Multisite seasonal ensemble forecast for twenty sites in the Upper Colorado River Basin

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**Abstract**

The generation of seasonal streamﬂow forecasts at several locations is crucial for operations of the Upper Colorado River Basin water resources system. We show that the skillful framework of Bracken et al. (2010) can be extended to generate monthly peak season (April-July) forecasts at twenty sites in the Upper Colorado River Basin at long lead times. We also improve the framework by incorporating the exible spatial and temporal disaggregation method of Nowak et al. (2010) to obtain ensemble forecasts for each location and month in the peak season. With few exceptions, skills are positive for all sites, months and lead times. The November 1 forecasts show an average of 13% increase in skill over climatology and as high as 20% increase in some months.

*Keywords:*

**1. Introduction**

In the last ten years water supply management in the Upper Colorado River Basin (UCRB) has come under increasing scrutiny and regulation. Drought (Fulp, 2005), climate change (Rajagopalan et al., 2009), environmental ﬂows and increasing demands (Bureau of Reclamation, 2008) have all put the reliability of the system into question. In 2007 the “Interim Guidelines” were passed as a response to some of these factors (Bureau of Reclamation, 2007). These guidelines lay a framework for coordinated operations of Lake Powell and Lake Mead which depend heavily on water supply forecasts. These factors all underscore the need for skilful forecasts at long lead times at many locations throughout the UCRB. The generation of forecasts at a number of sites on the river network is crucial for operations of the UCRB water resources system. The “24-Month Study” is the Bureau of Reclmation’s primary water supply forecast model in the Upper (and since January 2010) and Lower CRB. This model is run monthly and requires inﬂow forecasts at 12 locations throughout the Upper Basin. Operators use these inﬂow forecasts to generate reservoir outﬂows which are then run through the “24-Month Study” model to obtain projections of a suite of water resources system variables (e.g., reservoir levels, releases, power generation etc.) for the next 24 to 36 months. These then guide planning and operational decisions over the 24 month period. Beyond initial reservoir states, the predictive capability of the model depends largely on the skill of the inow forecasts – thus, skillful long lead forecasts of the peak season (Apr-Jul) are very important. The nonparametric multisite ensemble forecast framework developed by Bracken et al. (2010) showed skill at long lead times in forecasts of peak season streamﬂows. They demonstrated their approach on four key sites in the Upper Colorado River Basin (Colorado River near Cisco, Utah, Green River at Green River, Utah, San Juan River near Blu, Utah, and Colorado River at Lees Ferry, Arizona). The framework of Bracken et al. (2010) is similar to many recent studies (Moradkhani, 2010; Opitz-Stapleton et al., 2007; Regonda et al., 2006; Grantz et al., 2005). In this forecasts of an “index gauge” that is composed of the ow at all the sites in the network is ﬁrst generated based on a number of large scale climate predictors using local polynomial functional estimation approach Large scale climate predictors are identiﬁed for the index gauge ﬂow at several lead times and local polynomials is used to obtain the best model. The generated seasonal forecast of the index gauge is then disaggregated using the approach of Prairie et al. (2007) to obtain forecasts at the four locations and for each month of the peak season. As mentioned, signiﬁcant skills were obtained at the four locations. While promising, these results leave open the question of whether the skills translate to all the locations on the UCRB that are needed for planning and management of the water resources system. In this research we modiﬁed the approach of Bracken et al. (2010) and apply this to all the 20 locations on the UCRB. Study area and data sets used are ﬁrst described, followed by a brief description of the approach for the beneﬁt of the readers. The validation and results are then presented with a summary and discussion.

**2. Study Area and Data**

The UCRB has a drainage area of 279,300 square kilometers. The terrain varies over 4000 m from east to west. Lees Ferry is located at the outlet of the Upper Basin. The sites used in this study (Figure 1a) are all the natural ﬂow nodes in the upper basin. The sites used by the USBR in the 24-Month study model are a subset of these sites.

*2.1. Flow Data*

We obtained the most recent monthly natural ow data developed by the Bureau of Reclamation in the UCRB that currently extends to 2007. This dataset is developed and updated regularly by the United States Bureau of Reclamation. Naturalized streamﬂow are computed by removing anthropogenic impacts (i.e., reservoir regulation, consumptive water use, etc.) from the recorded historic ﬂows. Prairie and Callejo (2005) present a detailed description of methods and data used for the computation of natural ﬂows in the CRB. The data is availaable from (http://www.usbr.gov/lc/region/g4000/NaturalFlow/index.html). The data is provided as both intervening (gains since the last upstream gauge) or as total ow (sum of all upstream intervening ow at a gauge). We use the intervening data but convert to total ow internally for reasons described in the methodology section (Figure 1b). All the 20 locations are described In Table 2.

