

This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

Seasonal hydrologic prediction in the United States: understanding the role of initial hydrologic conditions and seasonal climate forecast skill

S. Shukla and D. P. Lettenmaier

Department of Civil and Environmental Engineering, University of Washington,
Seattle, WA, 98195, USA

Received: 30 June 2011 – Accepted: 4 July 2011 – Published: 8 July 2011

Correspondence to: S. Shukla (shrad@hydro.washington.edu)

Published by Copernicus Publications on behalf of the European Geosciences Union.

HESSD

8, 6565–6592, 2011

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Abstract

Seasonal hydrologic forecasts derive their skill from knowledge of initial hydrologic conditions (IHCs) and climate forecast skill (CFS) associated with seasonal climate outlooks. Depending on the type of hydrological regime and the season, the relative contributions of IHCs and CFS to seasonal hydrologic forecast skill vary. We seek to quantify these contributions on a relative basis across the Conterminous United States (CONUS). We constructed two experiments – Ensemble Streamflow Prediction (ESP) and reverse-ESP – to partition the contributions of the IHCs and CFS to overall forecast skill. In ESP hydrologic forecast skill is derived solely from knowledge of IHCs, whereas in reverse-ESP (second experiment), it is derived solely from atmospheric forcings (i.e. perfect CFS). Using the ratios of root mean square error (RMSE) in predicting cumulative runoff (CR) and mean monthly soil moisture (SM) of each experiment, we identify the variability of the relative contributions of the IHCs and CFS spatially throughout the year. We conclude that the IHCs generally have the strongest influence on the prediction of CR and SM at lead-1 (first month of the forecast period), beyond which CFS starts to have greater influence. Improvement in CFS alone will lead to better seasonal hydrologic forecast skill in most parts of the northeastern and southeastern US throughout the year and in the western US mainly during fall and winter months; whereas improvement in knowledge of the IHCs can potentially improve skill most in the western US during spring and summer months. We also observed that at short lead time (i.e. lead-1) contribution of the IHCs in SM forecasts is more extensive than in CR forecasts across the CONUS.

1 Introduction

Accurate seasonal hydrologic forecast information is a key aspect of drought mitigation (Hayes et al., 2005). Seasonal hydrologic/drought prediction systems, such as the Climate Prediction Center's (CPC) Seasonal Drought Outlook (SDO), the University

HESSD

8, 6565–6592, 2011

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



of Washington's Surface Water Monitor (SWM) (Wood, 2008; Wood and Lettenmaier, 2006), and Princeton University's (PU) drought forecast system (Li et al., 2008; Luo and Wood, 2007) provide information about the status of hydrologic conditions and their evolution across the Conterminous United States (CONUS). However, primarily due to the limited skill of climate forecasts beyond the seasonal time scale, seasonal hydrologic forecasts made with these systems are currently limited to lead times of 1–3 months. Central to the hydrologic forecasts made with these systems is the accurate knowledge of hydrologic and/or soil moisture (SM) conditions at the time of the forecast, and accurate weather/climate forecasts. For example, the SDO derives drought prediction skill from knowledge of initial hydrologic conditions (IHCs) taken from United States Drought Monitor (USDM) and from weather/climate forecasts at various time scales ranging from 6–10 days to 3 months. Alternately, SWM and the PU hydrologic monitoring systems obtain the IHCs by forcing one or more land surface models (LSMs) with observed gridded station data up to the time of forecasts, and then continue the model runs using either gridded climate data randomly resampled from a retrospective period (SWM) or seasonal climate forecasts over the forecast period downscaled to meet the needs of the LSMs (PU). Hence, two key factors limiting the seasonal hydrologic forecast skill in all of these systems are (1) uncertainties in the IHCs, associated with uncertainties in both the model's prediction skill and the model forcings over the recent past; and (2) climate forecast skill (CFS), over the forecast lead time. Thus, in order to make any significant improvements in the current state of seasonal hydrologic forecast skill, the focus should be towards improving the controlling factors (the IHCs or CFS), which presumably vary depending on location, forecast lead time, and time of year.

Numerous attempts have been made by the hydrologic and climate community to reduce the uncertainties associated with the aforementioned factors. For example, various researchers have investigated methods for assimilating snow and/or SM data (Andreadis and Lettenmaier, 2006; Clark et al., 2006; McGuire et al., 2006) into LSMs, to improve the IHCs for seasonal hydrologic prediction. Many attempts have been

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

made in parallel to improve CFS (Krishnamurti et al., 1999; Stefanova and Krishnamurti, 2010)

Nevertheless, the improvement in seasonal hydrologic forecast skill that could result from these efforts during any season and location depends on the relative contributions of the IHCs and CFS to the skill. For example, assimilating observed data to improve the IHCs is valuable mainly for those regions where, at least during the first few months of a seasonal hydrologic forecast, the IHCs dominate the prediction of SM and runoff. Likewise, improvements in CFS can most improve seasonal hydrologic forecasts where atmospheric forcings play a more significant role in influencing future SM and runoff than do the IHCs. Depending on factors such as SM variability at the time of forecast initialization, the seasonal cycle, and variability of precipitation and topology of the hydrologic regime, the contribution of IHCs and CFS to seasonal hydrologic forecast skill can vary significantly.

Previous studies have identified the major sources of hydrological predictability. Wood et al. (2002) assessed the role of IHCs and CFS in seasonal hydrological forecasts for the southeastern United States during the drought of 2000 and found that dry IHCs dominated CFS, whereas for the same region in the case of El Niño conditions from December 1997 to February 1998, both IHCs and CFS contributed to hydrologic predictability. Maurer and Lettenmaier (2003) evaluated the predictability of runoff throughout the Mississippi River basin both spatially and by season and prediction lead time by using a multiple regression technique to relate runoff and climate indices (El Niño-Southern Oscillation and the Arctic Oscillation) and components of the IHCs (SM and snow). They found that initial SM was the dominant source of runoff predictability at lead-1 in all seasons except in JJA in the western mountainous region, where snow water equivalent (SWE) was most important. Maurer et al. (2004) used Principal Component Analysis (PCA) to examine contributions to North American runoff variability of climatic teleconnections, SM, and snow for lead times up to a year. They concluded that knowledge of IHCs, especially when forecast initial conditions are dry, could provide useful predictability that can augment predictions of climate anomalies

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



work of Mahanama et al. (2011), it is somewhat difficult to draw general conclusions because the frameworks are somewhat inconsistent as are the study domains. In this work, we use the ESP-based framework outlined by Wood and Lettenmaier (2008). We explicitly address the relative contributions of IHCs and CFS to hydrologic forecast skill across the entire CONUS for forecast lead times up to 6 months. Specifically, we seek to (1) quantify the contributions of IHCs and CFS to seasonal prediction of cumulative runoff (CR) and SM during each month of the year, and (2) identify the months and regions within CONUS, where improvement in simulating the IHCs and/or CFS can have the greatest impact on seasonal hydrologic forecast skill.

