ON THE USE OF SNOW AND CLIMATE INFORMATION IN STATISTICAL SEASONAL STREAMFLOW FORECASTING

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EXTENDED ABSTRACT

Seasonal streamflow predictions provide a critical management tool for water managers in the American Southwest. These forecasts rely primarily on observations of snowpack and precipitation accumulation, which help to quantify the hydrologic memory that enables relatively accurate streamflow forecasts at seasonal lead times. In recent decades, persistent prediction errors for spring and summer runoff volumes have been observed in a number of watersheds in the American Southwest. While mostly driven by interannual to decadal precipitation variability, these errors also relate to the influence of increasing temperature on snow and streamflow in these basins. Here we show that incorporating seasonal temperature forecasts from operational global climate prediction models into streamflow forecasting models adds prediction skill for watersheds in the headwaters of the Colorado and Rio Grande River basins. Current dynamical seasonal temperature forecasts now show sufficient skill to reduce streamflow forecast errors in snowmelt-driven and temperature-sensitive basins. Such predictions can increase the reliability 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.

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 next decades (Reclamation 2016). Water resources in this region are currently almost 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 in the Upper Rio Grande and Upper Colorado river basin, for example, are used to predict the annual water delivery requirements between several US states, to plan for water storage and to inform associated reservoir management decisions.

Seasonal streamflow forecasts are extremely valuable (Hamlet et al., 2002; Raff et al., 2013; Pierce, 2010) and, in comparison, the costs of improvements to operational forecasting are small, especially when they represent an extension of the current approaches (Pappenberger et al., 2015). In recent decades the western US has seen variable streamflow forecasting skill and as a consequence an increased 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 needed (Milly et al., 2008; Lins and Cohn, 2011; Steinschneider and Brown, 2012).

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Operational seasonal streamflow forecasts in snowmelt driven basins commonly 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 (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., 2014). Operational forecasts are published by regional River Forecasting Centers and the US Department of Agriculture National Resources Conservation Service (NRCS).

The skill of statistical WSFs varies with lead time and also on decadal time scales. Pagano and Garen (2005) have argued that the decadal skill variations originate primarily from interannual to decadal climate variations, rather than basin-specific processes or human interference. As such, successful prediction of interannual to decadal climate variability has the potential to stabilize streamflow forecasting skill. Besides decadal climate variability, southwestern US water resources are also sensitive to the influence of anthropogenically-forced climate change (Lettenmaier and Gan, 1990; Christensen et al., 2004; Barnett et al., 2005; Mote et al., 2005). For semi-arid and snowmelt driven basins such as the Upper Colorado (UC) and Upper Rio Grande (URG), numerous studies have indicated that increasing temperature decreases streamflow (Christensen et al., 2004; Vano et al., 2012; Woodhouse et al., 2016; Griffin and Friedman, 2017; Udall and Overpeck, 2017). Specifically, runoff efficiency – the fraction of precipitation that ends up as streamflow – is more likely to be low when temperatures are above average (Nowak et al., 2012; Lehner et al., 2017a). As a consequence, the relationship between winter moisture accumulation (precipitation and SWE) and summer streamflow is evidently non-stationary and can be influenced by temperature.

The influence of temperature on runoff efficiency is problematic for WSFs in light of their underlying stationarity assumptions with regard to the background climate during the forecast period. Statistical models using observed accumulated precipitation and SWE at the start of the forecast without additional temperature information for the forecast period would under-predict streamflow for cool forecast periods and over-predict streamflow for warm forecast periods, in part because they do not include the information of the secular warming trend and associated evaporation losses over the entire period.

Here we investigate (1) recent hydroclimate trends and streamflow forecast errors in the study region, the URG and parts of the UC, (2) the seasonal predictability of temperature over this region, and (3) whether including predicted temperatures in WSFs improves seasonal streamflow forecasting skill. 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, as well as the sufficiency of current operational temperature forecasts for this purpose.

