Towards the Improvement of Drought Monitoring and Prediction in the United States

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Abstract

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Drought and heat waves resulted in economic losses of $171 billion in the United States between 1980 and 2007, losses which emphasize the need for a proactive risk management approach for drought management. The motivation for this study is to develop and evaluate approaches and tools to improve drought monitoring and prediction in the U.S., through the use of advanced macroscale hydrologic models and weather/climate forecasts. The value of a macroscale hydrologic model-based Drought Monitoring System (DMS) was assessed in terms of its potential use as a drought-monitoring tool in Washington State. The results show that had the DMS indicators been available during four major droughts from 1976 on, they would have detected the onset and recovery of drought conditions, in many cases, up to four months before state drought declarations. Subsequently, the relative contributions of the sources of seasonal hydrologic and drought predictability (i.e., initial hydrologic conditions (IHCs) and climate forecast skill) were identified over the Contiguous U.S. (CONUS). This analysis indicated that improvement in hydrologic forecasts can result from better knowledge of IHCs in the western U.S. during spring and summer. On the other hand, improved climate forecast skill is needed to improve hydrologic and drought forecast skill in most parts of the northeastern and southeastern U.S. throughout the year and in the western U.S. during fall and winter months. The effect of medium range weather forecast skill (i.e. 14 days) on seasonal hydrologic/drought forecast skill was then investigated. The analysis indicated that medium-range weather forecasts have the potential to improve seasonal hydrologic forecast skill beyond the initial hydrologic condition effect at 1-month lead-time and, in some cases, up to 3 months. Finally, the value of dynamical in contrast with statistical downscaling of seasonal climate forecasts was evaluated in terms of resulting improvement in seasonal hydrologic forecast skill. This analysis identified that dynamical downscaling does somewhat increase the seasonal hydrologic forecast skill over some parts of the Northwestern and North Central U.S.

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DEDICATION

This dissertation is dedicated to my parents Smt. Mithilesh Shukla and Shri Brahmanand Shukla who have nurtured my curiosity, developed my moral courage to persevere and like their parents before them have woven the love of learning into the fibers of my soul.

I. INTRODUCTION

Drought is among the most costly natural disasters (Lott and Ross 2006). In the U. S. alone drought losses average about $6-8 billion each year (FEMA 1995). In past century two drought events, 1930s "Dust Bowl" drought (1929–1940) and the 1950s Southwest drought (1946–1956) were particularly severe in terms of socio-economic impacts (Cook et al. 2007). Among more recent droughts, the 1999-2005 Western U.S. drought is noteworthy for its severity and areal extent (Sheffield and Wood 2011). As noted by Lawrimore and Stephens (2003), at its peak in July 2002, more than 50% of the contiguous U.S. was under moderate to severe drought conditions, with record or near-record precipitation deficits throughout the West. Although the human costs of drought have been mitigated in the developed world by development of water resources infrastructure (Cook et al. 2007) , at the same time agricultural intensification and an increasing population in water short regions have increased the economic impacts of drought. For example, the ongoing drought in Texas alone (since late fall of 2010) has resulted in almost $8 billion in losses by some estimates (Fannin 2012). One way in which these economic losses can be mitigated is by drought monitoring, prediction and early warning systems.

Significant strides have been made (particularly in the U.S.) to develop and implement new drought monitoring tools. These tools have increased the temporal and spatial resolution of drought monitoring and are available in near real-time (i.e. lags of one day to one week) (Hayes et al. 2005). One of the most widely used drought monitoring tools is the United States Drought Monitor (USDM, http://droughtmonitor.unl.edu/) (Svoboda et al. 2002). The USDM combines various objective drought indicators along with subjective information from local experts to provide an assessment of current drought conditions that is expressed in four drought severity categories: Moderate (D1), Severe (D2), Extreme (D3) and Exceptional (D4). While the USDM has proved to be a valuable tool for drought, major challenges nonetheless remain in real-time drought monitoring. One of these is the availability of consistent observations of long term and real-time soil moisture across the U.S. Because of such data are scarce, most objective drought indicators including the ones used by the USDM rely mainly on precipitation data. Although precipitation deficits are the main driver of drought events, , there can be a lag between when precipitation deficits (i.e. Meteorological Drought) and soil moisture (i.e. agricultural drought) and runoff deficits (i.e. hydrological drought) (Wilhite and Buchanan-Smith 2005). Furthermore, evaporative demand also plays a role in agricultural and hydrological drought, which is not recognized in precipitation-based measures. Through projects like North American Land Data Assimilation (NLDAS) (Mitchell et al. 2004; Xia et al. 2011b; a) macroscale land surface models (LSMs) have been developed and used to represent hydrometerlogical processes and land surface atmosphere interactions (Maurer et al. 2002; Luo et al. 2003; Pan et al. 2003; Sheffield et al. 2003) including soil moisture. These LSMs can be run in off-line mode wherein observations of atmospheric forcings such as precipitation and temperature are prescribed to allow simulation of hydrological variables such soil moisture and runoff. Due to their ability to translate readily available observations of atmospheric forcings to output predictions of hydrologic variables, LSMs are increasingly being used for drought monitoring and prediction. One example is the National Centers for Environmental