2 Approach

We conducted paired ESP and reverse-ESP experiments (Wood and Lettenmaier, 2008) to generate forecasts with up to 6 months lead time (i.e. up to 6 months beyond the forecast initialization date) for the 33-year reforecast period 1971–2003 over the CONUS. In ESP, an LSM is run using observed forcings up to the forecast initialization date to generate the IHC. During the forecast period, an ensemble of forcings is created from the time series of observations (gridded over the model domain, sampled from n historical years) starting on the forecast initialization date, and proceeding through the end of the forecast period (up to 6 months from the forecast initialization date for this analysis), for each of n historical years. In reverse-ESP, the IHCs on the forecast date are taken from each of the n historical years of simulation, but during the forecast period, the model is forced with the gridded observations for that year (essentially a perfect climate forecast). We used the Variable Infiltration Capacity (VIC); a macroscale hydrology model (Cherkauer et al., 2003; Liang et al., 1994) as the LSM, applied over the CONUS at spatial resolution of $1/2^\circ$ latitude by longitude. We then spatially aggregated the forecasts generated by each experiment to the scale of 48 hydrologic sub-regions across the CONUS (Table 1 and Fig. 1). These sub-regions were created by merging the 221, US Geological Survey (USGS) hydrologic

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



sub-regions. Each of the sub-regions is named after the water resources regions in which it is located (Table 1). We compared the spatially aggregated forecasted CR and mean monthly SM with the corresponding observations (Sect. 2.2) for each sub-region and lead time over the reforecast period. We then estimated a forecast evaluation score (Sect. 2.4) and quantified the contributions of the IHCs and CFS to seasonal hydrologic forecast skill.

2.1 Model implementation

The VIC model parameterizes the major surface, sub-surface, and land-atmosphere hydrometeorological processes and represents the role of sub-grid spatial heterogeneity in SM, topography, and vegetation on runoff generation (Liang et al., 1994). We ran the model in water balance mode, in which the moisture budget is balanced at a daily time step and model's surface temperature is assumed to equal surface air temperature for purposes of its energy computations (e.g. those associated with evapotranspiration and snowmelt). The model was run at a daily time step, except for the snow accumulation and ablation algorithm, which was run at a 3 hourly time step. The $1/2^\circ$ model parameters (i.e. vegetation, soils, elevation and snowbands parameters) used in this study are the same as in Andreadis et al. (2005). Those parameters were aggregated from the North America Land Data Assimilation System (NLDAS) parameters used in Maurer et al. (2002).

2.2 Synthetic truth dataset

For purposes of evaluating forecast skill, we utilized a set of baseline values of SM and CR, created by a VIC control run with gridded observed forcings, as synthetic truth. We constructed the standard set of VIC forcings (daily precipitation, maximum and minimum temperatures, and wind speed) using methods outlined in Maurer et al. (2002). Precipitation and temperature forcings were generated using the Index Station method (Tang et al., 2009; Wood and Lettenmaier, 2006) which uses a high quality

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



set of about 2131 precipitation and temperature stations across the CONUS that have relatively few missing data over our period of analysis. As in Maurer et al. (2002), we took surface wind from the lowest level of the National Centers for Environmental Protection/National Center for Atmospheric Research (NCEP/NCAR) reanalysis (Kalnay et al., 1996). Other model forcing variables (downward solar and longwave radiations; humidity) were derived from the daily temperature and temperature range as in Maurer et al. (2002). We first ran the model over 1916–1969 starting from a prescribed initial state and saved the IHC at the end of the simulation. Using that IHC, generated after 53 years of spin-up, we initialized the control run simulation over 1970–2003. The same IHC was further used for generating IHCs for the 1st day of each month during each year of the reforecast period (1971–2003). We aggregated the model’s daily output of runoff and SM to monthly values and spatially aggregated them to the 48 hydrologic regions. These model-derived values served in lieu of direct observations for the purposes of our analyses. Maurer et al. (2002) and others have shown that when the VIC model is forced with high quality observations, it is able to reproduce well SM and streamflow across the CONUS domain.

2.3 ESP and reverse-ESP implementation

In our implementation of ESP, we obtained the IHCs from a control run simulation (Sect. 2.2). Given the IHCs on the first day of each month from 1971–2003, we then forced the model with 31 ensemble members of observed (gridded) forcings (sampled from 1971–2001) starting on the forecast date for a period of six months. For example, to start the forecast on 01/01 (i.e. January, 01) of any year i , we used IHC at the 00:00 h of the day $i/01/01$ and forced the model with forcings from $n/01/01$ to $n/07/01$ of each year n between 1971–2001. Figure 2b shows a schematic of the experimental design where “true” IHCs were used to initialize the model and it was forced with resampled gridded observations.

The reverse-ESP experiments sampled 31 IHCs from the retrospective IHCs for each forecast initialization date (day 1 of each month) from 1971–2001. For example, to start

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



the forecast on 01/01 of any year i , we used IHC at the 00:00 h of the day $n/01/01$ of each year n between 1971–2001, and forced the model with gridded observations for the period $i/01/01$ to $i/07/01$. As shown in Fig. 2c, in the reverse-ESP experiment climatological IHCs (from the same simulation run used to extract the IHCs for the ESP runs) were used to initialize the model and it was forced with “true” observations during the forecast period. CR and SM were computed as in the ESP experiment.

2.4 Forecast evaluation

The skill of both ESP and reverse-ESP forecasts was calculated based on the Root Mean Squared Error (RMSE) of forecasts of both CR and SM at lead times of 1 to 6 months for each hydrologic sub-regions. Let N be the total number of IHC or forcing ensembles (1971–2001), and I be the number of years (1971–2003) for which the reforecasts were generated. We designate $E_{(inl)}$ as the CR or SM generated by the ESP experiment using the IHC of the year i and forcing of the year n at a lead time l . Let $O_{(iil)}$ be the observed CR or SM generated using the forcings and the IHC of year i , at a lead time l . $RMSE_{(ESP)}$ is then:

$$RMSE(ESP) = \sqrt{\frac{1}{I} \left[\sum_{i=1}^I \frac{1}{N} \sum_{n=1}^N (O_{(iil)} - E_{(inl)})^2 \right]} \quad (1)$$

Likewise let $R_{(nil)}$ be the CR or SM generated by the reverse-ESP experiment using the IHC of year n and forcing of year i at a lead time l so $RMSE_{(revESP)}$ can be estimated by:

$$RMSE(revESP) = \sqrt{\frac{1}{I} \left[\sum_{i=1}^I \frac{1}{N} \sum_{n=1}^N (O_{(iil)} - R_{(nil)})^2 \right]} \quad (2)$$

We then calculated, the ratio of RMSE of each experiment (Eq. 3).

$$RMSE \text{ Ratio} = RMSE_{(ESP)} / RMSE_{(revESP)} \quad (3)$$

6573

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Unless otherwise specified, we consider that if the ratio is less than 1 then IHCs dominate (in a relative sense) the seasonal hydrologic forecast skill and if it is greater than one then CFS dominates.

3 Results

In this section we examine the variation of relative contributions of the IHCs and CFS in the CR and SM forecast, with each forecast initialization date (i.e. day 1 of each month), lead time (1 to 6 months) across the CONUS. We also highlight the regions and forecast periods for which improvement in knowledge of IHCs or CFS would most improve seasonal hydrologic forecast skill.