DATA AND METHODS

Streamflow, Precipitation, Snow Water Equivalent, and Temperature Datasets

Estimates of naturalized monthly streamflow at a number of gages across the UC and URG are obtained from the NRCS (circles in Figure 1a). For each gage and year, the total streamflow for the respective forecasting "target period" (e.g., Apr-July cumulative flow) is calculated. Observations of water year-to-date cumulative precipitation and instantaneous SWE at the 1st of Jan, Feb, Mar, Apr, and May are extracted from the same snow telemetry monitoring (SNOTEL) stations as used in the operational forecasting by NRCS, but only if they cover the entire hindcasting period 1987-2016 (triangles in Figure 1a). Monthly mean temperature is taken from the Parameter Elevation Regression on Independent Slopes Model (PRISM) data set (Daly et al., 2008) averaged over the box indicated in Figure 1a. Precipitation used to calculate runoff efficiency in Figure 1b is taken from PRISM as well.

Seasonal Temperature Forecasts

Seasonal temperature forecasts are derived from 8 initialized coupled climate models that produce seasonal climate forecasts: the North American Multimodel Ensemble (NMME; Kirtman et al., 2014), which comprises of 7 models, and the System 4 seasonal forecasting model from the European Center for Medium-Range Weather Forecast (ECMWF; Molteni et al., 2011). These models issue forecasts each month for lead times of up to 12 months with various numbers of ensemble members (10-51). We use each model's ensemble mean of monthly mean 2-m temperature hindcasts issued from January 1987 to May 2016, averaged over the area indicated in Figure 1a. We then use an equal-weights multi-model mean across the 8 models to calculate one single hindcast time series.

For each streamflow forecast issue month (1st January, 1st February, etc), temperature is averaged from that issue month until the end of the main runoff period (July).

Streamflow Forecasting Procedure

The marginal benefit of including seasonal temperature information in WSFs is evaluated through benchmarking the performance of enhanced WSF models against models based on the current operational forecast practice. We mimic the operational forecasting procedure of the NRCS's WSF by using SNOTEL data in a principal component regression (PCR) trained on 30 years (1987-2016) of observed naturalized streamflow of the respective target period (Garen, 1992), hereafter 'baseline forecast'. See Garen (1992) and Lehner et al. (2017b) for further details.

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'). For a given year and forecast issue date (e.g., January 1, 1987), the mean temperature prediction from the forecast issue date to the end of July is averaged (i.e., January-July 1987). For all gages, the regression coefficients derived from the PCR are such that precipitation and SWE always exhibit a positive relationship with streamflow, and temperature always a negative one, indicating a physically plausible interaction of precipitation, SWE, and temperature in describing streamflow.

Skill Metrics

Prediction skill for the baseline and temperature-aided streamflow forecast is calculated via a leave-one-out cross validation from 1987 to 2016. Each year between 1987 and 2016 is hindcasted with a principal component regression model that has been calibrated on the remaining 29 years of data, and the resulting time series of 30 streamflow predictions are verified against the corresponding observations.

We quantify forecast skill using the following metrics: (i) correlation, (ii) relative root mean squared error (rRMSE, in %), (iii) the Brier Skill Score (BSS) for streamflow < 33rd percentile, and (iv) Continuous Ranked Probability Skill Score (CRPSS; Hersbach, 2000). Correlation and rRMSE describe how well the model predicts the variability and the absolute values, respectively, of the observed time series. BSS provides insight into the ability of the model to predict dry conditions relevant to droughts in the US Southwest, and CRPSS, which measures the ability of the forecast model to correctly predict the cumulative distribution function of the observed streamflow data, is used to quantify probabilistic prediction skill. See Lehner et al. (2017b) for further details.

RESULTS

Hydroclimate Trends and Streamflow Forecast Errors

Recent hydroclimate trends in the UC and URG headwaters are illustrated by plotting the runoff efficiency as a function of temperature anomalies for streamflow gages at the outflow of the headwaters of the Gunnison, San Juan, and Rio Grande (Figure 1b). A clear temperature sensitivity exists, leading to relatively reduced streamflow under positive temperature anomalies. Even in the absence of a strong precipitation trend, higher temperatures are shifting the partitioning of precipitation from snow to rain, a phenomenon that is detectable at virtually all SNOTEL stations in the region (Figure 1c), thereby changing the peaks and timing of both snowmelt and runoff. Higher temperatures also allow for more evaporative loss between when the snow falls and when the water arrives at the streamflow gages downstream, which is a key hydrologic dynamic leading to forecast errors.

