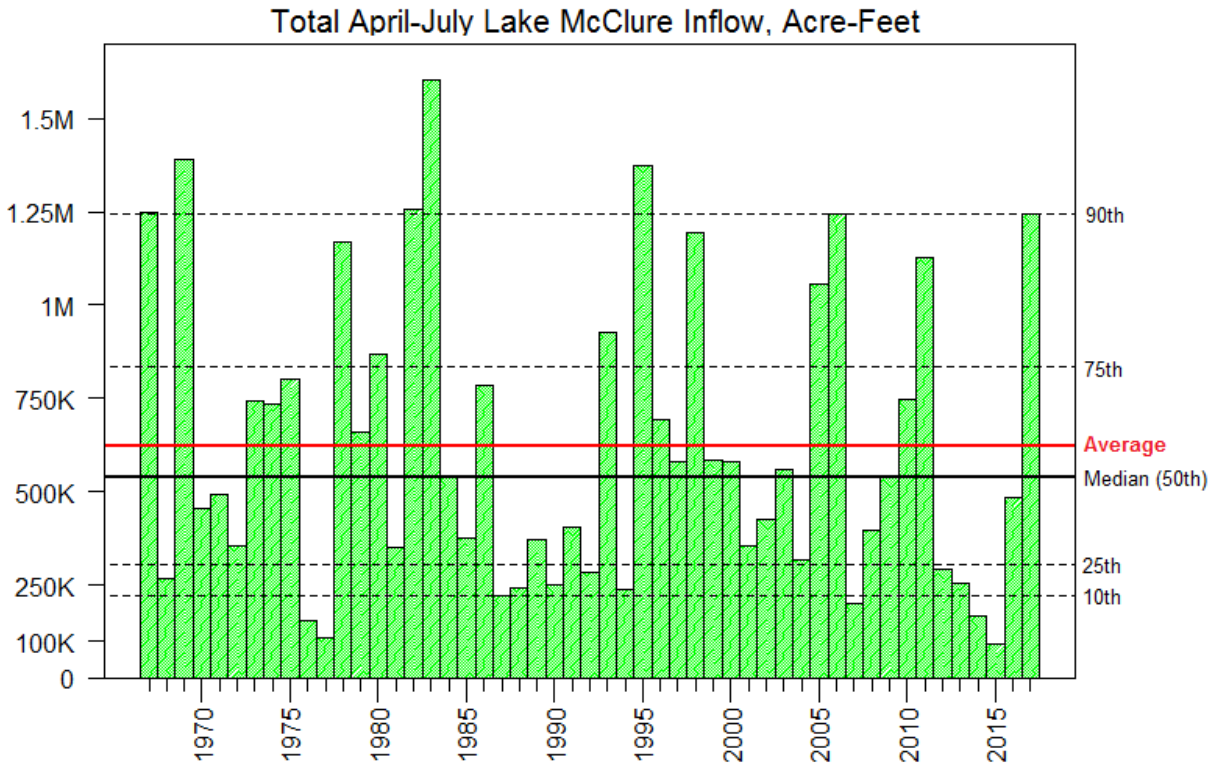

Figure 2: Total April-July volumetric inflow in the Lake McClure, 1967-2017. Key percentiles as well as the average flow are labeled on the right y-axis.

Motivated partially by the need to mitigate the threat posed by the large year-to-year streamflow variability, significant water storage structures such the New Exchequer Dam have been built. However, despite the dam's roughly 1 million acre-foot capacity, consecutive low flow years can still result in low water supply, reiterating the importance of routine monitoring of weather and climate in the region. **Recently, advances in the predictive skill of statistical and dynamical atmospheric models lead to the question of whether or not some of the large variability can be predicted well in advance of the impacts. If enough forecast skill and lead time can be shown, then it is possible that water supply operational decisions can be informed using forecasted flow volumes.**

DATA COLLECTION: PREDICTAND & PREDICTORS

Lake McClure Inflow (Predictand)

Figure 2 showed the interannual variability in April-July inflow at Lake McClure, the variable that we seek to predict with as much lead time as possible. **Table 2** provides some key statistics about April-July inflow variability. The average inflow over the 4-month period is 624,000 acre-feet (note that April-July constitutes ~62% of annual inflow), but the median is significantly lower at 537,000 acre-feet, signaling that the distribution of interannual is significantly non-Gaussian. A skewness of 0.71 implies a very strong right tail due to the relatively infrequent occurrence of very high flow years.

Table 2

Metric	Value	Units
10th percentile	220,000	acre-feet
25th percentile	306,000	acre-feet
50th percentile (Median)	537,000	acre-feet
75th percentile	834,000	acre-feet
90th percentile	1,244,000	acre-feet
Average	624,000	acre-feet
Skewness	0.71	---
Mean error with climatological mean forecast	329,000	acre-feet
Mean error with climatological median forecast	316,000	acre-feet

Figure 3 shows a histogram of flows, further revealing that not only is there a strong right tail, but the distribution is bi-modal (a primary peak in the 200-400K acre-foot range with a secondary peak around 1200-1300K acre-feet) and not well characterized by conventional "average" and "median" statistics. For example, the probability of the flow being within 10% of the "average" value is only 8% (4 times out of the 51 years; see **Figure 2**).