*2.2. Climate data*

The climate variables are the same as (Bracken et al., 2010) though we obtained the most recent observations for all of the predictors (through 2010 where available). The variables used were zonal and meridonal wind, SST, geopotential height and Palmer Drought Index (a surrogate for soil moisture) – all from the NOAA Earth Science Research Laboratory as predictors of large scale climate. Regions of high correlation with Lees Ferry Flow were determined using the ESRL linear correlation tool (http://www.esrl.noaa.gov/psd/data/correlation/). The variables are averaged over these regions and the resulting time series is used as a predictor. This analysis is repeated for each lead time to obtain a suite of climate predictors. This technique is described in detail in Grantz et al. (2005)and Regonda et al. (2006).

*2.3. Snow Data*

The amount of snow water equivalent (SWE) data was greatly increased over that used in Bracken et al. (2010). Bracken et al. (2010) used 10 representative sites obtained from Natural Resources Conservation Service (NRCS) (http://www.wcc.nrcs.usda.gov/snow). We use the 86 sites (Figure 2) that go into the UCRB snowpack report (http://www.usbr.gov/uc/water/notice/snowpack.html). As a result of using more data we were able to genrate a snowpack predictor for January 1 as well as improve the snow predictors for all other lead times.

**3. Methodology**

We use the the same framework as (Bracken et al., 2010, see their section 4) with some notable changes. Most importantly we (1) expand the disaggregation to include all 20 natural ﬂow nodes in the UCRB and (2) we include the ﬂexible disaggregation method of Nowak et al. (2010) instead of computationally intensive the disaggregation method of Prairie et al. (2007). As in Bracken et al. (2010) we created an “index” gauge peak season ﬂow which the sum of peak season ﬂows at all the 20 locations; this is forecasted using large scale climate variables in a multi-model ensemble approach Bracken et al. (2010); Regonda et al. (2006); which is subsequently disaggregated to ensemble monthly ﬂows at all the 20 locations. The nonparametric disaggregation method of Nowak et al. (2010) is known as proportion disaggregation is a computationally simple approach that preserves the summability criteria of the network (intervening ﬂows upstream sum to downstream total ﬂow at Lees Ferry). The method is able to simultaneously conduct space and time disaggregation through the use of proportion matricies (matricies whose contents sum to unity). Figure 3 shows schematically how the index gauge is split simultaneously to in space and time to all twenty sites. In space-time disaggregation there is one proportion matrix for each year in the historical record. For a given seasonal ﬂow value to be disaggregated, the method identiﬁes K nearest neighbors of the ﬂow value and selects a historical proportion vector which is multiplied by the total ﬂow to obtain space-time disaggregated values. For more details, the interested reader is referred to Nowak et al. (2010). Below we describe the implementation steps brieﬂy for the beneﬁt of the reader:

1. Create an “index” gauge ﬂow by summing all the total seasonal ow at each site, as mentioned above. Identify large scale climate predictors of index gauge ow. This is done by correlating it with global climate variables at diﬀerent lead times and creating average time series from regions of high correlation with physical reasons (Grantz et al., 2005; Bracken et al., 2010).
2. Identify a set of the ”best” set of models using locally weighted polynomial (Loader 1999) for each lead time. The best models are dened as those that have low generalized cross validation value (GCV) (Craven and Wahba, 1979) and do not exhibit multicolinearity A suite of best models is selected using their GCV values -typically, all models within a small range of the lowest GCV value are selected (see Bracken et al. (2010); Regonda et al. (2006), for details). The functional form of the models is the typical regression form

*y* = *f* (x) + ε (1)

where x is the vector of predictor variables, *f* is the function that is estimated locally using locally weighted polynomial approach and ε is the error with the standard assumption of Gaussian distribution and i.i.d based on regression theory. The details of this approach and applications can be found in the aforementioned references. Also, see Rajagopalan et al., (2010) and Lall (1995) for a general review of local functional estimation methods.

1. Identify a set of the best locally weighted polynomial models Loader (1999) for each lead time. The best models are deﬁned as those that minimize the generalized cross validation value (GCV) (Craven and Wahba, 1979) and do not exhibit multicolinearity Regonda et al. (2006).
2. Generate ensemble forecasts of index gauge ﬂow by weighting the best models according to their GCV value (lower GCV gets higher weight). Multimodel ensemble predictions are made by randomly selecting a model based on the GCV-based weights, obtaining the mean forecast from the model (of the form in equation 1 above) and generating a Normal deviate with the appropriate error variance. This is repeated to generate the ensemble.
3. Disaggregate the total seasonal ow at to the index gauge to intervening monthly ow at all the 20 sites.