3.1 Cumulative runoff forecasts

The variation of RMSE ratio for the forecast of CR at lead-1 to -6 months for each of the 48 hydrologic sub-regions, is shown in Fig. 3a and b; where CR at lead-1 (lead-6) is the CR over the first month (1 to 6 month) of the forecast period. RMSE ratios below 1 indicate that the relative forecast error due to uncertainties in the CFS is lower than the error due to uncertainties in the IHCs; which indicates the relatively high contribution of the IHCs in the CR forecasts skill.

The variation of the RMSE ratio is much different across sub-regions and forecast periods (Fig. 3). The IHCs strongly dominate CR forecasts during winter and spring (March and April mainly) months over GL, SRR, UM, and MI-1 sub-regions. In the western US, the sub-regions such as PNW, GB, LC, UC, CA, and RG-1, high skill due to the IHCs in lead 1–6 months CR forecasts is mainly apparent during spring (MAM) and summer (mainly June) months. This suggests that runoff forecasts in the above-mentioned regions and forecast periods could benefit substantially from improvements in knowledge of the IHCs. For sub-regions in the eastern US such as NE, MA, SAG-1 and -2, OH-1 and -2, and UM, RMSE ratios are less than one for lead 1–2 months,

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



for CR forecasts initialized during winter (DJF) and spring month (March and April, mainly). These sub-regions as well could potentially benefit from improvements in estimates of the IHCs during these seasons. Aside from those months and locations, CFS dominates the CR forecasts. Some sub-regions such as TN, LM, and SAG-3 stand out because their RMSE ratios throughout the entire year and for all lead times exceeds 1, which suggests that improved hydrologic forecasts must, for the most part, await improvements in CFS in those sub-regions.

There is also a clear difference between the variations of RMSE ratio initialized from wet vs dry IHCs. For example, in most of the sub-regions across the CONUS, forecasts initialized during summer months have RMSE ratios less than or equal to 1 for lead-1 month CR forecasts. Furthermore the rate of change in the RMSE ratio for 1-month vs. 6-month forecasts, is much higher in forecasts initialized in the summer months than in winter and spring months when the IHCs are generally wet. This property is particularly significant for predictions during droughts when the IHCs are dry. It potentially means that during a drought event when the IHCs are dry, the signal from the IHCs may dominate even at lags for which the RMSE ratio exceeds 1. Additionally, in climatologically wet periods followed by dry initial conditions, CFS may well be important in improving seasonal hydrologic forecasts.

Figure 4 shows the maximum lead time (in months) at which the RMSE ratio of CR forecasts is below 1; defining the maximum lead time the IHCs can play a significant role in CR forecasts relative to CFS. Beyond this lead, CFS dominates the CR forecast skill; hence improvement in the CFS would lead to higher forecast skill. For the most part, the regions in northeastern and southeastern US would benefit most from improvements in CFS, throughout the year because the IHCs dominate up to lead-2 only. In the mountainous west and Pacific Coast sub-regions CFS dominates mainly during fall and winter. On the other hand, IHCs dominate in those regions during spring and summer for up to 6 months lead time. GL, SRR, and UM regions overall would benefit most from improvement in knowledge of IHCs during winter and spring months (mainly March) and CFS during summer months.

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

3.2 Soil moisture forecasts

SM is a key hydrologic state variable, and a natural indicator of agricultural drought. Figure 5a and b show the RMSE ratios of the mean monthly SM forecast, at lead-1 (i.e. mean monthly SM of the first month) to 6 (i.e. mean monthly SM of the 6th month of the forecast period) for forecasts initialized on the beginning of each month. In contrast to forecasts of CR, the RMSE ratio at lead-1 is almost always less than 1, across the CONUS and for each forecast period, indicating the strong dominance of IHCs for short lead forecasts. The ratio increases for leads greater than 1.

In the NE, MA, SAG, OH, LM, and TN sub-regions the influence of IHCs beyond lead-1 is generally negligible, which in turn means that the improvement in CFS will be required to improve SM forecasts beyond lead-1. Conversely, in the majority of the sub-regions in the midwestern US, such as GL-1, -2, -3; SRR, UM, and the western US show strong IHC influence for SM forecasts up to lead-5, when the forecast is initialized in winter or spring months. In the snowmelt-dominated sub-regions in the western US, the skill of SM forecasts during spring and summer months is especially high. In UC, LC, PNW, GB, and CA sub-regions useful skill in SM forecasts can be derived from the IHCs for leads as long as 6 months for forecasts initialized during the summer months.

Overall, the relative contributions of IHCs are greater for forecasts of SM than for forecasts of CR. The contribution of IHCs is dominant over the western US, in particular during spring and summer months.

Following the same criterion as we used for CR forecasts, Fig. 6, shows the maximum lead time at which the RMSE ratio is below 1 for mean monthly SM forecasts. In general most of the regions have some SM forecasts skill derived by the IHCs, at least up to lead-1 (including sub-regions in the NE and SE). This means that the relative contribution of the IHCs in the SM forecasts is more extensive than in the CR forecasts at lead-1. The spatial contrast between the regions and forecast periods with high and small value of maximum lead time, at which the IHCs significantly influences the SM forecasts skill, is similar to the case of CR forecasts.

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

3.3 Controls on hydrologic forecast skill

Mahanama et al. (2011) introduced a parameter, κ , which is a ratio of the standard deviation of the initial SM + SWE (σ_w) to the precipitation during the forecast period (σ_p) (Eq. 4). High κ values correspond to high total moisture variability at the time of forecast initialization relative to precipitation variability during the forecast period and vice versa. Parameter κ is basically a measure of the hydrologic predictability derived solely from knowledge of the IHCs, at the start of the forecast period.

$$\kappa = \sigma_w / \sigma_p \quad (4)$$

Mahanama et al. (2011) found a first order relationship between IHC-based 3-month streamflow forecasts (that is, forecasts wherein CR was regressed on the IHCs) and κ . Following their analogy we expect a first order relationship between the inverse RMSE ratio and κ . Namely, we expect that $RMSE_{ESP}$ should be smaller for regions and forecast periods with higher κ . Scatter of the inverse RMSE ratio and κ are shown for forecast periods of 1, 3, and 6 months in Fig. 7a, b and c, respectively. Red circles and blue circles show the inverse RMSE ratio estimated across all the hydrologic regions and forecast initialization dates, for the forecast of CR and mean monthly SM at lead-1, lead-3 and lead-6. (Fig. 7a, b and c, respectively) The values of κ vary for different forecast periods; and in general, the number of hydrologic regions and forecast periods with $\kappa > 1$ decreases as the lead time increases. First order relationships between the inverse RMSE ratio and κ clearly exist, at each lead time. The range of inverse RMSE ratios for a given κ value seems to be higher for CR at lead-1 than for SM (Fig. 7a). Overall at lead-1, the inverse RMSE ratio is higher for SM than for CR. The values of the inverse RMSE ratio of SM and CR forecast is much more comparable in the plot for lead-3 forecast (Fig. 7b). The inverse RMSE ratio for lead-6, CR forecast is generally higher than its corresponding values for SM forecasts at lead-6 (Fig. 7c).

