Improving Seasonal Forecasting to Support Operational Decision-Making and Policy within Bureau of Reclamation Service Areas

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Abstract

In semi-arid and snow-melt dominated watersheds of the American Southwest, such as the Colorado River or Rio Grande, water managers and policy makers are reliant on seasonal streamflow forecasts, termed water supply forecasts (WSFs). These forecasts are issued several months ahead of the main runoff season when agriculture and municipalities have the greatest water demands and provide a fundamental basis for planning reservoir management, water resource allocations, and conservation efforts. All of these planning steps involve inter-agency communication and policy discussion, elevating WSFs to being a policy-relevant tool.

Recent studies have documented the influence of increasing temperature on streamflow across the American West. At the same time, some basins are reporting decreasing skill in WSFs over the recent decades, in part linked to the changing hydrological cycle with warming. Here we show that incorporating seasonal temperature forecasts from operational global climate prediction models into WSFs adds prediction skill for watersheds in the headwaters of the Colorado and Rio Grande River basins. Such predictions can increase the resilience of streamflow forecasting and water management systems in the face of continuing warming as well as decadal-scale temperature variability and thus help to mitigate the impacts of climate non-stationarity on streamflow predictability. In addition to the scientific analysis of the improved WSFs, implications for decision-making and policy within the Bureau of Reclamation are also discussed.

Introduction

With growing populations and rising temperatures, the pressure on water resources in the southwestern United States (US) is increasing and expected to continue to do so over the coming decades (Reclamation 2016). Water resources in this region are currently entirely allocated for agricultural, industrial and municipal uses and are heavily managed, with seasonal streamflow forecasts being a key tool used to inform this management. Seasonal streamflow forecasts for a range of lead times are among the most economically valuable streamflow predictions made in the US and around the world, given their significance for water management (Hamlet et al. 2002; Pierce 2010; Raff et al. 2013).

Seasonal streamflow forecasts in the Upper Rio Grande basin, for example, are used to predict the annual water delivery requirements between Colorado, New Mexico, and Texas under an interstate river allocation agreement, the Rio Grande Compact, to plan for water storage and to inform associated reservoir management decisions. Seasonal streamflow forecasts also indicate the likely supplemental water needs for endangered species, and the storage needs of Native American Pueblos to assure they receive adequate water to meet their Prior and Paramount water rights. The forecasts in combination with those decisions enable projections of the water supplies that will be available to farmers, which in turn can influence cropping decisions. In addition, supplemental water supply to the Upper Rio Grande basin is imported each year from the Colorado River system through trans-basin diversions. Forecasts of the water available for diversion are used to estimate the portion of the imported water that will be available for purchase by the Federal government to support the needs of endangered species, as well as for planning of drinking water operations in major municipalities. On the much larger Colorado River system, as well, water supply forecasts issued in spring are essential to make reservoir storage and release decisions that help avoid shortage conditions in Lake Mead and Lake Powell, and that determine water and hydropower allocations affecting 7 southwestern US states. These decisions influence water and energy costs for major American cities such as Los Angeles, Las Vegas and Phoenix, and major irrigation regions such as California's Imperial Valley and Arizona's Welton Mohawk Irrigation and Drainage District.

Seasonal streamflow forecasts in snowmelt driven basins derive skill from the stability of relationships between winter precipitation and snow water equivalent (SWE) with spring to summer melt season runoff (e.g., April-July streamflow). The simplest operational form of seasonal streamflow prediction relies on statistical models that quantify these relationships, such as principal component regression (PCR) models trained on observed in situ data records of ~30 years (Garen 1992). These 'water supply forecasts' (WSFs) have traditionally been made beginning in January of the same year with updates on the first day of each month to incorporate new precipitation and SWE observations (Pagano et al. 2014b). Operational forecasts are published by regional River Forecasting Centers and the US Department of Agriculture National Resources Conservation Service (NRCS). A second common form of seasonal streamflow prediction involves the use of dynamic watershed models to predict future watershed states and fluxes (Day 1985; Pagano et al. 2014a).