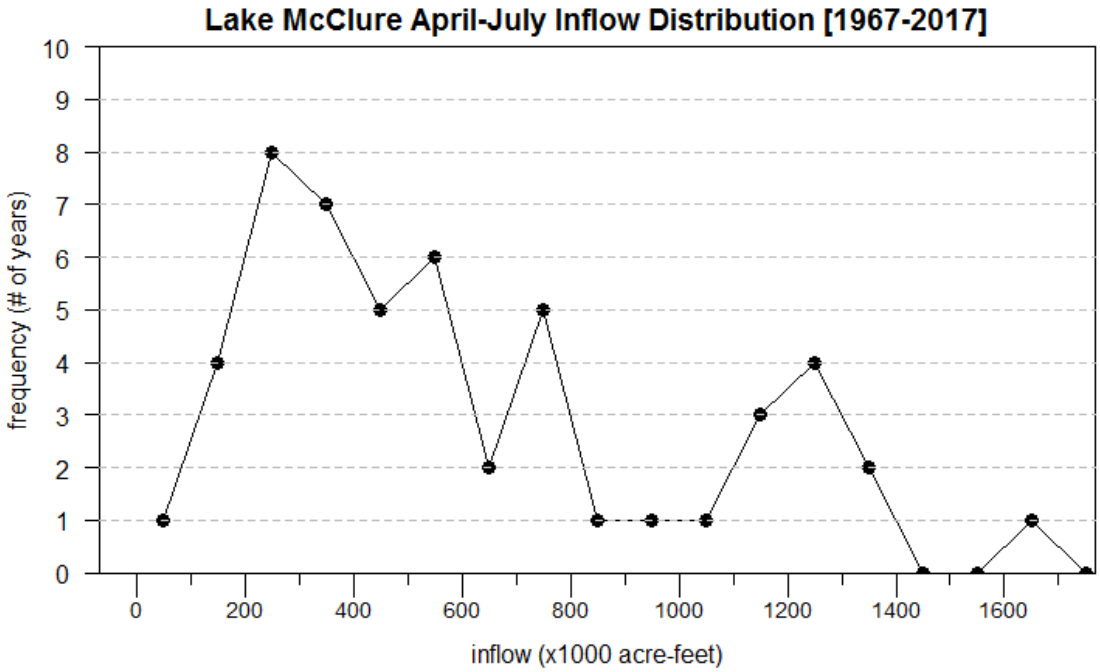

Figure 3: Histogram of Lake McClure April-July inflow from 1967-2017 (51 total years).Hydro-Climate Indices (Predictors)

An increasing number of Hydro-Climate Indices (HCIs) continue to be added to peer-reviewed literature, and a full investigation of all HCIs was not possible given the preliminary nature of this study. The selected HCIs, shown in **Table 3**, contains some of the more established HCIs. However, it is certainly plausible that other HCIs not included here may have predictive power for the Merced River basin.

Table 3: Hydro-Climate Indices used as predictors.

Index	Short-name	Source
North Atlantic Oscillation	NAO	http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/norm.nao.monthly.b5001.current.ascii.table
Pacific-North American Oscillation	PNA	http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/norm.mon.pna.wg.jan1950-current.ascii.table
Nino 1.2 Index	NINO1.2	http://www.cpc.ncep.noaa.gov/data/indices/ersst4.nino.mth.81-10.ascii
Nino 3+4 Index	NINO3+4	http://www.cpc.ncep.noaa.gov/data/indices/ersst4.nino.mth.81-10.ascii
Arctic Oscillation	AO	http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/monthly.ao.index.b50.current.ascii
Atlantic Multi-Decadal Oscillation	AMO	http://www.esrl.noaa.gov/psd/data/correlation/amon.us.data
North Pacific Gyre Oscillation	NPGO	http://www.o3d.org/npgo/npgo.php
Pacific Decadal Oscillation	PDO	http://research.jisao.washington.edu/pdo/PDO.latest
Madden Julian Oscillation, Phase 3/4	MJO3-4	http://www.cpc.noaa.gov/products/precip/CWlink/daily_mjo_index/proj_norm_order.ascii
Madden Julian Oscillation, Phase 6/7/8	MJO6-8	http://www.cpc.noaa.gov/products/precip/CWlink/daily_mjo_index/proj_norm_order.ascii

Palmer Drought Severity Index (Predictor)

The Palmer Drought Severity Index (PDSI) is a measure of the surface moisture balance, as first described by its creator Wayne Palmer (Palmer, 1965). Although the PDSI has its caveats, as described by Alley (1984), it remains an often used index for assessing drought conditions. Furthermore, it is routinely updated in near real-time, making it a particularly attractive measure to use for real-time operations. While the vast majority of its uses are in a backward-looking mindset (i.e. characterize the intensity of *current* drought based on recent conditions), we use it in a predictive fashion as supported by recent findings by Dewberry (2016) on the North and South Platte Rivers. We accessed PDSI data at the Climate Division level (see **Figure 4**) from the website below, which is updated in the first 10 days of every month.

ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/

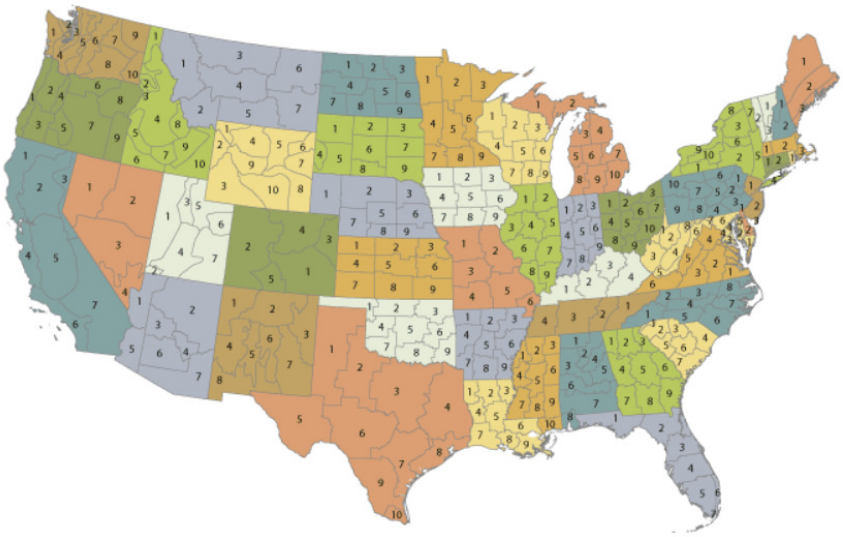

Figure 4: US Climate Divisions, used for calculating Palmer Drought Severity Index.

USGS Streamflow (Predictors)

Monthly streamflow at nine long-record USGS streamflow gages, shown in **Table 4**, was accessed for its predictive capabilities. Literature (Jefferson et al. 2008; Godsey et al. 2014; Shaw et al. 2014) , and past experience on the Platte River (Dewberry, 2016) has suggested that early winter streamflow could have predictive power for late spring flow due to the slow processes associated with groundwater infiltration and discharge into the stream system. Note that not all sites in **Table 4** are within the Merced River basin, and sites on nearby Tuolumne River, Eleanor and Cherry creeks was also included, since (i) groundwater flow lines are not expected to fully follow surface topography, and (ii) it is possible that combinations of gages could better characterize the sub-surface hydrologic state than any single gage.

Table 4: USGS streamflow gages used as predictors for Lake McClure inflow.