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

4 Summary and conclusions

The two key factors influencing seasonal CR and SM forecast skill are IHCs and CFS. In order to improve seasonal hydrologic forecast skill in the CONUS, it is important to understand the seasonal and spatial variability of relative contributions of these components. We performed two modeling experiments (1) ESP and (2) reverse-ESP, in which the hydrologic prediction skill exploits knowledge of IHCs and CFS respectively to quantify the relative contributions of each factors; and to identify the regions and the forecast periods which can benefit most by the improvement in the CFS or knowledge of the IHCs. Our key findings are:

1. IHCs generally have the strongest influence over CR and SM forecasts at lead-1, beyond which their influence decays at rates that depend on location, lead time, and forecast initialization date.
2. Beyond lead-1, IHCs primarily influence the CR and SM forecasts during spring and summer months, mostly over the western US.
3. CFS dominates CR and SM forecast skill beyond lead-1 mainly over the north-eastern and southeastern US, throughout the year. For the rest of the CONUS, CFS generally dominates CR and SM forecasts during fall and early winter months.
4. The relative contributions of IHCs and CFS have a first order relationship with the ratio of initial total moisture variability to the variability of precipitation during the forecast period, for the temporal scale of seasonal hydrologic prediction.

Our findings could have important implications for the improvement of seasonal hydrologic and drought prediction in the CONUS. Despite seasonal hydrologic forecast skill at 3-month and greater lead times being limited by CFS, the skill could potentially be improved by one or more months by improving the IHCs, for example through use of ground based or remote sensing data. Another possible way of improving seasonal

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



hydrologic forecasts with relative short leads is to exploit the skill of medium range weather forecasts over first 15 days of the forecast period.

Acknowledgements. We thank Elizabeth Clark, Ben Livneh and Mohammad Safeeq for their valuable comments and suggestions on earlier versions of this paper. This research was supported in part by the National Oceanic and Atmospheric Administration (NOAA) Grants No. NA08OAR4320899 and NA08OAR4310210 to the University of Washington.

References

- Andreadis, K. and Lettenmaier, D.: Assimilating remotely sensed snow observations into a macroscale hydrology model, *Adv. Water Resour.*, 29(6), 872–886, 2006.
- Andreadis, K. M., Clark, E. A., Wood, A. W., Hamlet, A. F. and Lettenmaier, D. P.: 20th century drought in the conterminous United States, *J. Hydrometeorol.*, 6(6), 985–1001, 2005.
- Cherkauer, K. A., Bowling, L. C., and Lettenmaier, D. P.: Variable infiltration capacity cold land process model updates, *Global Planet. Change*, 38(1–2), 151–159, 2003.
- Clark, M. P., Slater, A. G., Barrett, A. P., Hay, L. E., McCabe, G. J., Rajagopalan, B., and Leavesley, G. H.: Assimilation of snow covered area information into hydrologic and land-surface models, *Adv. Water Resour.*, 29(8), 1209–1221, 2006.
- Hayes, M., Svoboda, M., Le Comte, D., Redmond, K., and Pasteris, P.: Drought monitoring: New tools for the 21st century, in: *Drought and Water Crises: Science, Technology, and Management Issues*, edited by: Wihite, D. A., Taylor & Francis, Boca Raton (LA), 53–69, 2005.
- Kalnay, E. C., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K. C., Ropelewski, C., Wang, J., Leetmaa, A., Reynolds, R., Jenne, R., and Joseph, D.: The NCEP/NCAR 40-year reanalysis project, *B. Am. Meteorol. Soc.*, 77(3), 437–472, 1996.
- Koster, R. D., Mahanama, S. P. P., Livneh, B., Lettenmaier, D. P., and Reichle, R. H.: Skill in streamflow forecasts derived from large-scale estimates of soil moisture and snow, *Nat. Geosci.*, 3(9), 613–616, 2010.
- Krishnamurti, T. N., Kishtawal, C. M., LaRow, T. E., Bachiochi, D. R., Zhang, Z., Williford, C. E., Gadgil, S., and Surendran, S.: Improved weather and seasonal climate forecasts from multimodel superensemble, *Science*, 285(5433), 1548, 1999.

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

- Li, H., Luo, L., and Wood, E. F.: Seasonal hydrologic predictions of low-flow conditions over eastern USA during the 2007 drought, *Atmos. Sci. Lett.*, 9(2), 61–66, 2008.
- Li, H., Luo, L., Wood, E. F., and Schaake, J.: The role of initial conditions and forcing uncertainties in seasonal hydrologic forecasting, *J. Geophys. Res.*, 114(D4), D04114, doi:10.1029/2008JD010969, 2009.
- 5 Liang, X., Lettenmaier, D. P., Wood, E. F., and Burges, S. J.: A simple hydrologically based model of land surface water and energy fluxes for general circulation models, *J. Geophys. Res.*, 99(14), 14415–14428, 1994.
- Luo, L. and Wood, E. F.: Monitoring and predicting the 2007 US drought, *Geophys. Res. Lett.*, 34(22), L22702, doi:10.1029/2007GL031673, 2007.
- 10 Mahanama, S. P., Livneh, B., Koster, R. D., Lettenmaier, D. P., and Reichle, R. H.: Soil Moisture, Snow, and Seasonal Streamflow Forecasts in the United States, submitted to *J. Hydrometeorol.*, 2011.
- Maurer, E. P. and Lettenmaier, D. P.: Predictability of seasonal runoff in the Mississippi River basin, *J. Geophys. Res.*, 108(D16), 8607, doi:10.1029/2002JD002555, 2003.
- Maurer, E. P., Wood, A. W., Adam, J. C., Lettenmaier, D. P., and Nijssen, B.: A Long-Term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States, *J. Climate*, 15(22), 3237–3251, 2002.
- 15 Maurer, E. P., Lettenmaier, D. P., and Mantua, N. J.: Variability and potential sources of predictability of North American runoff, *Water Resour. Res.*, 40(9), W09306, doi:10.1029/2003WR002789, 2004.
- McGuire, M., Wood, A. W., Hamlet, A. F., and Lettenmaier, D. P.: Use of satellite data for streamflow and reservoir storage forecasts in the Snake River Basin, *J. Water Res. Pl.-ASCE*, 132, 97, 2006.
- 25 Stefanova, L. and Krishnamurti, T. N.: Interpretation of Seasonal Climate Forecast Using Brier Skill Score, The Florida State University Superensemble, and the AMIP-I Dataset, *J. Climate*, 15(5), 537–544, 2002.
- Tang, Q., Wood, A. W., and Lettenmaier, D. P.: Real-Time Precipitation Estimation Based on Index Station Percentiles, *J. Hydrometeorol.*, 10(1), 266–277, doi:10.1175/2008JHM1017.1, 2009.
- 30 Wood, A. W.: The University of Washington Surface Water Monitor: An experimental platform for national hydrologic assessment and prediction, in: *Proceedings AMS 22nd Conference on Hydrology*, 20–24, 2008.