The skill of statistical WSFs varies with lead time and also on decadal time scales, with basins such as the Upper Colorado River (UC) and Upper Rio Grande (URG) showing declining skill since the 1980s (Pagano et al. 2004; Pagano and Garen 2005). The proximate causes of variations and trends in forecast skill, at least from a hydroclimate perspective, are internal climate variability (e.g., the sequencing of wet and dry years and the timing of accumulation and melt relative to the forecast issue date) and secular trends due to more systematic changes in climate (e.g., warming leading to more evapotranspiration and changes in the snow-rain partitioning), as illustrated by numerous attribution studies (Woodhouse et al. 2016; Lettenmaier and Gan 1990; Barnett et al. 2005; Mote et al. 2005; Nowak et al. 2012; Vano et al. 2012; Christensen et al. 2004; Griffin and Friedman 2017; Udall and Overpeck 2017; Lehner et al. 2017a, 2018; Chavarria and Gutzler 2018). As a consequence, the relationship between winter moisture accumulation (precipitation and SWE) and summer streamflow is evidently non-stationary and influenced by changing temperature and other climatic factors. The influence of temperature on streamflow is problematic for WSFs in light of their underlying stationarity assumptions with regard to the background climate during the forecast period.

In comparison to their value, the costs of enhancements to operational water supply forecasting are small, especially when they represent an extension of the current forecasting approaches. In recent decades the western US has seen strong hydroclimatic trends and decadal variability, leading to variable streamflow forecasting skill and a likelihood of sub-optimal management decisions (Pagano and Garen 2005). To better grapple with water resource management challenges arising from hydroclimate non-stationarity and increasing water demands, improved efficiency in water management practices is critically needed (Milly et al. 2008; Lins and Cohn 2011; Steinschneider and Brown 2012).

With the advent of seasonal predictions by dynamical climate models, an opportunity arises to combine seasonal climate forecasts with traditional WSF based on snowpack observations. While seasonal forecast skill for precipitation remains limited, temperature has been shown to be skillfully forecasted for lead times of several months (Becker et al. 2014; Slater et al. 2016; Lehner et al. 2017b). Here we investigate whether including temperatures (as predicted by seasonal climate prediction models) in WSFs improves seasonal streamflow forecasting skill. To that end, we generate WSFs via the current operational strategy, termed 'baseline forecast', as well as WSFs that include seasonal temperature forecasts as a predictor, termed 'temperature-aided forecast'. The comparison of the two approaches enables us to assess the potential to improve streamflow forecasting skill by including temperature forecasts.

Data and methods

To best mimic the current operational WSF, we largely use the same underlying data as the NRCS. Estimates of naturalized monthly streamflow at 20 gages across the UC and URG are obtained from the NRCS. Observations of water year-to-date cumulative precipitation and instantaneous SWE at the 1st of January, February, March, April, and May are extracted from snow telemetry monitoring (SNOTEL) stations. Monthly mean temperature is taken from the Parameter Elevation Regression on Independent Slopes Model (PRISM) data set (Daly et al. 2008) averaged over 35.5-39.5°N, 108.5-105.0°W.

Seasonal temperature forecasts are derived from 8 initialized coupled climate models that produce seasonal climate forecasts. These models issue forecasts each month for lead times of up to 12 months with various numbers of ensemble members (10-51). Since we are interested in extracting the seasonally predictable signal, we use each model's ensemble mean (rather than all its individual ensemble members) of monthly mean 2-m temperature hindcasts, averaged over the same area as indicated above. We then use an equal-weights multi-model mean across the 8 models.

The WSF procedure is detailed in Garen (1992) and Lehner et al. (2017b) and summarized briefly here. The SNOTEL data is used in a principal component regression (PCR) trained on 30 years (1987-2016) of observed naturalized streamflow of the respective target period and cross-validated with a leave-one-out procedure (hereafter 'baseline forecast'). We then reforecast the same time period using the same information, but add the ensemble mean temperature anomaly of the 8 seasonal forecasting models as an additional predictor to the PCR (hereafter 'temperature-aided forecast'). Comparing the 'temperature-aided forecast' with the 'baseline forecast' allows us to determine whether there is skill improvement from adding temperature as a predictor to the WSF.