Gage Location	Gage ID
Merced River near Happy Isles Bridge	11264500
Merced River near Pohono Bridge	11266500
Tuolumne River near Hetch Hetchy (CA)	11276500
Tuolumne River above Early Intake near Mather (CA)	11276600
Tuolumne River below Early Intake near Mather (CA)	11276900

Cherry Creek below Valley Dam near Hetch Hetchy (CA)	11277300
Eleanor Creek near Hetch Hetchy (CA)	11278000
Cherry Creek near Early Intake (CA)	11278300
Cherry Creek near Tuolumne River confluence	11278400

RELATIONSHIP BETWEEN INFLOW AND THE ATMOSPHERE

Preliminary analysis of lagged relationships between the aforementioned predictors and April-July Lake McClure inflow were assessed through correlation. In addition, a lagged correlation analysis between inflow and the antecedent atmospheric conditions was conducted using the NOAA-ESRL NCEP/NCAR reanalysis. Although Bulletin 120 forecasts are first available in February (effective lead time of about 2 months), experience on the Platte River suggested longer lead time forecasts are possible. Thus, the analysis was extended through the previous year's November.

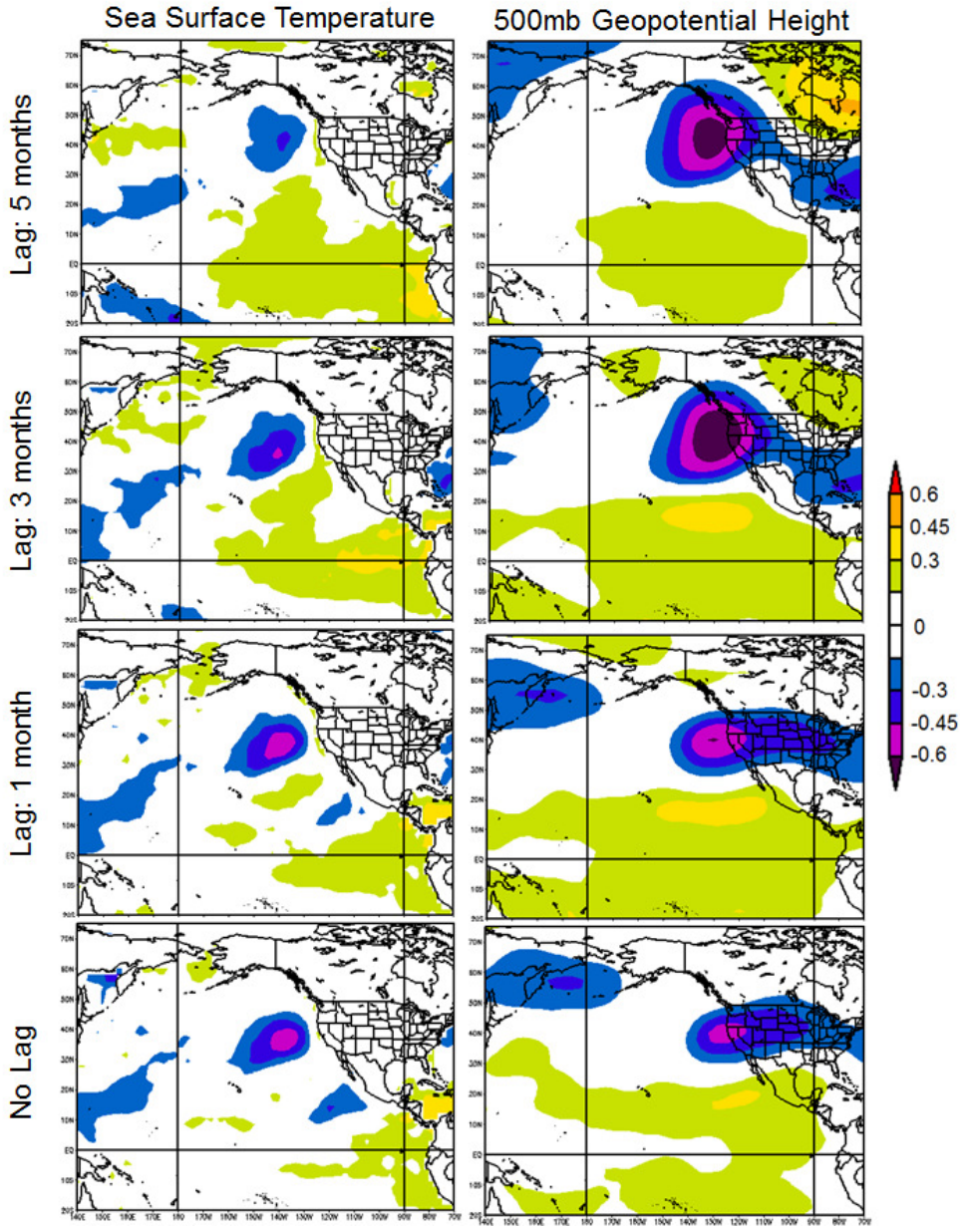

Figure 5: Lag correlation between April-July Lake McClure inflow and 3-month average (left) sea surface temperature anomalies, and (right) 500-mb geopotential height anomalies as a function of lag time. For example, the "Lag: 1 month" shows the correlation between April-June anomalies and inflow. Correlations exceeding 0.3 (or less than -0.3) are significant.

Figure 5 (previous page) shows the antecedent atmospheric conditions that occur during the winter and spring preceding times of high Lake McClure inflow. A strong relationship is noted, similar to the findings of Seager et al. (2014). The pattern is characterized by a large-scale anomalous low pressure trough, and associated counter-clockwise circulation, just off the western coast of North America. This pattern is also associated with colder than normal sea-surface temperatures, although it is difficult to discern the degree of feedback between the patterns (i.e. which one forces the other). Furthermore, it is unclear whether this pattern will be captured by any of the HCIs. For example, a relative lack of tropical Pacific sea-surface temperature anomalies suggests a weak or negligible footprint of the El Nino-Southern Oscillation phenomenon. Meanwhile, the position of the circulation anomaly appears to be in between the center of action of the well-known Pacific-North American pattern. Nonetheless, the high correlations at long lead times in **Figure 5** (i.e. first and second row, right column) suggests that a substantial portion of Lake McClure runoff may be predictable well in advance.

Table 5 shows a correlation table with all predictors, as a function of lead time extending to the previous November, which would represent a 5-month lead time if used in an operational setting. The MJO has moderately strong correlations at lead months of three months or less. However, given the preliminary nature of this study, we did not investigate the physical mechanism of this relationship and due to this uncertainty, did not choose to use the MJO in the forecasts at this time. The NAO and AMO showed marginally statistically significant correlation at relatively short lead times, but the strength of the relationships and the low lead time precluded us from using either in the forecasts. Interestingly, neither of the two El Nino-Southern Oscillation (ENSO) indices considered here (NINO1.2 and NINO3+4) have statistically significant skill for predicting inflow. As shown in **Figure 6**, this appears to be because the Merced River basin is positioned too far north to be affected by the southern lobe of ENSO-related anomalies (whereas southern California sees significantly stronger impacts). This does not rule ENSO's impact on the Merced River, but suggests that impact is not trivial to assess. In terms of tendencies in the Hydro-Climate Indices, the NINO1.2 has marginal predictive power during early winter, while the AMO has a slightly stronger correlation. However, scatter plots of these relationships suggested that the correlations may be biased by a few relatively outlying values. Thus, they were not used in the forecast.