Relatively persistent forecast errors are confirmed by the forecast record in the UC and URG: streamflow gage records in these two basins show a tendency to be under-predicted in the 1980s and 1990s and over-predicted in the 2000s and 2010s (Figure 1d). While these forecast errors are in part related to unusually wet springs and summers in the 1980-90s and unusually dry springs and summers in the 2000-10s, there exists evidence that streamflow in recent years was lower than expected from precipitation deficits alone (Woodhouse et al., 2016; Lehner et al., 2017a), pointing to a simultaneous influence of temperature on streamflow and thus on forecast error.

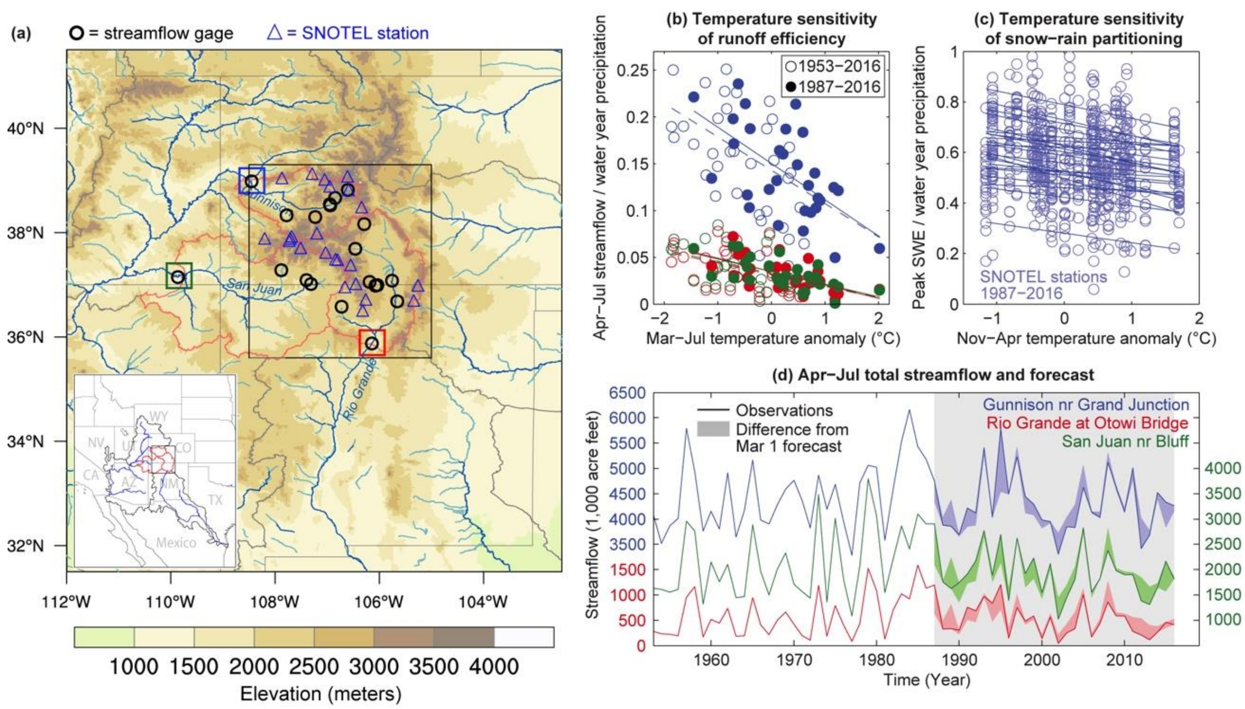

Figure 1. (a) Map showing the main rivers, basins, (circles) streamflow gages, and (triangles) SNOTEL stations analyzed in this study. (b) Runoff efficiency – spring-summer streamflow divided by water year precipitation – for 3 selected gages marked with colored boxes in (a). (c) Snow-rain partitioning – peak snow water equivalent (SWE) divided by water year precipitation – as a function of winter-spring temperature for all SNOTEL stations analyzed in this study (each linear trend line is for one SNOTEL station). (d) Observed and forecasted streamflow for the 3 selected gages; solid lines are the observed streamflow, while colored shading indicates the difference between the observed and forecasted streamflow, i.e., the larger the shading the larger the forecast error.