Results

The ‘temperature-aided forecast’ is more skillful than the ‘baseline forecast’ for most gages, skill metrics, and forecast lead times (Figure 1). The forecast skill is improved in terms of better capturing the year-to-year variability (‘correlation’) as well as in an mean error sense (relative root mean squared error , ‘rRMSE’). While the improvements are modest (~5%), they are robust in a bootstrapping-with-replacement exercise (not shown). The same holds true for an evaluation of the probabilistic forecast skill (cumulative rank probability skill score, ‘CRPSS’) illustrating that the ‘temperature-aided forecast’ better depicts the observed probability distribution of streamflow values. The only skill metric that does not show unanimous improvement is a probabilistic skill score aimed at low flow years (brier skill score for the lowest tercile, ‘BSS’). It shows that for some gages and lead times, adding temperature to the WSF does not improve the forecast skill for years of flow below the 33rd percentile of the climatological distribution. We also test how much skill improvement derives simply from the long-term warming trend by including the observed linear temperature trend over the study time period as a predictor (1987-2016), thereby excluding information on the interannual temperature variability. It is shown that the trend itself adds most of the skill. Thus, the interannual temperature variability, despite being forecasted skillfully, adds little additional streamflow forecasting skill above the secular warming trend.

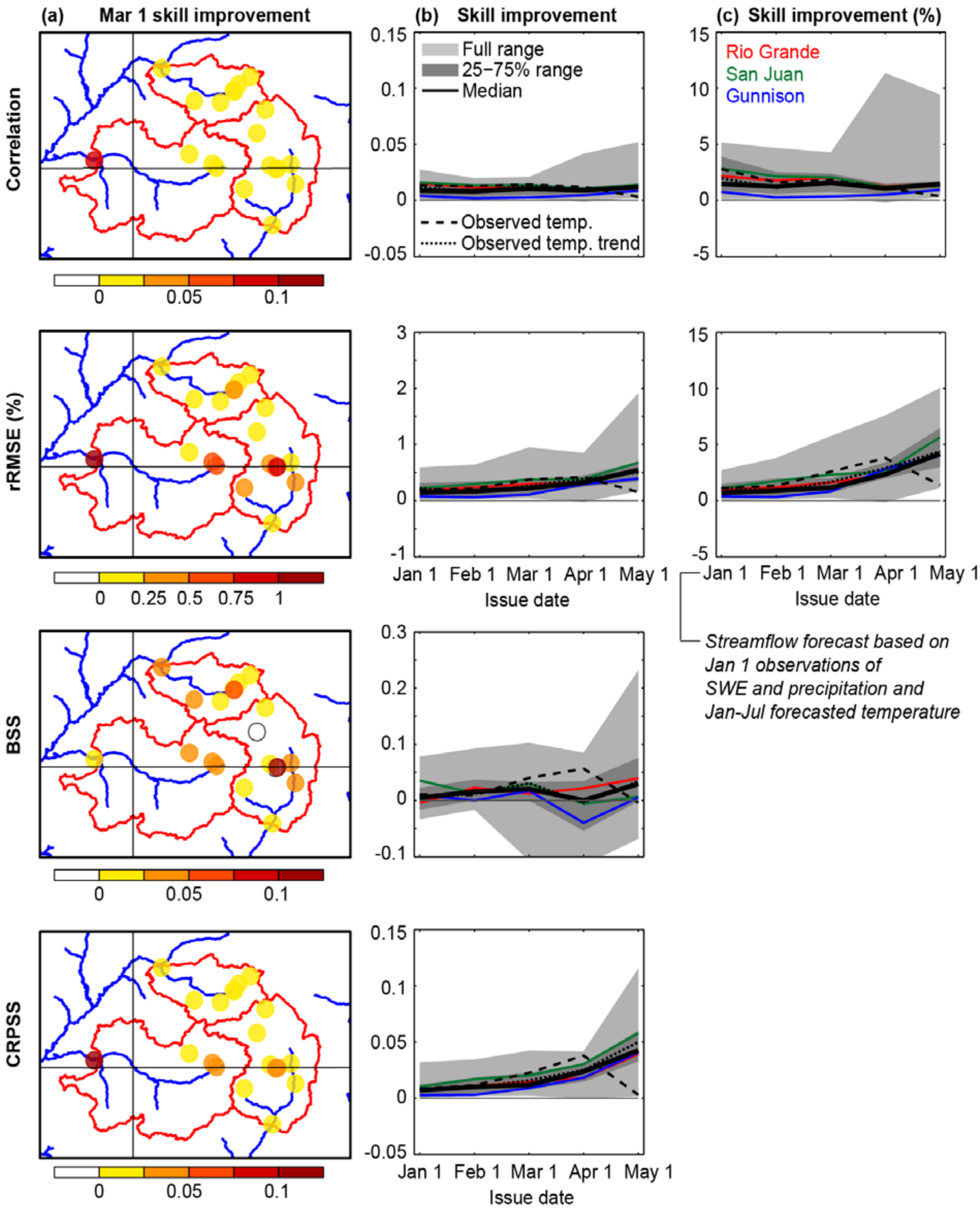

Figure 1. (a) Absolute skill improvement of the temperature-aided forecast relative to the baseline forecast at individual gages for issue date 1st March as an illustrative example. (b) Absolute skill improvement for all gages as a function of issue date. (c) Relative skill improvement for all gages as a function of issue date. Solid lines are the median across (black) all gages and (colors) the three basins. Dashed line is the median across all gages when using observed temperature, mimicking the hypothetical case where the future temperature is known at the time of forecast issue, and dotted line is the median when using only the linear trend of observed temperature (after Lehner, et. al., 2017b).

Conclusions, Implications, and Next Steps

The skill improvement demonstrated here for seasonal streamflow forecasts in the Upper Rio Grande and Upper Colorado River basins can be of significant value to State and Federal water managers, which, in turn, can benefit water users throughout these basins (Carolyn Donnelly, Bureau of Reclamation, Albuquerque, New Mexico and Craig Cotton, Colorado Division of Water Resources, personal communication). Despite its limited spatial extent, the study here is of relevance for other snow-melt driven basins across the US and the world, since streamflow forecast skill in such basins is often driven by the same temperature-sensitive processes.