Prediction's (NCEP) drought monitor (*http://www.emc.ncep.noaa.gov/mmb/nldas/forecast/TSM/prob/*). Another is the University of Washington's Surface Water Monitor (*http://www.hydro.washington.edu/forecast/monitor/outlook/index.shtml*). Numerous previous studies have evaluated the ability of LSMs to reconstruct historical drought events and provide a basis for consistent long term drought analysis (Sheffield et al. 2004; Andreadis et al. 2005; Mo 2008), however none of those studies investigated the applicability of LSM-based drought indicators to drought management decision processes.

In addition to the challenges with drought monitoring tools, seasonal drought prediction suffers from limited climate forecast skill beyond one month or so (Lavers et al. 2009), and hence on a practical level seasonal hydrologic and drought prediction skill mostly is derived from knowledge of initial hydrologic conditions (Lettenmaier and Wood 2009). In order to improve seasonal drought prediction it is imperative to know the relative contributions of IHCs and climate forecast skill to seasonal drought prediction skill, and the variations of that lead time with seasonal, spatially, and with lead-time. Moreover, one potential avenue for improvement in seasonal drought prediction that at present has largely been unexploited is the use of medium range weather forecasts, which generally are skillful for least over first few days of lead time (Hamill et al. 2004, 2006). Current practice used in generating seasonal ensemble climate forecasts involves temporal offsets of a few days among the multiple ensemble members, which has the effect of ignoring forecast skill at weather time leads (also a few days) Finally, seasonal climate forecasts are usually available at much coarser spatial resolution than that used by LSMs in off-line simulations, so spatial downscaling of climate forecasts is needed to use them for seasonal drought prediction. In practical applications, statistical downscaling methods have been favored to translate climate forecasts to the resolution of LSMs. Among the statistical methods that have been most widely used are Bias Correction and Spatial Downscaling (BCSD) (Wood et al. 2002) and Constructed Analog (CA) (Hidalgo et al. 2008). The major assumption behind the statistical downscaling methods is stationarity of the relationship between hindcasts performed using the model version and data assimilation system that was in place at the time of forecast. This assumption clearly is not valid for global climate change scenarios (Clark and Hay 2004). In contrast, dynamical downscaling methods are more physically realistic, as they assure physical consistency across the regional and global scales. In dynamical downscaling regional climate models (RCMs) use prescribed lateral boundary conditions from the global climate model and are run at higher spatial resolution to represent in greater detail both topographic and land cover variations, while also allowing description of smaller-scale atmospheric processes which lead to the formation of mesoscale weather phenomena (Leung et al. 2003).

This dissertation seeks to evaluate approaches to addressing the above-mentioned challenges, and to explore ways to improve drought monitoring and prediction by addressing the following overarching science and applications questions:

1. How well do drought management decisions based on an LSM-based Drought Monitoring System (DMS) compare with decisions made in practice during historical drought events?

2. What are the relative contributions of the primary hydrologic moisture storage variables (i.e. snowpack, soil moisture) and the atmospheric forcings (i.e. precipitation and temperature) to seasonal drought prediction and how do they vary spatially and seasonally across the United States?

3. Can seasonal drought prediction be improved by merging weather forecasts with seasonal climate forecasts, and to what extent?

4. What is the value added in improvement of seasonal drought prediction through dynamical as contrasted with statistical downscaling of climate forecasts?

These questions are addressed in four chapters in this dissertation. **Chapter II** (published as Shukla et al., 2011) evaluates an LSM-based drought monitoring system using actual drought management decisions made during four major historical drought events in Washington State. **Chapter III** (published as: Shukla and Lettenmaier, 2011) investigates the relative contributions of IHCs and seasonal climate forecast skill in seasonal hydrologic predictions for the continental U.S. **Chapter IV** (in review as Shukla et al., 2012) explores the impact of 14-day weather forecasts on seasonal hydrologic and drought prediction across the continental U.S. Finally, **Chapter V** (to be submitted to the *Journal of Geophysical Research* as Shukla et al., 2012) determines the relative value of dynamically vs statistically downscaled winter season CFS forecasts in terms of the improvement in seasonal hydrologic forecast skill.