Table 5: Correlation between possible predictors and Lake McClure April-July inflow. A Pearson correlation method was used and only values that are statistically significant at the 90% confidence interval are shown. Inflow was scaled by taking its logarithm due to the strong skewness in the distribution (see **Table 2**). All predictors were smoothed with a 3-month running average (ending on the indicated month) before calculating the correlation.

Predictor	Correlation					
Hydro-Climate Indices	April (Lead=0)	March (Lead = 1)	February (Lead = 2)	January (Lead = 3)	December (Lead = 4)	November (Lead = 5)
NAO	-0.24					
PNA						
NINO1.2						
NINO3+4						
AO						
AMO	0.26	0.26				
NPGO						
PDO						
MJO3-4	0.45	0.52	0.43	0.33		
MJO6-8		-0.48	-0.46	-0.34		
Hydro-Climate Indices Tendencies	April (Lead=0)	March (Lead = 1)	February (Lead = 2)	January (Lead = 3)	December (Lead = 4)	November (Lead = 5)
NAO						
PNA						
NINO1.2					0.37	0.28
NINO3+4						
AO						

AMO				0.43	0.48	0.42
NPGO						
PDO	0.30	0.31			-0.26	-0.28
Antecedent Streamflow	April (Lead=0)	March (Lead = 1)	February (Lead = 2)	January (Lead = 3)	December (Lead = 4)	November (Lead = 5)
11264500	0.47	0.53	0.53	0.47	0.47	0.32
11266500	0.52	0.54	0.52	0.46	0.47	0.34
11276500	0.52	0.31	0.3	0.25		
11276600	0.61	0.42	0.35	0.28		
11276900	0.7	0.56	0.46	0.34	0.27	
11277300						
11278000	0.37				0.3	0.25
11278300	0.54	0.42	0.39	0.35	0.37	0.28
11278400	0.67	0.61	0.54	0.43	0.41	0.3
PDSI (select Climate Divisions)	April (Lead=0)	March (Lead = 1)	February (Lead = 2)	January (Lead = 3)	December (Lead = 4)	November (Lead = 5)
MN 01	0.64	0.66	0.67	0.65	0.64	0.63
MN 02	0.58	0.61	0.63	0.63	0.62	0.59
CA 04	0.89	0.88	0.83	0.73	0.56	0.39
CA 05	0.92	0.9	0.84	0.72	0.53	0.35
PDSI Tendency (select Climate Divisions)	April (Lead=0)	March (Lead = 1)	February (Lead = 2)	January (Lead = 3)	December (Lead = 4)	November (Lead = 5)
NV 02	0.63	0.61	0.45	0.39	0.37	0.3
CA 03	0.28	0.45	0.54	0.61	0.6	0.48

Antecedent streamflow becomes an increasingly stronger predictor of April-July inflow as lead time decreases. This follows intuition, and could arise by several processes including the enhanced snowmelt runoff during warm periods (signaling an anomalously large snowpack), or a gradual increase in groundwater flow in cases of wet/snowy and/or warm early winter periods. Interestingly, the correlations of the two Merced River gages (11264500 and 11266500) did not have the highest values of the gages, highlighting the complexity of attributing cause and effect from just a single gage. Nonetheless, correlation values of antecedent streamflow were high enough to warrant inclusion into the model development.

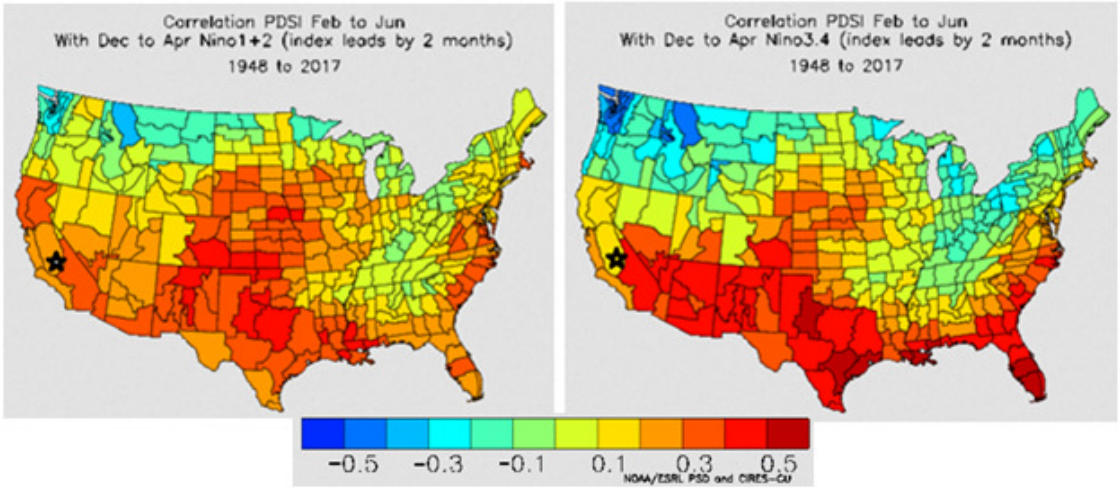

Figure 6: Correlation between December-April (right) NINO1+2 and (right) NINO3.4 indices and February-June PDSI, which is a strong predictor of Lake McClure inflow. Note that only weak correlations are noted in the Merced River basin's climate division (noted by star).

In consistency with the conclusions of Dewberry (2016) for the North and South Platte River, the most notable correlations in **Table 5** arose from PDSI and PDSI tendency predictors across several areas of the US. **Figure 7** and **Figure 8** show the lagged correlation between PDSI and its tendency with Lake McClure inflow from no lag to a lag of 5 months. As the PDSI is expected to be a very good proxy for snowpack (despite not actually using snow gage data), the high short-lead correlation in California are not surprising. For instance, **Figure 7**, panel (a) shows that the February-April PDSI has a correlation exceeding 0.8 with Lake McClure April-July inflow. However, note that this represents essentially no lead time in an operational setting, since this forecast would not be available until the April PDSI was updated, which occurs by the first week of May.