We leverage the fact that current seasonal climate prediction models are skillful in forecasting seasonal temperature for this region. This temperature information adds skill to existing 'water supply forecasts' (WSFs), mitigating some of the forecast errors introduced through climate non-stationarity, and moving the WSFs closer to their maximally expected forecast skill based on relationships between observed snow, precipitation, and temperature.

It is important to note that the largest source of forecast error remains the (unknown) precipitation that falls after a forecast issue date (i.e., spring and summer precipitation). Thus, additional streamflow predictability might be available once seasonal precipitation forecasts become more skillful, although expectations for such skill are damped by the established theory of stochastic weather variability at lead times greater than a couple of weeks for this region of the world. Meanwhile, so-called sub-seasonal climate forecasts (lead time of a few weeks) are an interesting new tool to bridge the gap between the lead times of conventional weather forecasts and the longer lead times of seasonal climate forecasts used here.

Other conventional forecasting approaches based on hydrologic models (such as Ensemble Streamflow Prediction, or ESP, a popular operational method that is not discussed in this paper) are also commonly dependent on climate stationarity assumptions and thus are also likely to benefit from additional temperature forecast information. In the US Southwest, and similar hydroclimates around the world, expanding the use of model-based seasonal climate predictions, and particularly temperature forecasts, appears to be one pragmatic strategy for improving streamflow prediction skill in the face of a non-stationary climate.

Despite the evidence of forecast skill improvement through inclusion of temperature, this study does not support detailed conclusions regarding the hydrologic processes that underpin changes in prediction skill, as the temperature influence on streamflow can be dampened or amplified due to other effects and non-linear interactions (e.g., related to groundwater use or vegetation alterations or the co-variance with precipitation itself). Similarly, using low-dimensional statistical models only, we are unable to disentangle why certain gages show greater improvement than others. Process-based observation and modeling studies tackling this question may therefore be a valuable next step for the hydrologic forecasting community.