II. DROUGHT MONITORING FOR WASHINGTON STATE: INDICATORS AND APPLICATIONS

This chapter has been published in its current form in the Journal of Hydrometeorology: Shukla, S., A. C. Steinemann, and D. P. Lettenmaier. 2011. Drought monitoring for Washington state: Indicators and Applications. *J. Hydrometeor.* 12: 66–83, 10.1175/2010JHM1307.1.

1. Introduction

Droughts can cause significant economic losses that reach all levels of society. Between 1980 and 2005, droughts and heat waves in the U.S. inflicted an estimated $174 billion (2009 dollars) in damages (Lott and Ross, 2006). Since 1963, 46 federal drought declarations have been made across the U.S (FEMA, 2009). Despite its water-abundant reputation, the state of Washington has experienced two major statewide droughts in the last decade (2000-2001 and 2004-2005). Both droughts resulted in large economic losses: about $359 million and $542 million (2009 dollars), respectively (Fontaine and Steinemann, 2009).

Future water availability in the state is projected to decline, owing in part to global warming and resultant declines in snowpack (Barnett et al., 2008; Mote et al., 2005, 2008; Elsner et al., 2009). This suggests an increased likelihood of future droughts, and a need to shift drought management strategies from reactive to proactive (Wilhite, 2000). Proactive drought management systems depend on timely and accurate information about the evolution of drought conditions and water supply outlooks (Hayes et al., 2004). Drought indicators are one element of proactive strategies that can detect and characterize drought conditions. Drought triggers, or specific values of drought indicators, can represent classes of drought severity and be linked to drought responses to reduce impacts (Steinemann, 2003).

In addition to the characterization of drought based on hydrologic variables (e.g., precipitation, runoff, SM), drought can also be characterized by its temporal extent and persistence. The impact of drought depends on not only the indicator, but also on the potential uses of water over the time period and region of interest. For example, SM deficiencies with duration as short as one month can result in severe impacts on agricultural production if they occur during times of maximum crop water use. One of the costliest U.S. droughts to date was the 1988 drought, when the federal government spent $6.7 billion on drought relief programs and $4.3 billion (both in 2009 dollars) on farm credit programs (Riebsame et al., 1991). That drought lasted less than six months, but was closely aligned with the spring and summer growing season in the most agriculturally productive part of the U.S. Lack of streamflow to sustain low flows is another key drought concern, with environmental consequences that are less amenable to economic valuation. Furthermore, in the case of streamflow, the temporal lag between drought onset and its impact can be influenced by reservoir storage. Taken together, all of these factors highlight the importance of drought monitoring systems (DMSs) that can provide information about drought conditions at different time scales and for different water users.

Common indicators of drought include precipitation, streamflow, and soil moisture (SM). However, long-term SM (and to a lesser extent, streamflow for unregulated streams) observations across the U.S. are scarce. Therefore, SM and runoff data sets produced by the Land Surface Models (LSMs) that comprise the North-American Land Data Assimilation System (NLDAS); Mitchell et al., 2004) have become a valuable source of information for drought monitoring and prediction (Mo, 2008). The LSMs produce nowcasts (model representations of current hydrologic conditions) that simulate the time lag between precipitation (deficiency) and SM and runoff deficiencies. These latter two variables are directly related to the availability of water for agricultural and municipal users. A strength of LSM-based indicators is that they can be aggregated to any geographical area, such as counties, watersheds, or hydro-climate zones, whereas indicators such as the Palmer Drought Severity Index (PDSI, Palmer 1965) are usually calculated at the relatively coarse spatial resolution of the NOAA climate divisions. The use of LSMs is also desirable because real-time estimates can be related to long-term climatologies derived by running the models using retrospective forcings (typically precipitation and temperature) that go back many years, often approaching a century, depending on data availability.

Retrospective LSM simulations are especially valuable for reconstructing and characterizing the severity of multi-year drought events. One increasingly common method of relating current conditions with historical simulations is to express LSM-derived variables, such as SM, in terms of percentiles relative to a retrospective simulation. This approach has been used by Sheffield et al. (2004), Andreadis et al. (2005), Andreadis and Lettenmaier (2006), and Mo (2008). Retrospective LSM simulations have also been used to evaluate trends in drought-related variables. For instance, Andreadis and Lettenmaier (2006) found that trends in model-simulated runoff over the 20th century compared well with similar studies by Lins and Slack (1999) that were based on observed streamflow. Sheffield et al. (2004) found LSM-simulated SM performed well as an indicator of vegetative growth. Shukla and Wood (2008) and Mo (2008) showed that model-derived runoff percentiles and a model-derived SRI reflected the seasonal lag in the influence of precipitation and snowmelt on streamflow.