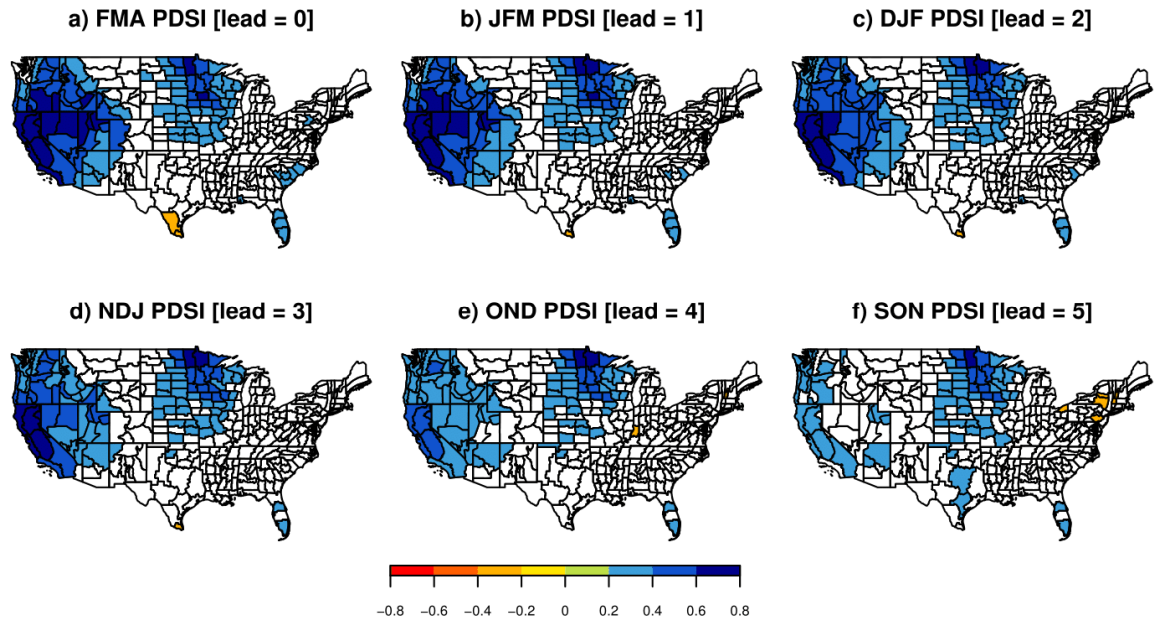

Figure 7: Lag correlation between 3-month average PDSI and April-July inflow into Lake McClure.

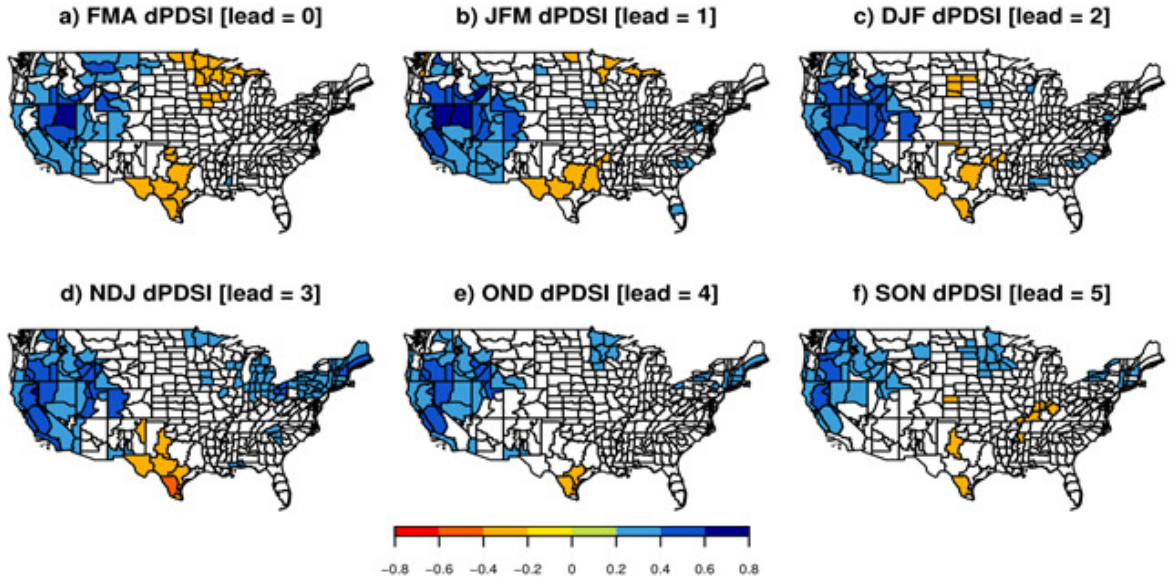

Figure 8: Same as **Figure 7** except using the 3-month average PDSI *tendency*.

The more surprising and useful findings (from the standpoint of real-time operation) from **Figure 7** and **Figure 8** are two-fold: first, the long persistence of the relatively high correlation California, and second, the fact that there are other regions (notably the northern Great Plains) that have strong correlation with Lake McClure inflow. **Figure 9** shows lead/lag correlations between two regions of high correlation in **Figure 7** (central California and northern Minnesota) and atmospheric conditions. For instance, the second row (No Lead) shows the simultaneous relationship between the PDSI time series and atmospheric conditions.