**4. Validation**

As mentioned we applied the methodology described above to generate monthly ensemble streamﬂow forecasts at 20 locations in the UCRB for the peak season (Apr-Jul) at diﬀerent lead times from the ﬁrst of each month starting November 1st. We validated the results using the same methods as Bracken et al. (2010) – Leave-one-out cross validation and “retroactive” forecasts. Leave-one-out cross validation removes the current year form the model, and then predicts that year using the remaining data. Retroactive veriﬁcation only uses the data available prior to the forecast year, as would be the case in real operations. This way it is possible to compare directly to operational forecasts of the CBRFC. The leave-one-out validation was performed for the period 1949-2007 and the retroactive for 1993-2007. The ranked probability skill score (RPSS) Wilks (1995) was computed for each year in the history and then the median value is presented. RPSS value of, 1 indicates a perfect categorical forecast, 0 indicates no diﬀerent from climatology and negative values suggest worse than climatological forecast. The median correlation (MC), the correlation between the historical data and the median of the ensembles for each year, was also computed for each site/month combination.

**5. Results**

We computed the skill scores for all the locations and at all lead times. Here we present results at three lead times Nov 1st, Jan 1st and Apr 1st. Table 3 shows the models used at each lead time. The RPSS values of the index gauge (Lees Ferry total ﬂow) ﬂow at these lead times for the two validation method are shown in Table 4. These are similar to the skills from Bracken et al. (2010). The skills are substantially higher than climatology at long lead time (e.g., Nov 1st) and progressively increase with decrease in lead time. This indicates that the methodology is able to provide useful information of the streamﬂow distribution well in advance. The retroactive skills are lower because of the use of less data. Table 1 shows the RPSS and MC for all the locations and all months in the peak season for the three lead times mentioned above. In general we see the skills decreasing as lead time increases, as to be expected. Some sites such as the Duchesne River Near Randlett, UT (14) have consistently positive skill back to the Nov 1 lead time. June had the highest overall skill of any month, likely because the average peak ow occurs in June. The sites included in the original study (8, 16, 19 and 20, outlined in bold) all tend to do very well. These “key” gauges represent the major contributions to Lees Ferry ow and thus important for planning purposes. This is reasonable because these are the largest tributaries and will have a stronger response to large-scale climate. Another trend we see is that the skills tend to be better as we move toward the outlet of the basin. That is consistent with the result that the larger tributaries perform better and that by aggregating the ﬂows the impact of large scale climate signal is stronger. Magnitudes of the disaggregated skills tend to be less that those seen in Bracken et al. (2010). Its seems that some of the skill is “distributed” among the new sites. One possible extension to improve skills in smaller tributaries would be disaggregate in chunks based on regions (such as the San Juan basin) to better capture regional behavior. Figure 4 and 5 show seasonal and monthly (June) ensembles respectively at The Gunnison River near Grand Junction (Site 6) for three leaad times (Apr1, Jan1, Nov1). This site was chosen because it was not present in the four sites used by Bracken et al. (2010) and it is an important site for water resources planning in the UCRB. These plots show the general trend that applies across most sites, ensemble variability increases and skill decreases as lead time increases. They also capture the high and low ﬂow variability quite well at Jan 1st and Apr 1st forecasts, which are very useful for management. Figure 6 shows the forecasts in retroactive mode. Skill in this example also decreases with lead time and the variance of the forecasts is much smaller for Apr1 than for any other lead time. These forecasts are compared directly to the CBRFC coordinated forecasts at the same site and show similar if not better performance.

**6. Conclusions**

We have shown that the framework of Bracken et al. (2010) can be extended successfully to twenty sites in the UCRB. This method is parsimonious and requires very little data input compared to existing physically based forecast models. We make slight modiﬁcations to the method including incorporating the disaggregation method of Nowak et al. (2010). The modiﬁcations and the incorporation of the most recent data caused out results to diﬀer slightly but not notably from the original method. To a large extent the skills are positive even after spatial and temporal disaggregation. We see a degradation of the skill as lead time increases which is to be expected. June has the highest predictability because that is the peak ﬂow month in the UCRB on average. We also see that larger tributaries tend to have higher skill. While individual sites do show negative skills, taken as a whole, we see a vast improvement over climatology. Even greater improvement in skill could likely be gained by combining this method with existing forecasts such as the CBRFC coordinated forecast. The only remaining step to make these forecasts truly useful would be to provide them as unregulated ﬂow. The 24-Month Study takes input as unregulated ﬂow to avoid explicitly modeling demands. In many cases this is as simple as subtracting a constant but in others it requires intimate knowledge of regional consumptive use. Using these forecasts as input to a decision model, the operational impacts of improved forecasts could be assessed.

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