In this study, we evaluate how a DMS for Washington State, based on an LSM, would perform with respect to identification of four major droughts that occurred in Washington State over the last 30 years. Our objectives are to (1) describe DMS indicators and their application; (2) reconstruct four historical droughts using DMS products; and (3) compare DMS drought indicators with drought conditions and management decisions during each of the four drought events.

2. Methodology

In the following sub-sections, we first describe the major hydroclimatological features of Washington State and the methodology adopted to calculate the drought indicators used in our DMS. We then illustrate the drought severity classification method used for this study.

2.1 Study domain

Our study domain is Washington State. Annual average precipitation over the state varies from less than 25.4 cm (10 inches) to more than 381 cm (150 inches), with high precipitation areas mostly on the western slopes of the Cascade Mountains, and the lowest precipitation in the east central interior of the state. The nature of water supply systems, and hence the characteristics of DMS, varies across the state with its hydroclimatology. For instance, in the arid and semi-arid eastern part of the state, water is managed primarily for agricultural water supply and (in the case of the Columbia River system) hydropower production, whereas in the more humid western part of the state, municipal water supply and hydropower production dominate. In both parts of the state, in-stream flow requirements are a serious consideration, as related especially to protection and enhancement of native salmonids.

During the last century, the state has experienced 24 major drought events (King 1978, EWEC 1988, Hart et al., 2001, and Andreson et al., 2005). In the State's drought contingency plan, developed in 1992, water supply monitoring and forecasting responsibilities were assigned to the *Water Supply Advisory Committee (WSAC)*. The WSAC advises the governor to convene the *Executive Water Emergency Committee (EWEC)* during drought conditions. The EWEC is responsible for assessing the overall impacts of ongoing droughts and coordinating the State's response. As defined by the Washington Administrative Code, "Drought conditions are water supply conditions where a geographical area or a significant part of a geographical area is receiving, or is projected to receive, less than seventy-five percent of normal water supply as the result of natural conditions and the deficiency causes, or is expected to cause, undue hardship to water users within that area" (WAC, 2010). The state's climatological and hydrological features play a key role in drought declarations, as they relate directly to the drought declaration criterion of being likely to receive "less than seventy-five percent of normal water supply."

Washington State is divided into 62 Water Resource Inventory Areas (WRIAs) (Figure 2.1), which are similar to the U.S. Geological Survey 5th and 6th layer Hydrologic Unit Codes. Before starting this study, we met with state and regional water managers, and other stakeholders, to determine ways that an indicator system might be most useful to them, and an appropriate scale for decision-making. Based on those discussions, we determined that the WRIAs would be a useful and appropriate unit for the indicator system.

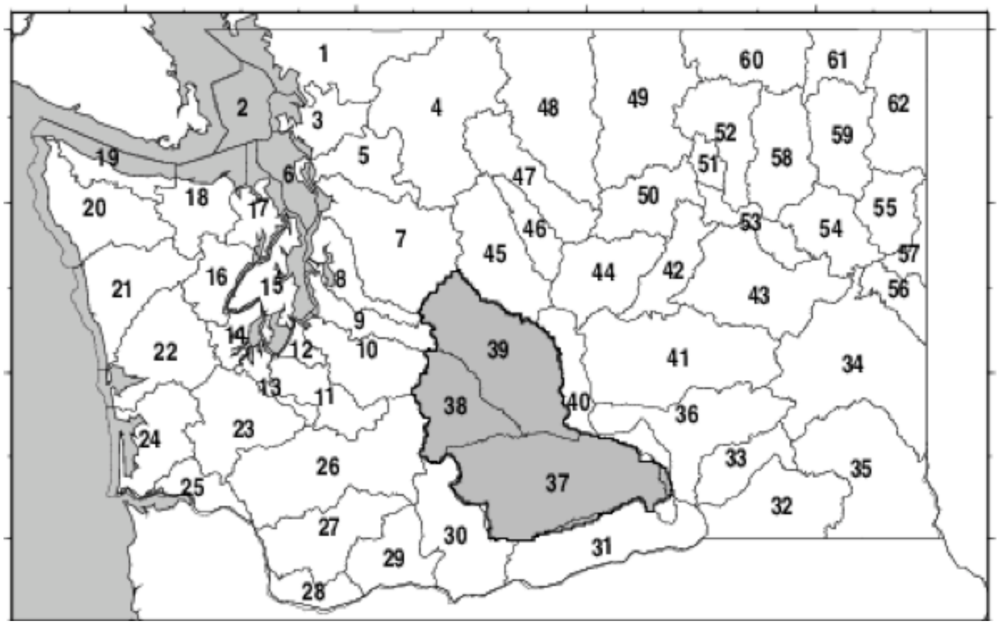


Figure 2.1: Map of Water Resource Inventory Areas (WRIAs). (Yakima basin is highlighted in grey.)