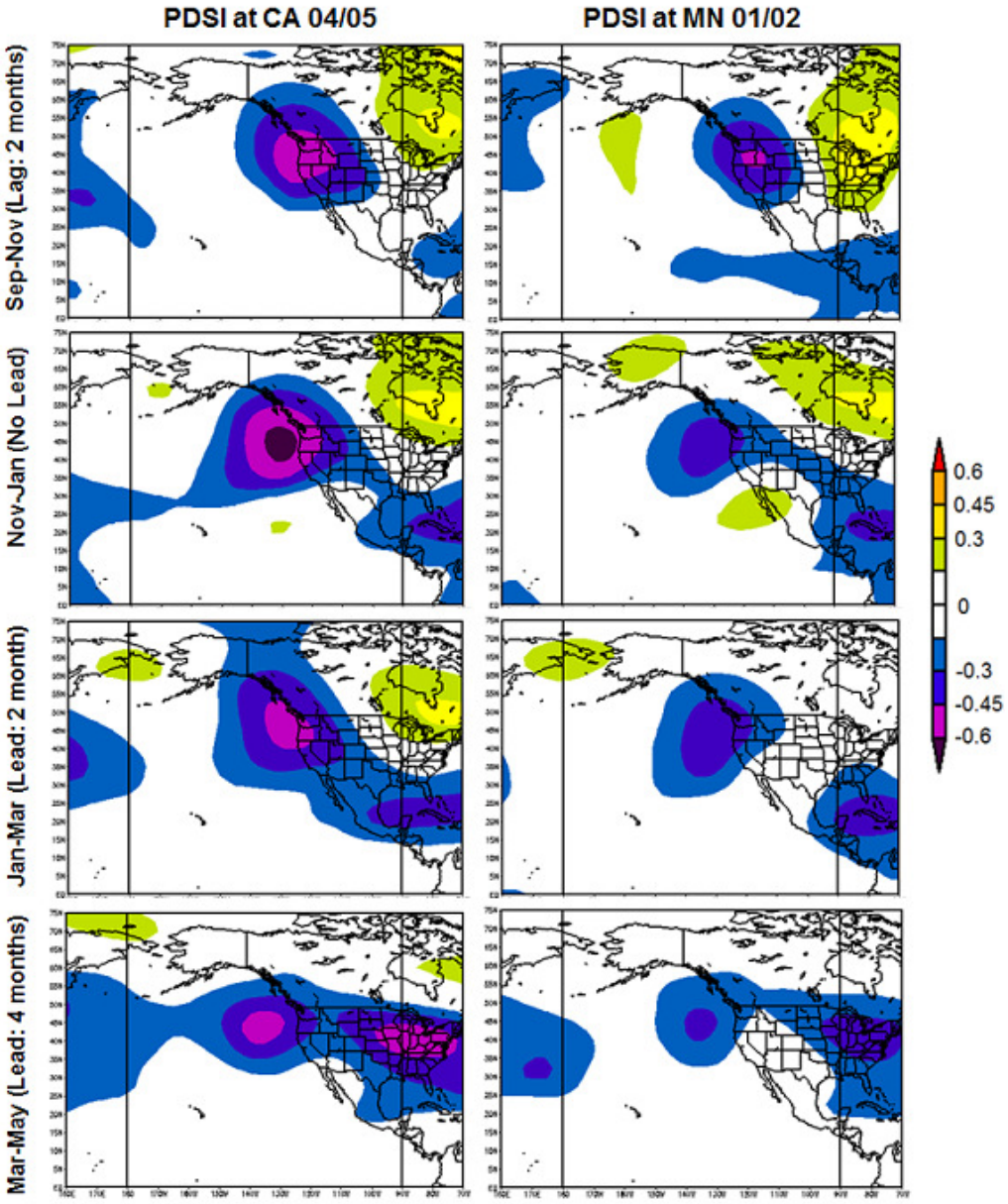

Figure 9: Lead/lag correlations between 500-mb geopotential height anomalies and November-January average PDSI at (left) CA Climate Divisions 04/05 and (right) MN Climate Divisions 01/02. Negative anomalies are associated with a counter-clockwise circulation and enhanced storminess; vice versa for positive anomalies.

There are several observations from **Figure 9** that have relevance to seasonal forecasting in the Merced River basin:

(1) The circulation anomaly in the left column of **Figure 9**, namely a negative correlation implying below normal heights and likely above normal storminess, should intuitively favor higher precipitation and above normal PDSI in California. This acts as a consistency check on the physical interpretation of results.

(2) PDSI anomalies can be used to inform what the large-scale and regional anomalous atmospheric circulation looks like. This is because the PDSI is largely drive by antecedent atmospheric conditions. Furthermore, using 3-month average PDSI provides a low-frequency filter that highlights the more persistent circulation anomalies.

(3) The PDSI anomalies in the northern Great Plains (see **Figure 7**) have similar atmospheric association as that in California, suggesting that the atmospheric footprint may have similar origin. Note that, in no way does this suggest that the PDSI anomalies are *causing* the atmospheric anomalies; they are merely a useful way to characterize the anomalous atmospheric flow.

(4) The patterns in both columns in **Figure 9**, especially in the left column, are remarkably persistent, implying that the precursor to high Lake McClure inflow may not have a strong seasonal dependence. In turn, this implies that the same predictors could be used to forecast inflow at various lead times.

Based on **Table 5**, **Figure 7** and **Figure 9**, two PDSI regions are selected to test for predictive skill in forecasting Lake McClure inflow: (i) California climate divisions 04 and 05 (averaged), and (ii) Minnesota climate divisions 01 and 02 (averaged). In the following section, inflow forecasts based on these predictors are developed and compared to those based on climatology as well as Bulletin B120.

MODEL DEVELOPMENT & PERFORMANCE

To combine the PDSI predictors into a single forecast, a multiple linear regression of the following form (1) was developed:

$$Y = A_0 + A_1X_1 + A_2X_2 + \cdots + A_NX_N, \qquad (1)$$

where X_i is the i-th predictor, N is the number of predictors, A is the regression coefficient of the i-th predictor and A_0 is the y-intercept. Y is the variable that is being predicted, which is the *natural logarithm of Lake McClure inflow* over the 1967-2017 period. The logarithm of inflow was used because it results in a more linear relationship between the predictors and inflow (due to the non-Gaussian nature of the inflow). This was preferred over a more complicated approach such as using raw inflow, but allowing for a non-linear relationship through a second or third-order polynomial relationship with X.

Five equations of type (1) were developed: one for each month beginning in December and continuing through April. Note that for simplicity, the same two predictors were used for each forecast, which was determined to be reasonable given the persistence patterns shown in **Figure 7**. **Table 6** shows the regression coefficients of the predictors. Note that the "Forecast Month" indicates when a forecast could be available in real-time operations. Realistically, a forecast could be developed by the 15th day of the indicated month.

In the December forecast, which relies on September-November data, the northern Great Plains PDSI has more predictive strength than the California region. This could be due to the seasonality of California precipitation; stated differently, since rainfall in California does not begin in earnest until mid-November or later, the PDSI anomaly in this region does not have as much utility as later in the season. From January through April, the importance of the California PDSI increases, while the impact of the northern Great Plains PDSI decreases, though both are still strongly statistically significantly different from zero with at least 95% confidence.

Table 6: Regression coefficients and standard error as a function of lead time. Also shown in the cross-correlation (X-Corr.) between the two predictors. Asterisk next to the coefficient denote significance at the 95%, 98% and 99% level for one, two asterisk, respectively.