Beyond the direct improvement of streamflow forecast skill, better climate information (on seasonal and longer time scales) also has the potential to inform decisions related to daily water management operations. Streamflow forecasts today provide an estimate of the seasonal flow total, but not of the shape of the associated hydrograph. Water agencies often rely on analogs from historically observed hydrographs to anticipate the timing and shape of a given year's forecasted streamflow total. However, in an inherently non-stationary climate, historical hydrographs might be suboptimal analogs for next year's hydrographs. Due to systematic changes in the melt behavior and overall lengthening of the growing season (Musselman et al.

2017), hydrographs might look different even in cases where a forecasted flow total happens to have a historical analog. Here, seasonal climate forecasts could help create synthetic hydrographs that better reflect current climate-hydrology dynamics to be used in daily operations of water agencies.

References

Barnett, T. P., J. C. Adam, and D. P. Lettenmaier, 2005: Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature*, **438**, 303–309, doi:10.1038/nature04141.

Becker, E., H. Van den Dool, and Q. Zhang, 2014: Predictability and forecast skill in NMME. *J. Clim.*, **27**, 5891–5906, doi:10.1175/JCLI-D-13-00597.1.

Chavarria, S. B., and D. S. Gutzler, 2018: Observed Changes in Climate and Streamflow in the Upper Rio Grande Basin. *J. Am. Water Resour. Assoc.*, **54**, 644–659, doi:10.1111/1752-1688.12640.

Christensen, N. S., A. W. Wood, N. Voisin, D. P. Lettenmaier, and R. N. Palmer, 2004: The effects of climate change on the hydrology and water resources of the Colorado River basin. *Clim. Change*, **62**, 337–363, doi:10.1023/B:CLIM.0000013684.13621.1f.

Daly, C., M. Halbleib, J. I. Smith, W. P. Gibson, M. K. Doggett, G. H. Taylor, J. Curtis, and P. P. Pasteris, 2008: Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *Int. J. Climatol.*, **28**, 2031–2064, doi:10.1002/joc.1688.

Day, G. N., 1985: Extended Streamflow Forecasting Using NWSRFS. *J. Water Resour. Plan. Manag.*, **111**, 157–170, doi:10.1061/(ASCE)0733-9496(1985)111:2(157).

Garen, D. C., 1992: Improved Techniques in Regression-Based Streamflow Volume Forecasting. *J. Water Resour. Plan. Manag.*, **118**, 654–670, doi:10.1061/(ASCE)0733-9496(1992)118:6(654).

Griffin, E. R., and J. M. Friedman, 2017: Decreased Runoff Response to Precipitation, Little Missouri River Basin, Northern Great Plains, USA. *JAWRA J. Am. Water Resour. Assoc.*, **80526**, 1–17, doi:10.1111/1752-1688.12517.

Hamlet, A. F., D. Huppert, and D. P. Lettenmaier, 2002: Economic Value of Long-Lead Streamflow Forecasts for Columbia River Hydropower. *J. Water Resour. Plan. Manag.*, **128**, 91–101, doi:10.1061/(ASCE)0733-9496(2002)128:2(91).

Lehner, F., E. R. Wahl, A. W. Wood, D. B. Blatchford, and D. Llewellyn, 2017a: Assessing recent declines in Upper Rio Grande runoff efficiency from a paleoclimate perspective. *Geophys. Res. Lett.*, **44**, 4124–4133, doi:10.1002/2017GL073253.

——, A. W. Wood, D. Llewellyn, D. B. Blatchford, A. G. Goodbody, and F. Pappenberger, 2017b: Mitigating the Impacts of Climate Nonstationarity on Seasonal Streamflow Predictability in the U.S. Southwest. *Geophys. Res. Lett.*, **44**, 12,208-12,217, doi:10.1002/2017GL076043.

——, C. Deser, I. R. Simpson, and L. Terray, 2018: Attributing the U.S. Southwest's Recent Shift Into Drier Conditions. *Geophys. Res. Lett.*, **45**, 6251–6261, doi:10.1029/2018GL078312.

Lettenmaier, D. P., and T. Y. Gan, 1990: Hydrologic sensitivities of the Sacramento-San Joaquin River Basin, California, to global warming. *Water Resour. Res.*, **26**, 69–86, doi:10.1029/WR026i001p00069.