2.2 Climatology of the State

Figure 2.2 shows the long term monthly mean precipitation, SWE, SM, and runoff, spatially averaged over the state, where precipitation is gridded from observations following methods outlined in Elsner et al. (2010) and Maurer et al. (2002), and the other variables are output from the Variable Infiltration Capacity (VIC; Liang et al., 1994) hydrology model. As is evident from the plot, maximum precipitation is concentrated in fall and winter months, the wettest of which are November, December, January and February (NDJF).

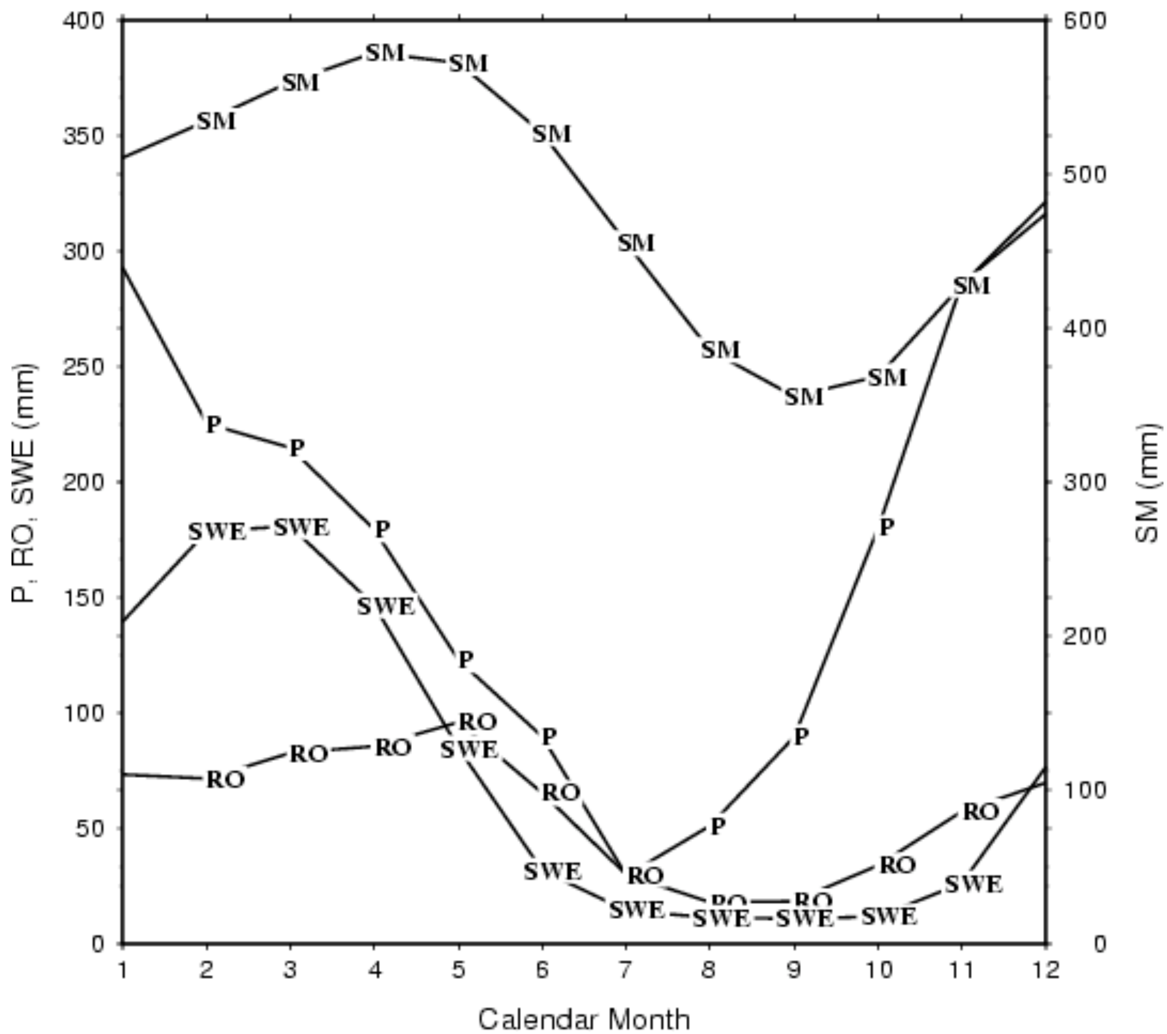


Figure 2.2: Monthly cycle of precipitation (P), snow water equivalent (SWE), soil moisture (SM), and runoff (RO), averaged over the state based on 1950-2005 averages.