- Wood, A. W. and Lettenmaier, D. P.: A test bed for new seasonal hydrologic forecasting approaches in the western United States, *B. Am. Meteorol. Soc.*, 87(12), 1699–1712, 2006.
- Wood, A. W. and Lettenmaier, D. P.: An ensemble approach for attribution of hydrologic prediction uncertainty, *Geophys. Res. Lett.*, 35(14), L14401, doi:10.1029/2008GL034648, 2008.
- 5 Wood, A. W., Maurer, E. P., Kumar, A., and Lettenmaier, D. P.: Long-range experimental hydrologic forecasting for the eastern United States, *J. Geophys. Res.*, 107(D20), 4429, doi:10.1029/2001JD000659, 2002.

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Table 1. List of USGS water-resources regions.

Region 01	New England (NE)
Region 02	Mid-Atlantic (MA)
Region 03	South Atlantic-Gulf (SAG)
Region 04	Great Lakes (GL)
Region 05	Ohio (OH)
Region 06	Tennessee (TN)
Region 07	Upper Mississippi (UM)
Region 08	Lower Mississippi (LM)
Region 09	Souris-Red-Rainy (SRR)
Region 10	Missouri (MI)
Region 11	Arkansas-White-Red (AR)
Region 12	Texas-Gulf (TX)
Region 13	Rio Grande (RG)
Region 14	Upper Colorado (UC)
Region 15	Lower Colorado (LC)
Region 16	Great Basin (GB)
Region 17	Pacific Northwest (PNW)
Region 18	California (CA)

Table A1. Abbreviations used.

AR	Arkansas-White-Red
CA	California
CFS	Climate Forecast Skill
CONUS	Conterminous United States
CPC	Climate Prediction Center
CR	Cumulative Runoff
DJF	December-January-February
ESP	Ensemble Streamflow Prediction
GB	Great Basin
GL	Great Lakes
IHC	Initial Hydrologic Conditions
JJA	June-July-August
LC	Lower Colorado
LM	Lower Mississippi
LSM	Land Surface Model
MA	Mid-Atlantic
MAM	March-April-May
MI	Missouri
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Protection
NE	New England
NLDAS	North American Land Data Assimilation Systems
OH	Ohio
PCA	Principal Component Analysis
PNW	Pacific Northwest
PU	Princeton University
RG	Rio Grande
RMSE	Root Mean Square Error
SAG	South Atlantic-Gulf
SDO	Seasonal Drought Outlook
SM	Soil Moisture
SON	September-October-November
SRR	Souris-Red-Rainy
SWE	Snow Water Equivalent
SWM	Surface Water Monitor
TN	Tennessee
TX	Texas-Gulf
UC	Upper Colorado
UM	Upper Mississippi
USDM	USDM
USGS	United States Geological Survey
UW	University of Washington
VIC	Variable Infiltration Capacity

HESSD

8, 6565–6592, 2011

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



HESSD

8, 6565–6592, 2011

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

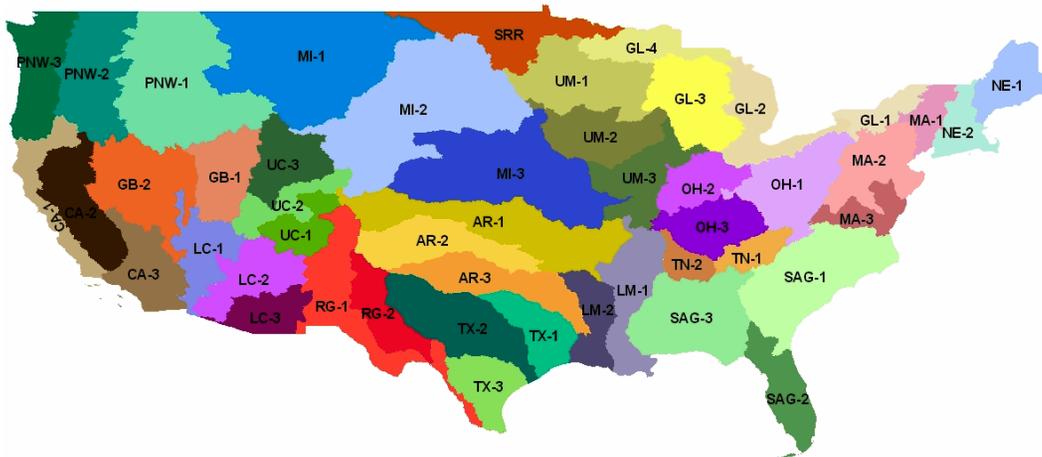


Fig. 1. 48 hydrologic sub-regions of the CONUS as used in this study, based on aggregation of 221 sub-regions of USGS.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



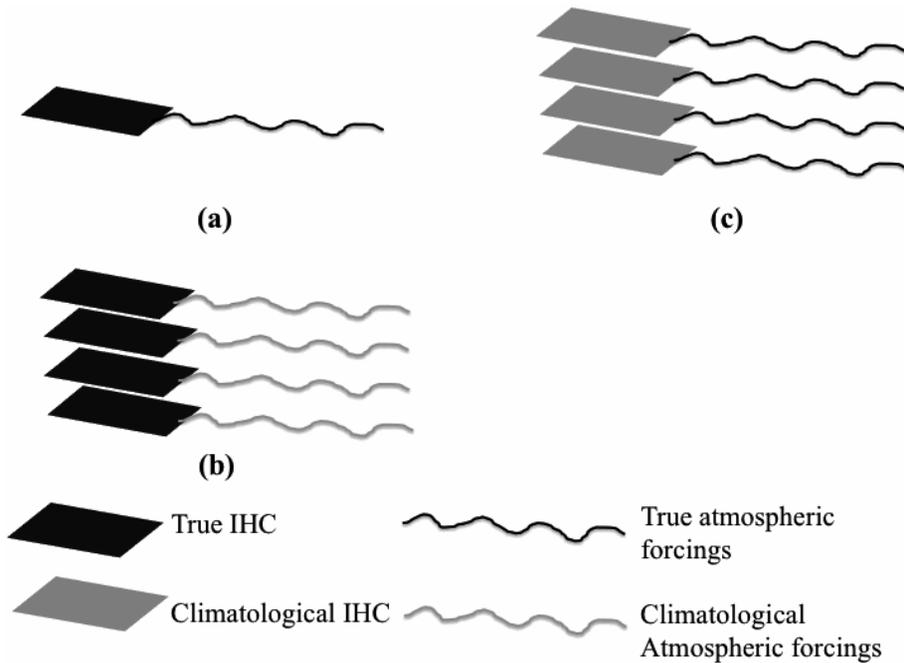


Fig. 2. Schematic diagram of **(a)** observational analysis **(b)** ESP and **(c)** reverse-ESP experiments.