Lins, H. F., and T. A. Cohn, 2011: Stationarity: Wanted dead or alive? *J. Am. Water Resour. Assoc.*, **47**, 475–480, doi:10.1111/j.1752-1688.2011.00542.x.

Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer, 2008: Climate change. Stationarity is dead: whither water management? *Science*, **319**, 573–574, doi:10.1126/science.1151915.

Mote, P. W., A. F. Hamlet, M. P. Clark, and D. P. Lettenmaier, 2005: Declining mountain snowpack in western north America. *Bull. Am. Meteorol. Soc.*, **86**, 39–49,

doi:10.1175/BAMS-86-1-39.
Musselman, K. N., M. P. Clark, C. Liu, K. Ikeda, and R. Rasmussen, 2017: Slower snowmelt in a warmer world. *Nat. Clim. Chang.*, **7**, 214–220, doi:10.1038/NCLIMATE3225.
Nowak, K., M. Hoerling, B. Rajagopalan, and E. Zagona, 2012: Colorado River Basin Hydroclimatic Variability. *J. Clim.*, **25**, 4389–4403, doi:10.1175/JCLI-D-11-00406.1.
Pagano, T., D. Garen, and S. Sorooshian, 2004: Evaluation of Official Western U.S. Seasonal Water Supply Outlooks, 1922–2002. *J. Hydrometeorol.*, **5**, 896–909, doi:10.1175/1525-7541(2004)005<0896:EOOWUS>2.0.CO;2.
——, A. Wood, K. Werner, and R. Tama-Sweet, 2014a: Western U.S. water supply forecasting: A tradition evolves. *Eos (Washington. DC).*, **95**, 28–29, doi:10.1002/2014EO030007.
Pagano, T. C., and D. Garen, 2005: The recent increase in Western US streamflow variability and persistence. *J. Hydrometeorol.*, **6**, 173–179, doi:10.1175/JHM410.1.
——, and Coauthors, 2014b: Challenges of Operational River Forecasting. *J. Hydrometeorol.*, 140516115449007, doi:10.1175/JHM-D-13-0188.1. http://journals.ametsoc.org/doi/abs/10.1175/JHM-D-13-0188.1.
Pierce, J. A. S., 2010: *A Measure of Snow: Case Studies of the Snow Survey and Water Supply Forecasting Program*. Salt Lake City, UT, 109 pp. https://www.wcc.nrcs.usda.gov/ftpref/downloads/factpub/MeasureofSnowFullReport.pdf.
Raff, D., L. Brekke, K. Werner, A. Wood, and K. White, 2013: *Short-Term Water Management Decisions: User Needs for Improved Climate, Weather, and Hydrologic Information*. 231 pp. http://www.ccawwg.us/.
Reclamation, B. of, 2016: *Climate Change Adaptation Strategy*. 33 pp. https://www.usbr.gov/climate/docs/2016ClimateStrategy.pdf.
Slater, L. J., G. Villarini, and A. A. Bradley, 2016: Evaluation of the skill of North-American Multi-Model Ensemble (NMME) Global Climate Models in predicting average and extreme precipitation and temperature over the continental USA. *Climate Dynamics*.
Steinschneider, S., and C. Brown, 2012: Dynamic reservoir management with real-option risk hedging as a robust adaptation to nonstationary climate. *Water Resour. Res.*, **48**, 1–16, doi:10.1029/2011WR011540.
Udall, B., and J. Overpeck, 2017: The 21 st Century Colorado River Hot Drought and Implications for the Future. *Water Resour. Res.*, doi:10.1002/2016WR019638.
Vano, J. A., T. Das, and D. P. Lettenmaier, 2012: Hydrologic Sensitivities of Colorado River Runoff to Changes in Precipitation and Temperature. *J. Hydrometeorol.*, **13**, 932–949, doi:10.1175/JHM-D-11-069.1.
Woodhouse, C. A., G. T. Pederson, K. Morino, S. A. McAfee, and G. J. McCabe, 2016: Increasing influence of air temperature on upper Colorado River streamflow. *Geophys. Res. Lett.*, **43**, 2174–2181, doi:10.1002/2015GL067613.