Because annual precipitation is so heavily dependent on precipitation during these months, in years when there is a substantial accumulated precipitation deficit at the end of this four-month period, it is unlikely the deficit can be offset later in the water year. Therefore, for any given water year, precipitation is crucial for drought planning purposes.

In winter (DJF), most precipitation in headwater areas of the state's major streams falls in the form of snow (noting that while November is an important contributor to wet season precipitation, substantial accumulations of snow in the mountainous regions of the state do not usually begin until December). As winter snowpack melts in spring and summer, it provides much of the water year's runoff, especially for rivers with high elevation headwaters draining the eastern slope of the Cascades. Snowmelt also contributes to SM in much of the eastern part of the state, and high elevation areas in the western part of the state, and to runoff over most of the state during the relatively dry spring (MAM) and summer (JJA) months.

SM is usually high in the low elevation areas of the state during winter (DJF) due to high precipitation and low evapotranspiration. Although in the highest elevation areas, where relatively little melt occurs during winter, low SM may persist throughout the winter as a result of end-of-summer dry conditions, until it is replenished by snowmelt. Therefore, SM can be a useful and integrative drought indicator for much of the year and over many parts of the state, although it may not be as suitable for winter months in the high elevation areas. Below-normal SM during spring (MAM) and summer (JJA) typically occurs due to lack of precipitation in winter (DJF) in high elevation areas. For both high and low elevation areas, below-normal SM conditions during spring (MAM) and summer (JJA) usually prevail through the end of the water year.

Runoff generally shows a stronger seasonal cycle than does SM, and follows the cycle of precipitation and SWE with some temporal lag. For snowmelt dominant watersheds (most of the state, aside from some coastal and western interior streams), runoff is high during spring and early summer due to snowmelt and rainfall, and declines rapidly through the summer dry season. For this reason, drought indicators based on late winter and spring conditions (observed or forecasted) can be especially useful for drought management.

2.3 Hydrology model

The physically based, semi-distributed VIC model (Liang et al., 1994) was used to derive SM and runoff over the study domain. The VIC model balances both surface energy and water over each grid cell (in this case, 1/16th degree). The VIC model represents sub-grid variability in soils, topography and vegetation and this allows representation of the non-linear dependence of the partitioning of precipitation into infiltration and direct runoff as determined by soil-moisture in the upper layer and its spatial heterogeneity. The VIC model partitions the subsurface into three layers. The first layer has a fixed depth of 10 cm, and responds quickly to changes in surface conditions and precipitation. The second and third soil layer depths are the same as in the LDAS retrospective simulations (Maurer et al., 2002). Moisture movement between the first and second, and second and third soil layers is governed by gravity drainage, with diffusion from the second to the upper layer allowed in unsaturated conditions. Water from the second layer drains to the third layer is entirely gravity controlled. Base flow is a non-linear function of the moisture content of the third soil-layer (see Liang et al., 1994 for details).

The VIC model has been successfully used in numerous drought studies. Mishra et al. (2009) analyzed historical droughts over the U.S. Midwest using the VIC model. Sheffield et al. (2004) and Andreadis et al. (2005, 2006) applied the model over the continental U.S. to reconstruct 20th century droughts. Sheffield et al. (2008) reconstructed global droughts over the second half of the 20th century, and Sheffield et al. (2009) evaluated potential changes in 21st century drought using the model forced by downscaled global climate model scenarios.

2.4 Retrospective Simulations

We performed a reconstruction of drought conditions over Washington state similar to the studies cited above, but at a higher (1/16 degree latitude-longitude) spatial resolution. We ran the VIC model from 1915 to 2006 to produce gridded SM, SWE, and runoff, as well as precipitation (model forcing). The period selected was intended to include the major known droughts of the 20th century, consistent with the availability of data to produce realistic model simulations. (Prior to 1915, the number of stations at which precipitation and temperature have been observed falls off rapidly, and this is therefore the beginning of our period of analysis.) We performed model simulations at a daily time step in water balance mode, meaning that the model's effective surface temperature is equal to surface air temperature, rather than iterating to close the surface energy balance (Liang, et al., 1994). There are 5,282 1/16th degree grid cells in the domain. We used a data set developed by Elsner et al. (2010), which is based on daily precipitation, and maximum (Tmax) and minimum (Tmin) temperature data from Cooperative Observer stations, which were gridded using methods outlined in Maurer et al. (2002). Additional model forcings (downward solar and longwave radiation, and humidity) were estimated from the daily air temperature and temperature range following methods outlined in Maurer et al. (2002). Surface wind was taken from the lowest level of the NCEP/NCAR reanalysis (Kalnay et al., 1996); prior to 1949, average wind values from the reanalysis were used. A total of 196 precipitation and temperature stations within and near the boundaries of the domain were used in the development of the gridded data set(s) by Elsner et al. (2010). Temperature data were lapsed using a pseudo-adiabatic lapse rate based on the difference between the station and grid elevations. Both precipitation and temperature were then rescaled to match the long-term average of the parameter-elevation regressions on independent slopes model (PRISM) climatology (Daly et al., 1994 and 1997) for the period 1971-2000.