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

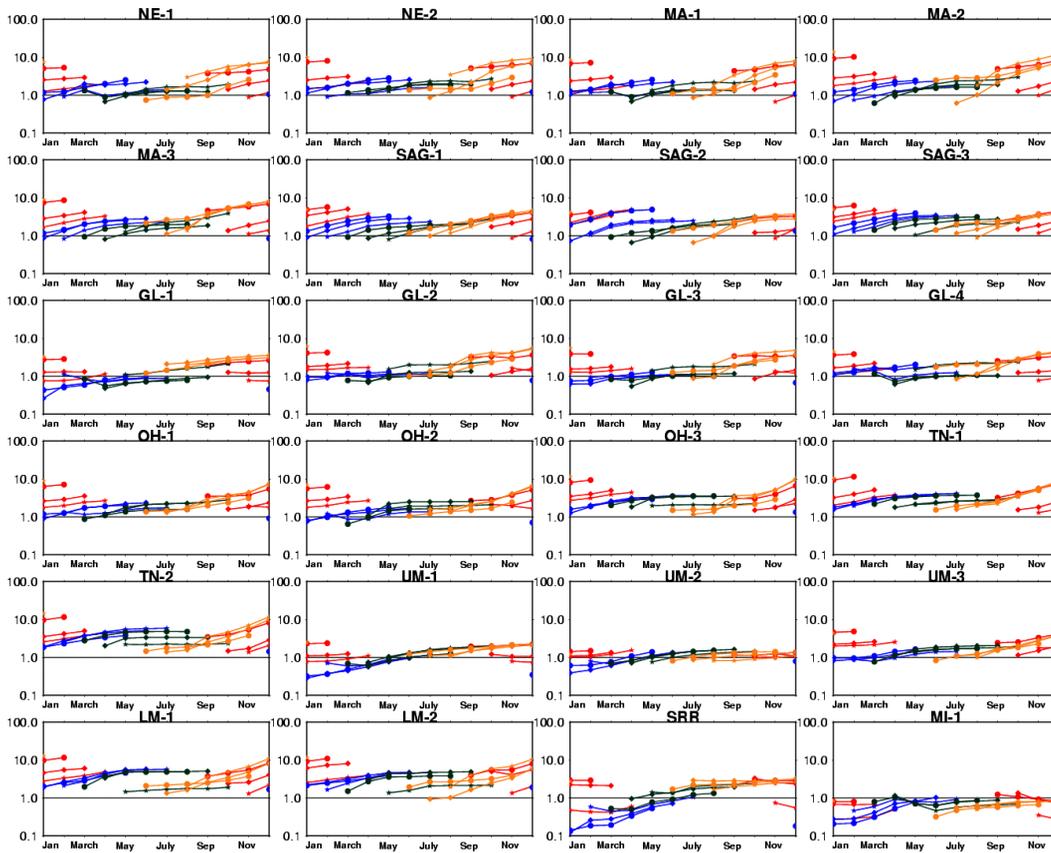
Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



(a)

Fig. 3. See caption on next page.

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

[Title Page](#)
[Abstract](#) [Introduction](#)
[Conclusions](#) [References](#)
[Tables](#) [Figures](#)
◀ ▶
◀ ▶
[Back](#) [Close](#)
[Full Screen / Esc](#)
[Printer-friendly Version](#)
[Interactive Discussion](#)



Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

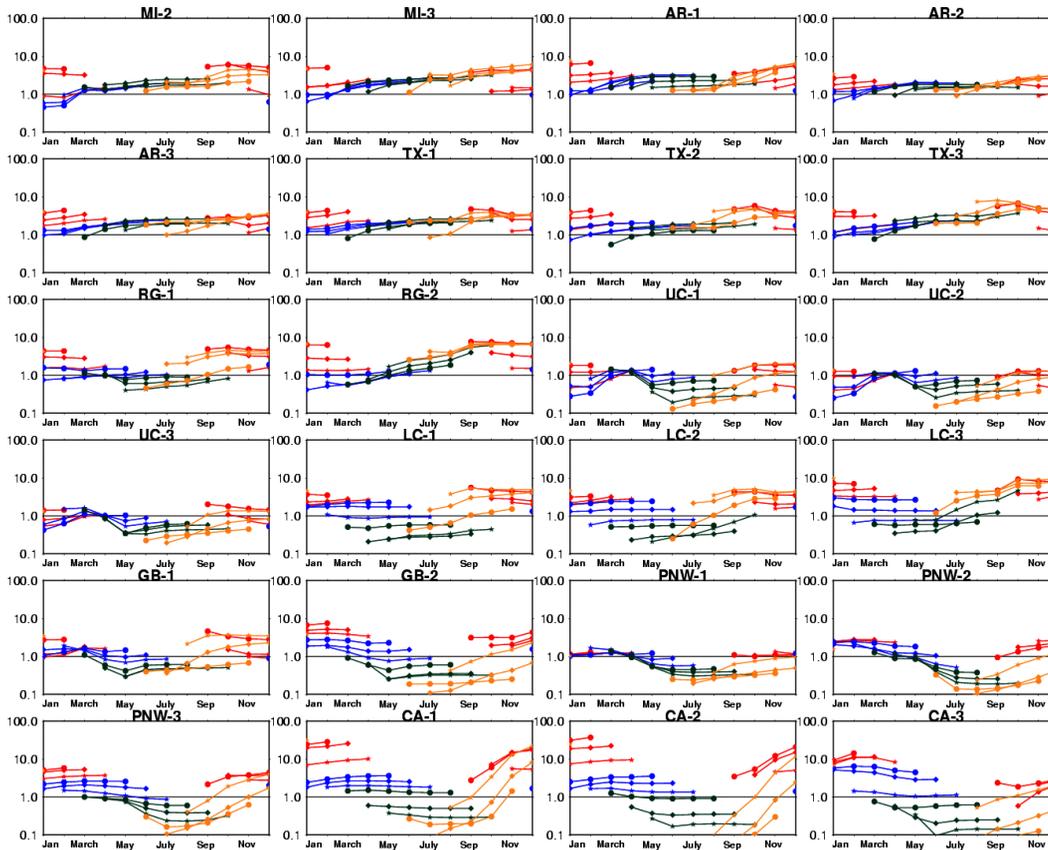
Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



(b)

Fig. 3. (a) and (b): Variation of RMSE ratio ($RMSE_{(ESP)}/RMSE_{(revESP)}$) with lead-time over 48 hydrologic sub-regions, for the CR forecasts at lead 1–6 months, initialized on the beginning of the each month. (DJF: blue, MAM: green, JJA: light brown and SON: red.)