		Predictor #1: $PDSI_{CA04/05}$		Predictor #2: $PDSI_{MN01/02}$		
Forecast Month	Intercept	Coefficient	Error	Coefficient	Error	X-Corr.
December	13.0	0.085*	0.033	0.155***	0.035	0.47
January	13.0	0.117***	0.031	0.127***	0.031	0.53
February	13.1	0.167***	0.023	0.077**	0.025	0.60
March	13.1	0.171***	0.021	0.066**	0.023	0.62
April	13.1	0.179***	0.016	0.064**	0.019	0.57

While the strongly statistically significant values in **Table 6** are encouraging, the main question is how accurately these predictors can forecast the Lake McClure inflow. A historical hindcast over the 1967-2017 period was prepared, with the hindcast values compared to observed Lake McClure inflow. **Table 7** shows the forecast performance using four metrics: (i) hindcast versus observed correlation, (ii) mean absolute error (MAE), (iii) mean bias (hindcast – observed) and (iv) error quantiles for the 10th, 25th, 50th, 75th and 90th percentiles. The error quantiles can be used to estimate the answer to the following question: "what fraction of the time will the forecast error be below a certain value"? **Table 8** is analogous to **Table 7** except limited to the 1990-2017 period during which Bulletin 120 forecasts were available. **Table 9** presents the analogous performance metrics for Bulletin 120.

Table 7 shows that all four forecast performance metrics improve steadily from December through April. However, even for the December forecast, the MAE is 233K acre-feet, which is 27% lower than the climatological

forecast's 317K. Thus, **it is possible that December (or earlier) forecasts could have utility in an operational setting**. For reference, **Figure 10** shows a scatter plot of predicted versus observed inflow for the February forecast. Note the negative (i.e. underestimate) bias especially when inflows are forecasted in the 700-1000K acre-feet range. **Table 7** shows that the negative bias improves steadily from December through March and nearly disappears in the April forecast. It is possible that this bias could be eliminated given consideration of non-linear effects of predictors.

Table 7: Summary of forecast performance as a function of forecast month. For correlation, a Pearson correlation is used. MAE = mean absolute error, in acre-feet; Bias is the mean bias, in acre-feet. Error quantiles are shown for the 10th, 25th, 50th (median), 75th, and 90th percentile, in acre-feet.

Forecast Month	Correlation	MAE	Bias	Abs. Error Quantiles (10 | 25 | 50 | 75 | 90)
December	0.64	233K	-64K	42K | 62K | 175K | 367K | 539K
January	0.67	218K	-53K	15K | 68K | 151K | 325K | 526K
February	0.83	154K	-27K	25K | 49K | 90K | 211K | 330K
March	0.88	138K	-22K	29K | 47K | 96K | 180K | 272K
April	0.88	134K	-7K	24K | 42K | 92K | 159K | 293K
Climatology	N/A	317K	-86K	46K | 148K | 252K | 409K | 707K

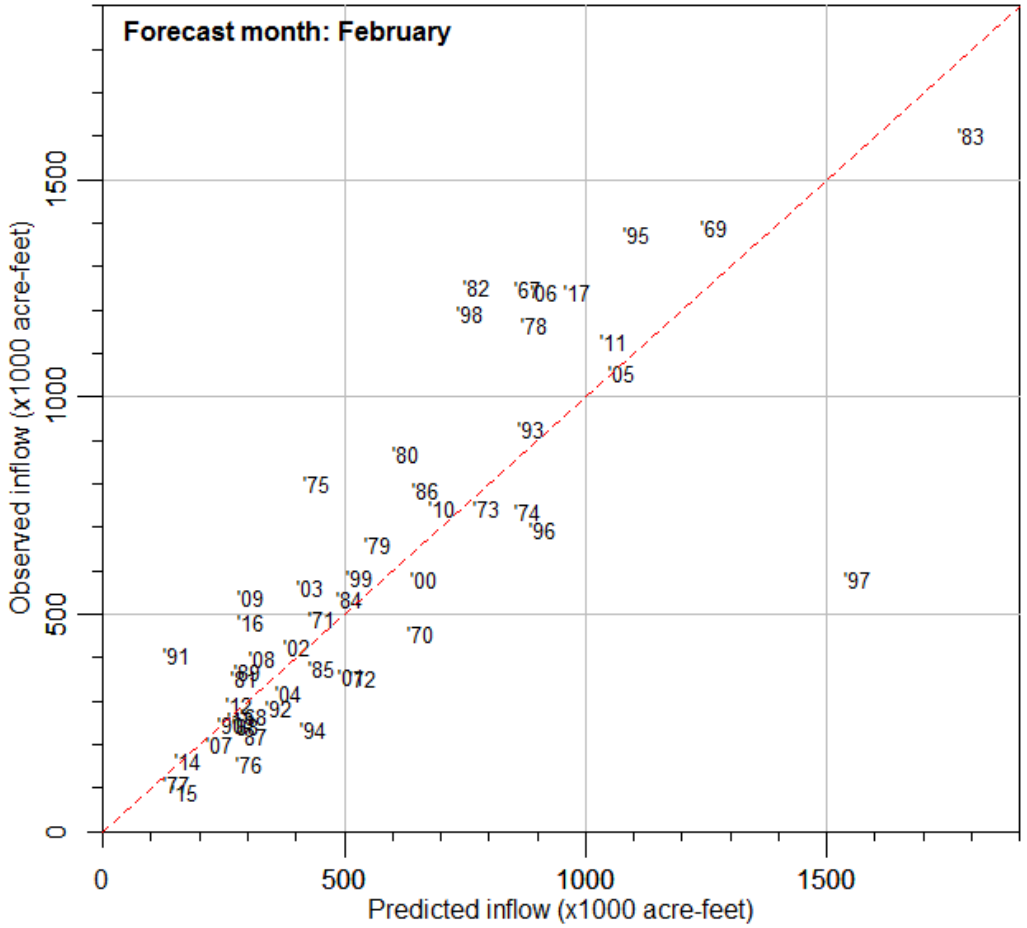

Figure 10: Predicted versus observed April-July inflow into Lake McClure for the February forecast (see **Table 6** for predictor coefficients), which would have a lead time of about 45 days in a real-time setting. Numbers show the last two digits of the hindcast year. The hindcast period is 1967-2017.

Comparison of Table 7 and Table 8 shows that the HCI-based forecast developed here outperforms Bulletin 120 by all four metrics during February and March, while the latter outperforms during April. This is very likely to arise from the difference in methodology: whereas the HCI-based forecast takes significant account of regional and large-scale conditions, we believe Bulletin 120 relies nearly exclusively on local snow gage data. From December through March, consideration of large-scale and regional conditions outweighs knowledge of local snowpack. However, by April, knowledge of the local snow pack becomes the most important predictor. Thus, further improvement to the forecast developed herein can be achieved by including snow gages such as those belonging to the California Department of Water Resources.