2.5 Model-based drought indicators

Hydrologic model-derived SM and runoff values, in addition to SPI and SRI, are the drought indicators used in this study. In this section we describe the development of these indicators.

2.5.1 Standardized Precipitation Index (SPI)

SPI (McKee et al., 1993) is a widely used drought indicator. It is calculated directly from precipitation data. It allows expression of droughts (and wet periods) in terms of precipitation deficits (Heim 2002).

We used monthly gridded precipitation data to compute SPI for each grid cell. To estimate an n-month SPI (where n was 1, 3, 6, 12, 24, and 36), precipitation was averaged over the n-months and a Gamma distribution was fit to the time series. To promote ease of understanding and application to decision-making, based on interactions with water managers and stakeholders, we used percentiles of these indicators, rather than a standard normal deviate (McKee et al., 1993; Heim, 2002; Mo, 2008). Therefore, our SPI values lie between 0 and 1.

2.5.2 Standardized Runoff Index (SRI)

The Standardized Runoff Index (Shukla and Wood, 2008; Mo, 2008) uses model-derived runoff data (overland plus baseflow in the VIC model) to derive an indicator, based on essentially the same methodology as the SPI (McKee et al., 1993). We first aggregated daily runoff data into monthly values, and fit Gamma distributions to the derived runoff climatologies for each grid cell and month as described in Shukla and Wood (2008). Again, we used percentiles for this indicator, rather than a standard normal deviate.

2.5.3 Soil Moisture Percentile (SMP)

SM can serve as an indicator of different types of drought. The availability of high quality SM observations is highly limited. However, model-derived SM provides a reasonable alternative for large scales studies (see e.g. Maurer et al., 2002; Wood and Lettenmaier, 2006). Several past studies (e.g. Sheffield et al., 2004; Andreadis et al., 2005 and 2006) have used model-derived SM in ways that are similar to our approach here.

We used total column SM (sum of the three model layers) averaged by month. The 91 years of monthly values formed the climatology for each grid cell and month. We converted the SM into percentiles using the Weibull probability distribution. The method adopted is essentially the same as was used by Andreadis et al. (2005) and Wood and Lettenmaier (2006).

2.6 Drought severity classes

We used SPI, SRI, and SMP as drought indicators. As indicated above, our percentile values of SPI, SMP, and SRI lie between 0 and 1. We categorized the individual drought indicators into six drought severity classes based on Steinemann (2003), acknowledging that other thresholds for drought classes could be used as well. Table 2.1 describes the values of individual drought indicators, based on percentiles. We used a percentile approach because it offers statistical consistency and comparability among indicators over time and space, which is not necessarily offered by other approaches, such as percent-of-normal.

Table 2.1 Drought severity classifications, according to percentiles.

Standardized Precipitation Index (SPI) (percentiles)	**Standardized Runoff Index (SRI) (percentiles)**	**Soil Moisture Percentile (SMP)**	**Drought Severity Class**
0.50 to 1.0	0.50 to 1.0	0.50 to 1.0	**1**
0.35 to 0.50	0.35 to 0.50	0.35 to 0.50	**2**
0.20 to 0.35	0.20 to 0.35	0.20 to 0.35	**3**
0.10 to 0.20	0.10 to 0.20	0.10 to 0.20	**4**
0.05 to 0.10	0.05 to 0.10	0.05 to 0.10	**5**
0 to 0.05	0 to 0.05	0 to 0.05	**6**

3. Analysis of Indicators and Droughts

Washington State has experienced numerous drought events over the last century. Figure 2.3 shows the number of WRIAs with drought severities of class 3 or higher (more severe), as defined in Table 1, in terms of SMP, SPI -12, -24, -36 and SRI -12, -24, -36 from 1925 to 2006.

In figure 2.3, the drought years of the 1930s, 1940s, 1976-77, 1987-1989, 2000-2001 and 2004-2005 stand out as the major drought events. We used DMS indicators to reconstruct four of these drought events: 1976-1977, 1987-1989, 2000-2001, and 2004-2005. We also surveyed the literature on drought conditions and responses relevant to Washington applicable to these events, including the *drought report* (Hart et al., 2002; Anderson et al., 2005), and *initial drought action program* prepared by EWEC in 1978 and 1988 and local newspapers (e.g., The Seattle Times and Yakima Herald).