Temperature Forecast Skill

While uncertainty in multi-decadal projections of precipitation in the US Southwest remains high, climate models such as those included in the 5th phase of the Coupled Model Intercomparison Project (CMIP5) project future temperature increases (Figure 2a) with far more certainty. Similarly, dynamical seasonal climate prediction models, such as the 8 models from the NMME and ECMWF, are more skillful in predicting temperature than

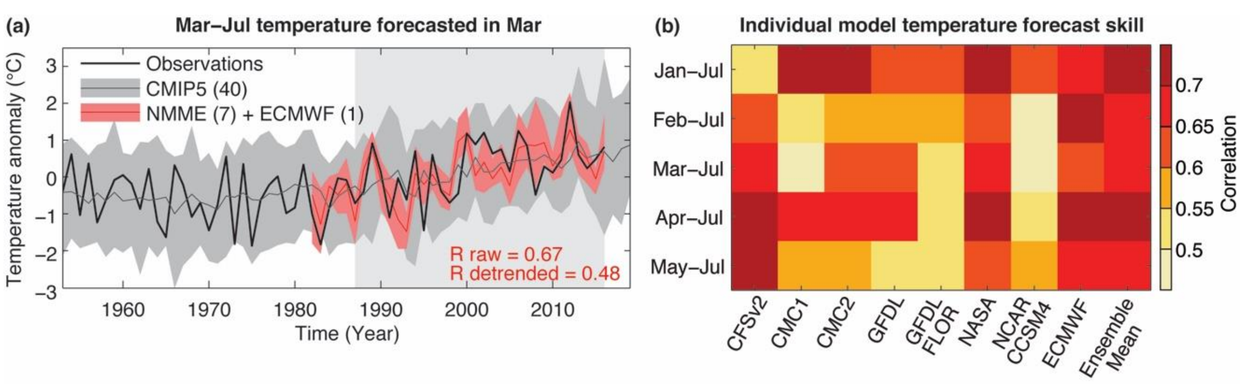

Figure 2. (a) March-July mean temperature anomalies from observations, 40 CMIP5 models, and seasonal prediction models (NMME+ECMWF), averaged over the box indicated in Figure 1a. The red line is the mean across NMME-ECMWF models, the gray line is the mean across CMIP5 models, and the black line is observations. Shading indicates the 5-95% range. (b) Correlation between observed and forecasted temperature for different temperature targets and seasonal prediction models for 1982-2016. Forecasts are initialized at the start of each predicted period. All correlations are significant at 95% confidence.

precipitation (Becker et al., 2014; Slater et al., 2016). The seasonal forecasting models capture the observed warming trend of recent decades as well as part of the interannual variability of spring-to-summer temperature over the UC and URG headwaters region at lead times of up to 5 months (Figure 2a, b). The combination of these two results leads to a usable temperature forecast skill in the context of streamflow prediction in this region.

Improved Streamflow Forecast Skill

We find that augmenting the baseline forecasting approach through the use of temperature predictors adds skill across the majority of streamflow gages and issue dates in the study region. These benefits are illustrated through the skill difference between the baseline and temperature-aided forecasts for all skill metrics considered (Figure 3). The median relative improvement across gages and skill metrics is between 1% and 10% with some spread across gages. The vast majority of these improvements are statistically significant in light of sampling uncertainty (not shown; see Lehner et al., 2017b for details). Probabilistic skill is improved to a similar extent for drought conditions (BSS) as it is for the entire distribution of streamflow values (CRPSS).

Since temperature in the study region over the period 1987-2016 shows a strong positive trend, the question arises how much of the added skill is attributable to the temperature trend alone. Using the observed linear temperature trend from 1987-2016 as a predictor in the WSF model (thereby excluding any interannual variability that might be predictable by seasonal prediction models), we show that the trend alone adds skill, but never more than about 60% of the skill improvement achieved through using the temperature predicted by the seasonal prediction models (Figure 3b, c). This confirms both the important role of the increasing temperature as well as the additional added value of predictable interannual temperature variability for WSFs.

DISCUSSION AND CONCLUSIONS

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. 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 show that current seasonal climate prediction models are skillful in forecasting both the long-term trends and interannual variability of seasonal temperatures 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. Additional predictability might be available once seasonal precipitation forecasts become more skillful.

The inclusion of operational temperature forecasts represents a straightforward and thus cost-effective adjustment to current operational practices, yielding modest but robust improvements in forecast skill. With a changing climate and diminishing snow pack, it may be impossible to protect or increase streamflow prediction skill in all locations, but expanding the use of model-based seasonal climate predictions, and particularly temperature forecasts, appears to be one pragmatic strategy for hydroclimates that are similar to the US Southwest.