Cross validation of results was tested in two ways: (i) sensitivity to time period, and (ii) sensitivity to random sample. For (i), regression fitting was done for the 1967 – 1997 and 1987 – 2017 periods separately, followed by preparation of forecasts for the omitted years. For (ii), ten regressions were fit to each forecast month after randomly selecting 30 years and predicting values for the omitted 21 years. In both cases, it was found that the regression coefficients in **Table 7** were not sensitive to cross validation. However, it is stressed that additional cross validation be undertaken before this system is used operationally.

Table 8: Same as **Table 7** except for only the overlapping period with Bulletin 120 (1990-present). Green font indicates outperformance, while red font indicates underperformance compared to Bulletin 120 (see **Table 9**).

Forecast Month	Correlation	MAE	Bias	Abs. Error Quantiles (10 | 25 | 50 | 75 | 90)
December	0.69	207K	-53K	34K | 57K | 145K | 293K | 501K
January	0.73	188K	-54K	9K | 51K | 127K | 261K | 471K
February	**0.77**	**157K**	**-14K**	**19K | 41K | 81K | 221K | 286K**
March	**0.88**	**132K**	**-22K**	**21K | 46K | 78K | 200K | 282K**
April	0.93	115K	-23K	18K | 50K | 98K | 157K | 220K
Climatology	N/A	296K	-82K	63K | 100K | 231K | 417K | 696K

Table 9: Same as **Table 7** except for Bulletin 120 forecasts (compare with **Table 8**).

Forecast Month	Correlation	MAE	Bias	Abs. Error Quantiles (10 | 25 | 50 | 75 | 90)
December	Bulletin 120 not available until February.			
January				
February	**0.77**	**195K**	**-33K**	**43K | 99K | 153K | 242K | 471K**
March	**0.80**	**165K**	**-29K**	**32K | 60K | 119K | 220K | 331K**
April	0.96	79K	-23K	4K | 23K | 53K | 96K | 185K

Despite the strong correlations noted in **Table 7** and **Figure 10**, it is essential to note that this study does not undertake a full investigation of the physical mechanism. Understanding the physical mechanism is a recommended step towards better understanding where predictive skill originates, and perhaps more importantly, to determine the possibility of additional refinement to improve forecast performance.

CONCLUSION

A feasibility study of long-range predictability of Lake McClure April-July inflow was undertaken based on the statistical approach outlined in Dewberry (2016). Predictors were Hydro-Climate Indices as well as the Palmer Drought Severity Index, and antecedent streamflow. Time-series of predictors were accessed and tested for predictive power using lagged correlations. In addition, lagged spatial correlations with atmospheric data were analyzed to determine what kind of atmospheric circulations favor above/below normal flow at Merced. It was found that a low-pressure trough in the northeast Pacific Ocean strongly favors above normal inflow likely due to enhanced storminess and a snowpack. Although this relationship was not captured in any conventional HCIs such as El Nino-Southern Oscillation, it was implicitly captured when using the Palmer Drought Severity Index (PDSI) as a proxy. Two regions were outlined as particularly strong predictors: central/northern California and northern Minnesota. The former region is intuitive (i.e. indirectly measures snowpack in the Merced basin) although the persistence of the predictive signal, lasting through early winter, was somewhat unexpected. The latter region likely acts as a predictor through correlations with large-scale atmospheric anomalies that promote enhanced storminess over California. The physical mechanism was not investigated here, however.

For simplicity, only the two aforementioned PDSI predictors were used in a multiple linear regression model of Lake McClure inflow. Hindcasts were developed over the 1967-2017 period, and compared to climatology as well as Bulletin 120 (over the 1990-2017 period over which Bulletin 120 forecasts were publically available). Results showed that:

i. Hindcast skill far exceeding simple climatology was observed through at least the previous December, representing a ~4 month lead time forecast.
ii. Hindcast skill outperformed Bulletin 120, in some cases significantly, during February and March, while Bulletin 120 was superior in the April forecast. Thus, it is recommended that real-time local snow gage data be added as predictors.
iii. The findings in (ii) were reconciled by hypothesizing that the HCI-based forecasts are based to a large extent on regional and large-scale conditions compared to the Bulletin 120's near exclusive reliance on local snow gage data. Results suggest that the local conditions are outweighed by non-local factors through March, at which point local conditions.

RECOMMENDATIONS

Based on the preliminary findings herein, it is recommended that additional research could significantly refine and expand a system for predicting Lake McClure inflow weeks to months in advance with sufficient skill to be used for decision support. Furthermore, such forecasts would be complementary to real-time hydrologic forecasts being provided to MID by Dewberry as part of the MIDH2O project. For example, under MIDH2O, seasonal forecasts currently use the "initial conditions" approach outlined in **Figure 1**. However, it is suggested that this can be improved further by using the predictions developed herein. Thus, instead of simply using the historical 10th, 50th and 90th percentile precipitation traces, the forecast developed herein could be used to determine what historical years are similar to the current year *in a predictive*, not backward-looking mindset. This would constrain the range of possible flows to make the forecast have more utility, and thus value.

In addition, the following topics are specifically noted as having potentially significant benefit on forecast performance and utility:

- Consideration of long-record snow gages within and in close proximity of the Merced basin, which is expected to significantly improve forecast performance at the 1 month and shorter lead-times. This will likely result April forecast skill being on par with or exceeding Bulletin 120.
- The preliminary forecast developed herein is deterministic (i.e. single number), analogous to predicting only the 50th percentile (see **Figure 2**) or "Most Likely" expected flow. Forecast utility can be improved by predicting the probability of one or more of the following events occurring during the April-July runoff season:
    - high flow (e.g. exceeding the 75th percentile)
    - low flow (e.g. below the 25th percentile),
    - not a low flow (e.g. above the 25th percentile).
- Following Dewberry (2016), probabilistic forecasts can be developed using a logistic regression model based on the same predictors as described herein.
- Consideration of Madden Julian Oscillation (MJO), including an exploration of physical mechanism. Inclusion of the MJO could significantly increase forecast skill at the 2+ month lead time.
- Assessment of potential predictive skill of National Center for Environmental Prediction's Climate Forecast System precipitation and/or runoff forecasts. These forecasts are updated daily and could significantly improve forecast skill.
- Inclusion of the PDSI tendency into the forecast, as noted by the strong correlations at lead times up to 4 months. An investigation of physical mechanism is recommended to confirm this is a robust signal and not a statistical artifact.

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