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

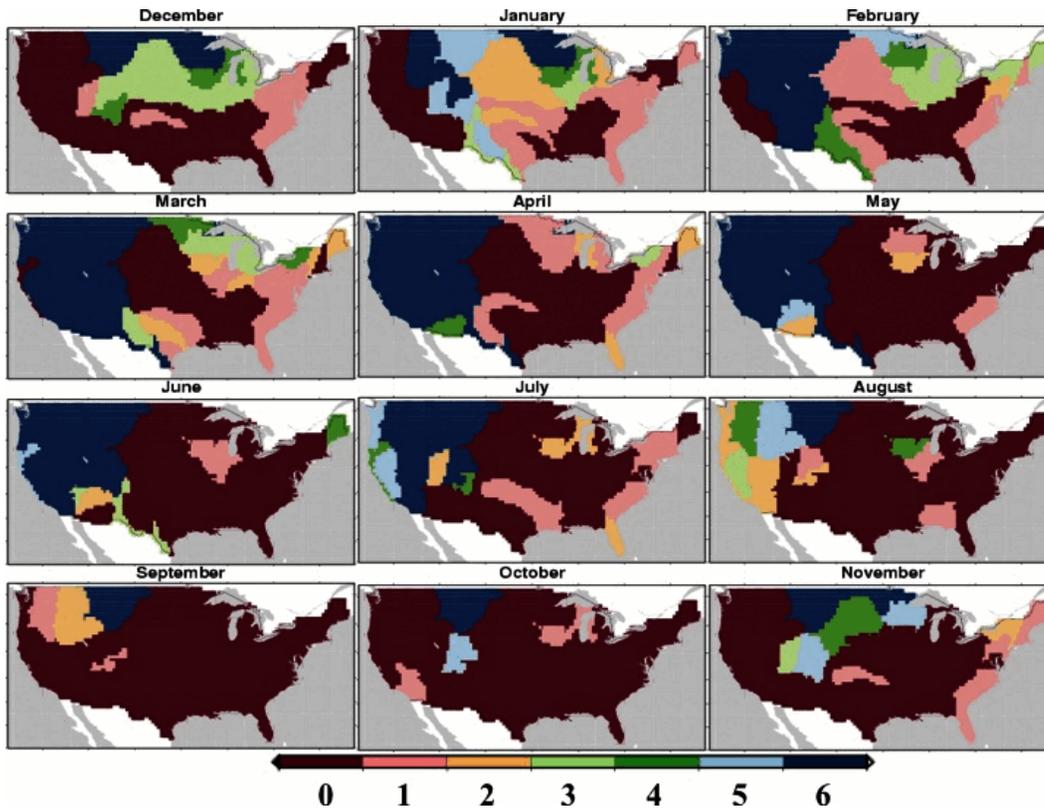
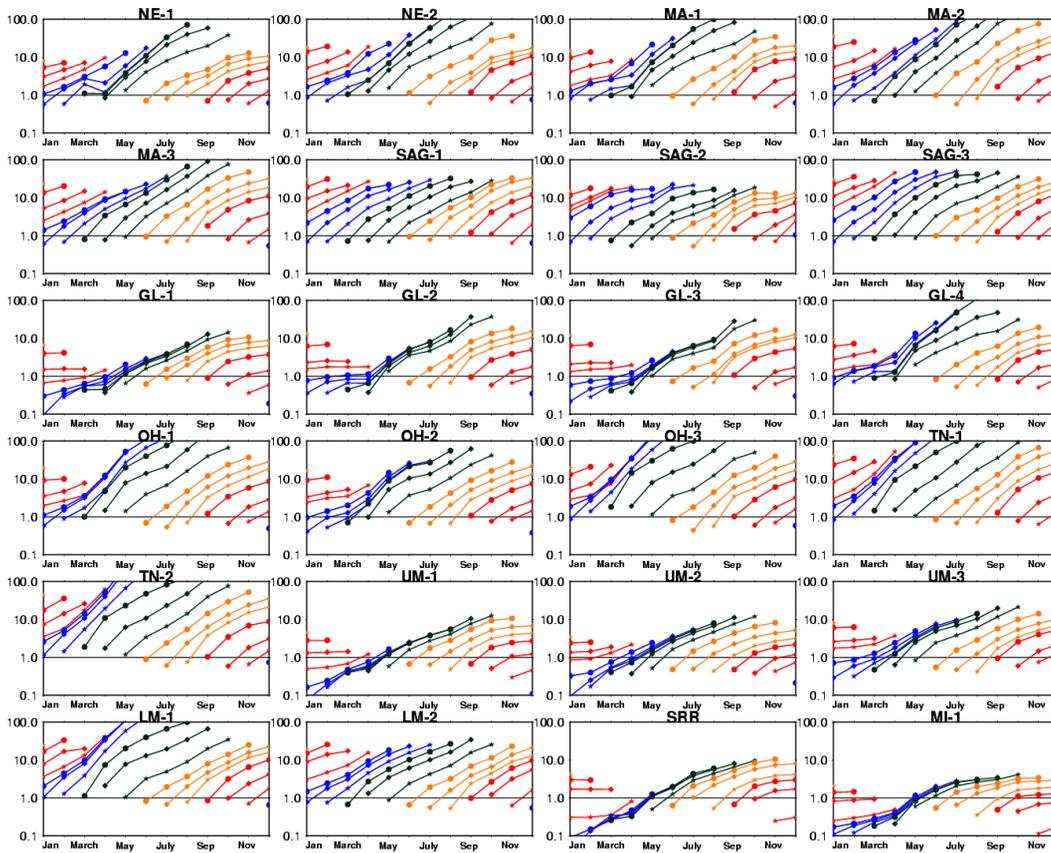


Fig. 4. Plot of the maximum lead (in months) at which RMSE Ratio is less than 1, for CR forecasts, initialized on the beginning of each month.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)



(a)

Fig. 5. See caption on next page.

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract Introduction

Conclusions References

Tables Figures

◀ ▶

◀ ▶

Back Close

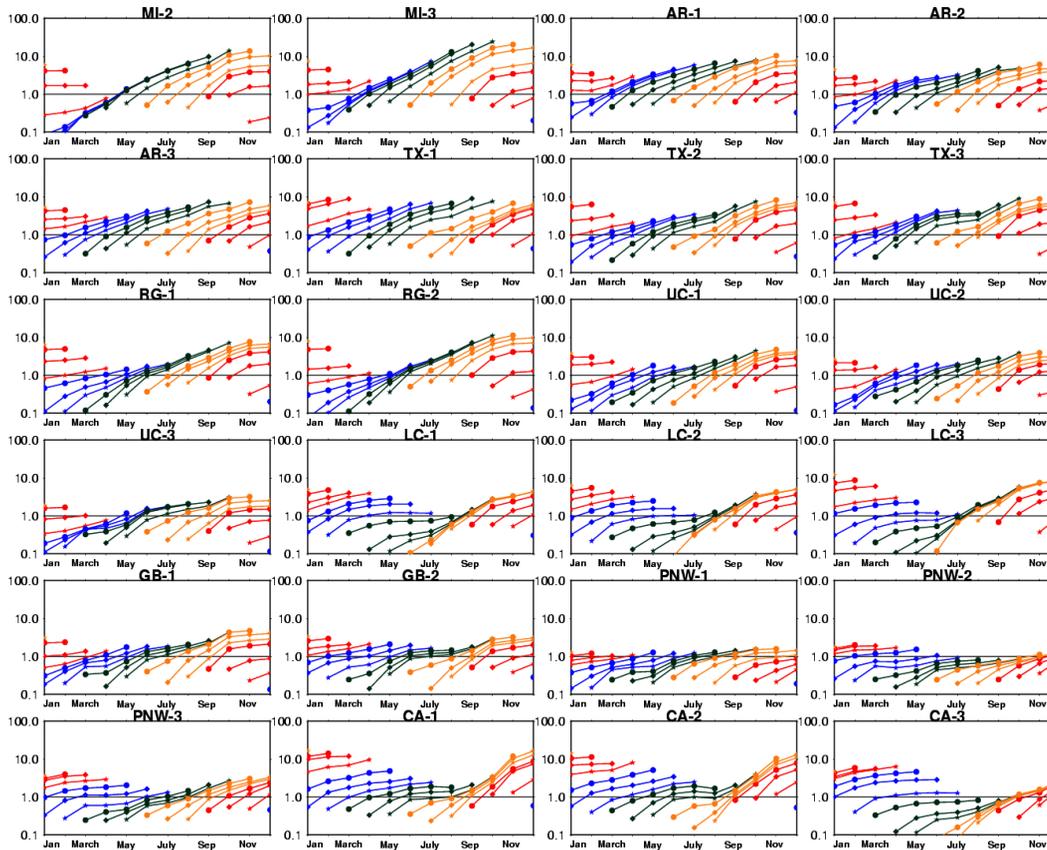
Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier



(b)

Fig. 5. (a) and (b): Variation of RMSE ratio (i.e. $\text{RMSE}_{(\text{ESP})} / \text{RMSE}_{(\text{revESP})}$) with lead-time over 48 hydrologic sub-regions, for the SM forecasts at lead-1 to 6 months, initialized on the beginning of the each month. (DJF: blue, MAM: green, JJA: light brown and SON: red.)

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

HESSD

8, 6565–6592, 2011

Seasonal hydrologic prediction in the United States

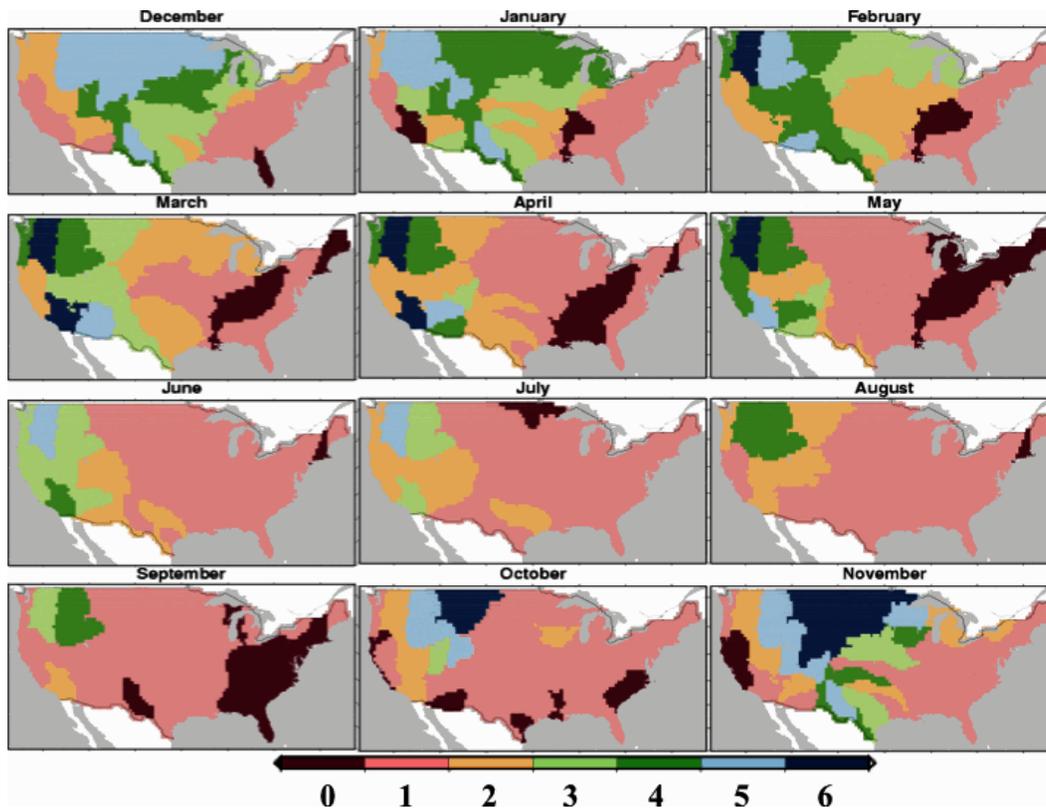
S. Shukla and
D. P. Lettenmaier[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

Fig. 6. Plot of the maximum lead (in months) at which RMSE Ratio is less than 1, for mean monthly SM forecasts, initialized on the beginning of each month.

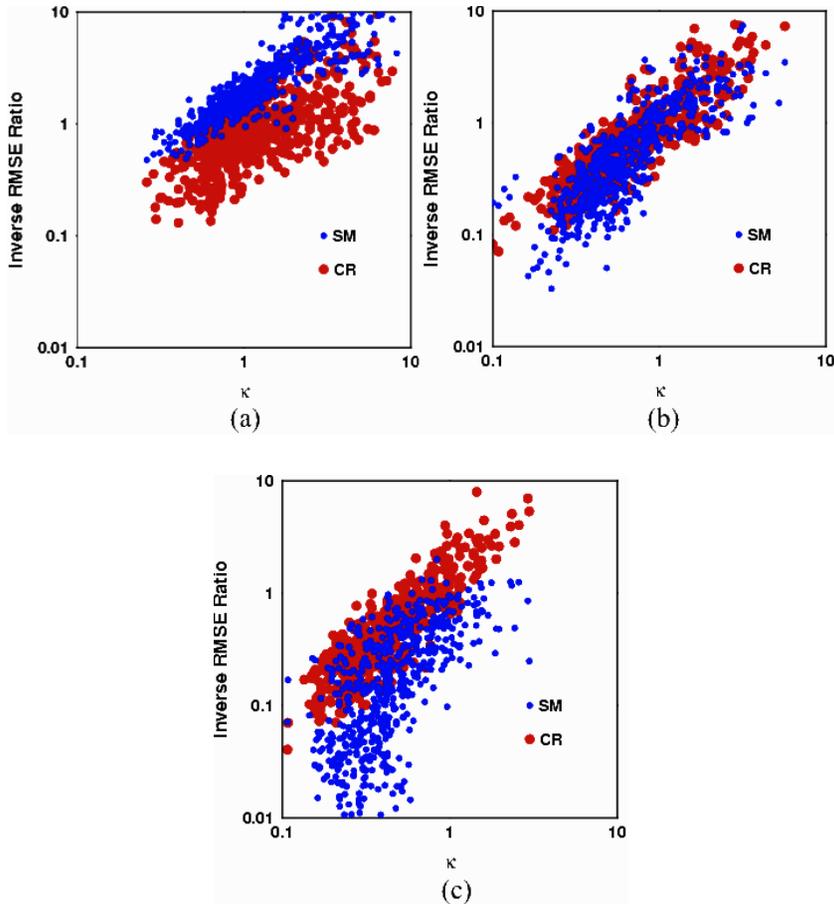


Fig. 7. Inverse RMSE ratio (i.e. $RMSE_{(revESP)} / RMSE_{(ESP)}$) of CR and mean monthly SM forecasts at **(a)** lead-1 **(b)** lead-3, and **(c)** lead-6 plotted against κ parameter of each forecast period (i.e. 1 month, 3 months, and 6 months, respectively).

Seasonal hydrologic prediction in the United States

S. Shukla and
D. P. Lettenmaier

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion