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

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Abstract

The generation of forecasts at a large number of sites is crucial for operations of the Upper Colorado River Basin. We show that the 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 to incorporate the ﬂexible disaggregation method of Nowak et al. (2010) into the framework to perform spatial and temporal disaggregation. 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 (of Reclamation, 2008) have all put the reliability of the system into question. In 2007 the “Interim Guidelines” were passed as a repsonse to some of these factors (of Reclamation, 2007). These guidelines lay a framework for co-

ordinated 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 large number of sites is crucial for operations of the Upper Colorado River Basin. The “24-Month Study” is the Bureau of Re­clmation’s primary water supply forecast model in the Upper (and since January 2010) and Lower Colorado River Basin. This model is run monthly and requires inﬂow forecasts at 12 locations throught the Upper Basin. Operators use these inﬂow forecasts to gerate reservoir outﬂows which are then run through the “24­Month Study” model to obtain a picture of water resources for the next 24 to 36 months. Beyond initial reservoir states, the predictive capability of the model largely on the skill of the inﬂow forecasts.

The nonparametric multisite ensemble forecast framework developed by Bracken et al. (2010) was able to show skill at long lead times in forecasts generated for four key sites in the Upper Colorado River Basin (Colorado River near Cisco, Utah, Green River at Green River, Utah, San Juan River near Bluﬀ, 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). This framework generated forecasts of an “index gauge that is composed of the ﬂow at all the sites in the network. The form of the forecast model is

*y* = *f* (x) + ε (1)

where *y* is the index gauge seasonal ﬂow, x is a matrix of predictors and ε is the residual assumed to be normally distributed. This framework includes (1) identifying large scale climate predictors for index gauge ﬂow, (2) calibrating the model by selecting the best sets of predictors of seasonal ﬂow volume for each lead time and estimating , (3) generating ensemble forecasts of index gauge sea­sonal ﬂow and (4) disaggregating these forecasts in space and time to four sites in the UCRB. While promising, these results leave open the question of this skill translating to a larger number of sites on the same river network.

2. Study Area

The Upper Colorado River Basin has a drains 279,300 square kilometers. The terain 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 are all the natural ﬂow nodes in the upper basin. Figure 1 (b) shows the UCRB with natural ﬂow node location. Figure 1 (a) shows the network relationship of the nodes. This network structure is exploited in the conversion from total ﬂow to intervening.

3. Data

*3.1. Climate data*

The data inputs are the same as (Bracken et al., 2010) though we obtained the most recent observations for all of the predictors (through 2010 where available). We use zonal and meridonal wind, SST and geopotential height from the NOAA Earth Science Research Laboratory as predictors of large scale climate. Regions of high correlation with Lees Ferry Flow are 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 timeseries 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) Soil moisture data was obtained by climate division and averaged over a region covering the UCRB (http://www.esrl.noaa.gov/psd/data/timeseries/).

*3.2. 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 gerate a snowpack predictor for January 1 as well as improve the snow predictors for all other lead times.

*3.3. Flow Data*

We obtained the most recent natural ﬂow data developed by the Bureau of Reclamation in the UCRB that currently extends to 2007. The data is avail­able 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 ﬂow (sum of all upstream intervening ﬂow at a gauge). We use the intervening data but convert to total ﬂow internally for reasons described in the methodology section.

4. Methodology

We use the the same framework as Bracken et al. (2010) with some notable changes. Most importantly we (1) expand the disaggregation to include all 20 nat­ural ﬂow nodes in the UCRB, (2) We include the ﬂexible disaggregation method of Nowak et al. (2010) instead of the disaggregation method of Prairie et al. (2007), (3) we use Lees Ferry total seasonal ﬂow as our “index” gauge and (4) we make forecasts in total ﬂow space but then convert to intervening for the ﬁnal result.

This disaggregation method of Nowak et al. (2010) is known as proportion disaggregation is a ﬂexible nonparametric that preserves the sumability criteria of the network (upstream gauges sum to downstream gauges). The method is able to simultaneously conduct space and time disaggregation through the use of proportion matricies (matricies whose contents sum to unity). Figure 2 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 multiplies the proportion matrix by the ﬂow value to disaggregate. The process is then re­peated to generate ensembles for each value to be disaggregated. For more details, the interested reader is referred to Nowak et al. (2010).

Concerning the third and fourth change, Nowak et al. (2010) suggest perform­ing disaggregation of total ﬂow as opposed to intervening ﬂow. This eliminates incorrect weighting of negative intervening values (losing reaches). Streamﬂow forecasts as intervening ﬂow are also more useful as input to other models (such as planning models) so we perform disaggregation on the total ﬂow then transform back for the ﬁnal results. The transformation is done by exploiting the network structure of the 20 sites. Total ﬂow is computed by summing all the upstream intervening ﬂow at a given site. Intervening ﬂow is computed by subtracting the total ﬂow at the next upstream gauge from a given site.

We now describe the framework in its entirety, for details of speciﬁc compo­nents:

1. Create a total ﬂow index gauge by summing all the total seasonal ﬂow at each site to create an index gauge Bracken et al. (2010).
2. Identify large scale climate predictors of index gauge total ﬂow (Grantz et al., 2005).
3. 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).
4. Generate ensemble forecasts (Regonda et al., 2006; Hagedorn et al., 2005; Rajagopalan et al., 2002; Krishnamurti et al., 2000) of index gauge ﬂow by weighting the best models according to their GCV value (lower GCV gets higher weight). Predictions are made by randomly selecting a model based on the given weights, predicting from the model, resampling the model stan­dard error and repeating the process.
5. Disaggregate the total seasonal ﬂow at Less Ferry to total monthly ﬂow at each site using the method of Nowak et al. (2010).
6. Convert the total ﬂow at each site to intervening ﬂow to obtain a ﬁnal fore­cast.

5. Validation

We validate the results using the same methods as Bracken et al. (2010). Leave-one-out cross validation, “retroactive” validation was carried out. 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 Colorado Basin River Forecast Center. The ranked probability skill score (RPSS) Wilks (1995) was computed for each year in the history and then the median value is presented. The median correlation, the correlation between the historical data and the median of the ensembles for each year, was also computed for each site/month combination.

6. Results

When this analysis was repeated with the most recent ﬂow data, some of the correlation regions were slightly but not notably diﬀerent than those using the four site index gauge from Bracken et al. (2010) so we will not reproduce them here. Interestingly enough, the results with the slight modiﬁcations described in the methodology are somewhat diﬀerent than those from Bracken et al. (2010). For instance the RPSS values for the index gauge in this study are slightly lower except for the earliest lead times where they are slightly higher (Table 3). One reason for this may be that we saw slightly diﬀerent models being selected during predictor identiﬁcation.

Table 1 gives the results in terms of the RPSS after spatial and temporal dis­aggregation. The retroactive results show similar trends with slightly lower skills. In general we see the skills decreasing as lead time increases. 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 ﬂow 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 contibutions to Lees Ferry ﬂow. This makes intuitive sense 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. 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 shows some sample ensemble forecasts for three sites and months. These plots show the general trend that applies across most sites, ensemble vari­ability increases and skill decreases as lead time increases. Figure 5 shows the forecasts in retroactive mode at Duchesne River Near Randlett, UT. In this exam­ple, skill does not greatly decrease with lead time but we can see that the variance of the forecasts is much smaller for Apr1 than for any other lead time.

7. Conclusions

We have shown that the framework of Bracken et al. (2010) can be extended successfully to twenty sites in the Upper Colorado River Basin. 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.

C. Bracken, B. Rajagopalan, J. Prairie, A multisite seasonal ensemble streamﬂow forecasting technique, Water Resources Research 46 (3) (2010) W03532.

K. Nowak, J. Prairie, B. Rajagopalan, U. Lall, A nonparametric stochastic ap­proach for multisite disaggregation of annual to daily streamﬂow, Water Re­sources Research 46 (8) (2010) W08529.

T. Fulp, How low can it go, Southwest Hydrology .

B. Rajagopalan, K. Nowak, J. Prairie, M. Hoerling, B. Harding, J. Barsugli,

A. Ray, B. Udall, Water supply risk on the Colorado River: Can management mitigate?, Water Resources Research 45.

B. of Reclamation, Upper Colorado River Basin Consumptive Uses and Losses Report: 2006–2010 .

B. of Reclamation, Final environmental impact statement Colorado River interim guidelines for lower basin shortages and coordinated operations for lakes Pow­ell and Mead .

H. Moradkhani, Long-Lead Water Supply Forecast Using Large-Scale Climate Predictors and Independent Component Analysis, Journal of Hydrologic Engi­neering .

S. Opitz-Stapleton, S. Gangopadhyay, B. Rajagopalan, Generating streamﬂow forecasts for the Yakima River Basin using large-scale climate predictors, Jour­nal of Hydrology 341 (2007) 131–143.

S. K. Regonda, B. Rajagopalan, M. Clark, E. Zagona, A multimodel ensemble forecast framework: Application to spring seasonal ﬂows in the Gunnison River Basin, Water Resources Research 42.

K. Grantz, B. Rajagopalan, M. Clark, E. Zagona, A Technique for Incorporating Large-Scale Climate Information in Basin-Scale Ensemble Streamﬂow Fore­casts, Water Resources Research .

J. Prairie, B. Rajagopalan, U. Lall, T. Fulp, A stochastic nonparametric technique for space-time disaggregation of streamﬂows, Water Resources Research 43 (2007) 1–10.

C. Loader, Local Regression and Likelihood, Statistics and Computing, Springer, New York, 1999.

P. Craven, G. Wahba, Smoothing noisy data with spline functions: estimating the correct degree of smoothing by the method of generalized cross-validation, Numerical Mathematics 31 (1979) 377–403.

R. Hagedorn, F. J. Doblas-Reyes, T. N. Palmer, The rationale behind the success of multi-model ensembles in seasonal forecasting. Part I: Basic concept, Tellus, Ser. A 57 (2005) 219–233.

B. Rajagopalan, U. Lall, S. Zebiak, Optimal categorical climate forecasts through multiple GCM ensemble combination and regularization, Monthly Weather Re­view 130 (2002) 1792–1811.

T. N. Krishnamurti, C. M. Kishtawal, Z. Zhang, T. E. LaRow, D. R. Bachiochi,

C. E. Williford, S. Gadgil, S. Surendran, Multimodel ensemble forecasts for weather and seasonal climate, Journal of Climatology 13 (2000) 4196–4216.

D. Wilks, Elsevier: Statistical Methods in the Atmospheric Sciences by Wilks Earth and Environmental Science Books and ebooks Online, Academic Press, San Diego, 1995.