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). Process-based observation and modeling studies tackling this question may therefore be a valuable next step for the hydrologic forecasting community. (KEYWORDS: streamflow forecasting, snow water equivalent, subseasonal to seasonal, climate models, operational)

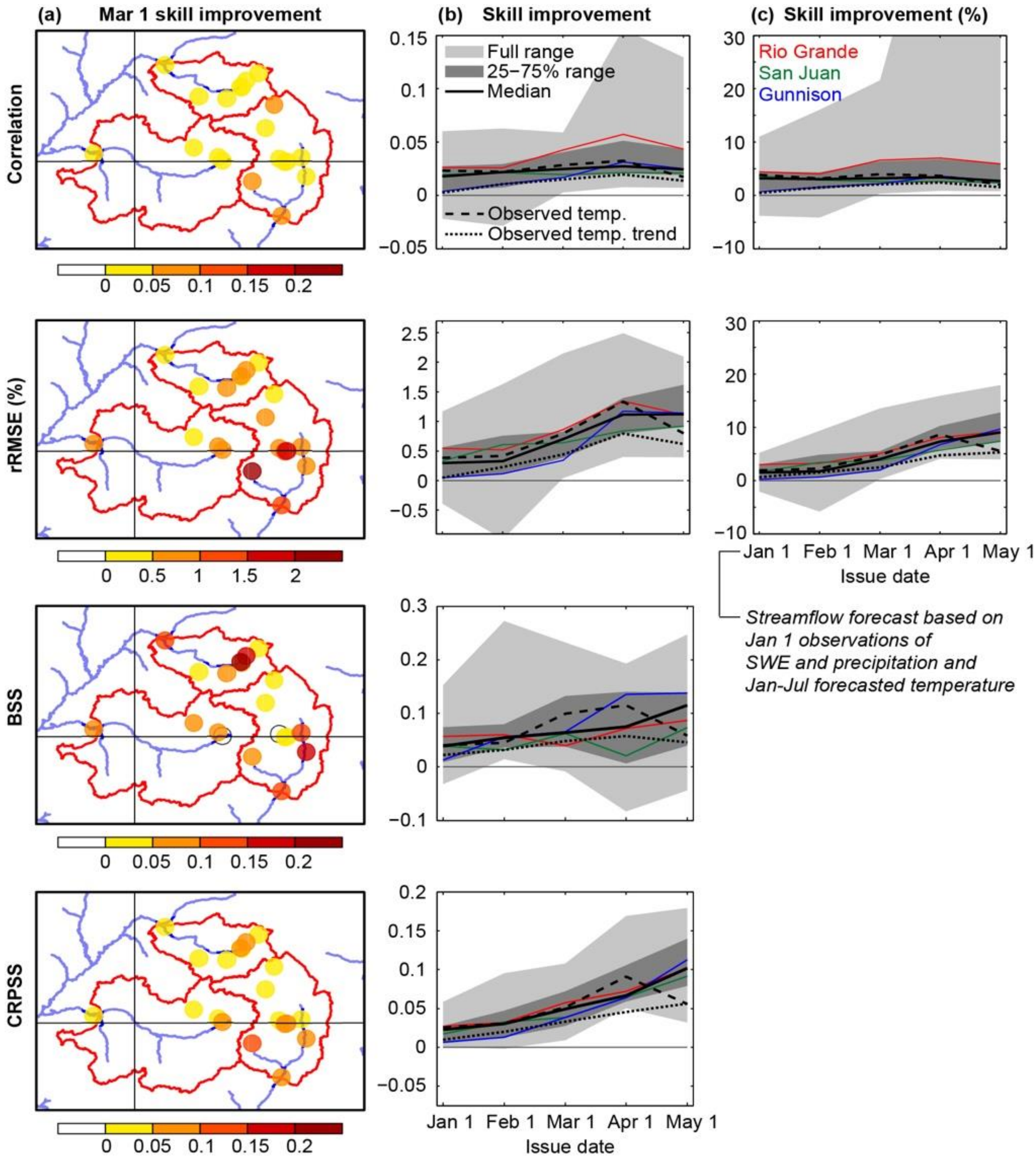

Figure 3. (a) Absolute skill improvement of the temperature-aided forecast relative to the baseline forecast at individual gages for issue date 1st March as an illustrative example. (b) Absolute skill improvement for all gages as a function of issue date. (c) Relative skill improvement for all gages 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.

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