In the following sections, we compare the reconstructed droughts using DMS indicators for each WRIA. For each individual drought event, we first examine how each drought evolved in terms of DMS indicators. To do so, we calculate the number of WRIAs with a drought severity of class 3 or higher, which corresponds roughly to the threshold used by the Washington State Department of Ecology to declare drought in a given area. We then examine the progression, persistence, and recession of drought, analyzing the severity class of each drought indicator for each month throughout the duration of the four drought events. Then, for a more focused case study, we use the highly droughtvulnerable Yakima River Basin, whose irrigated crops, and potential drought losses, represent the highest agricultural economic value in the state.

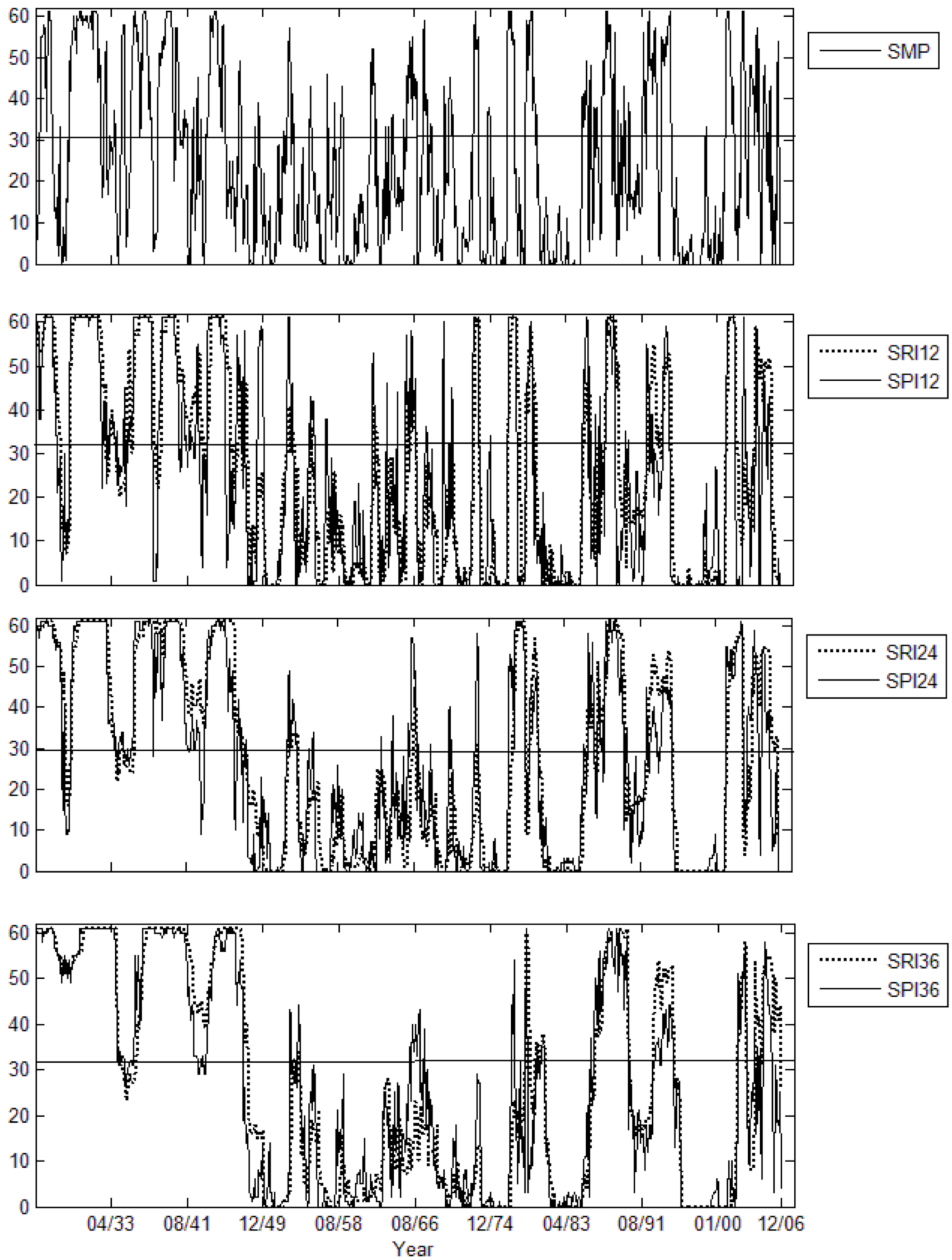


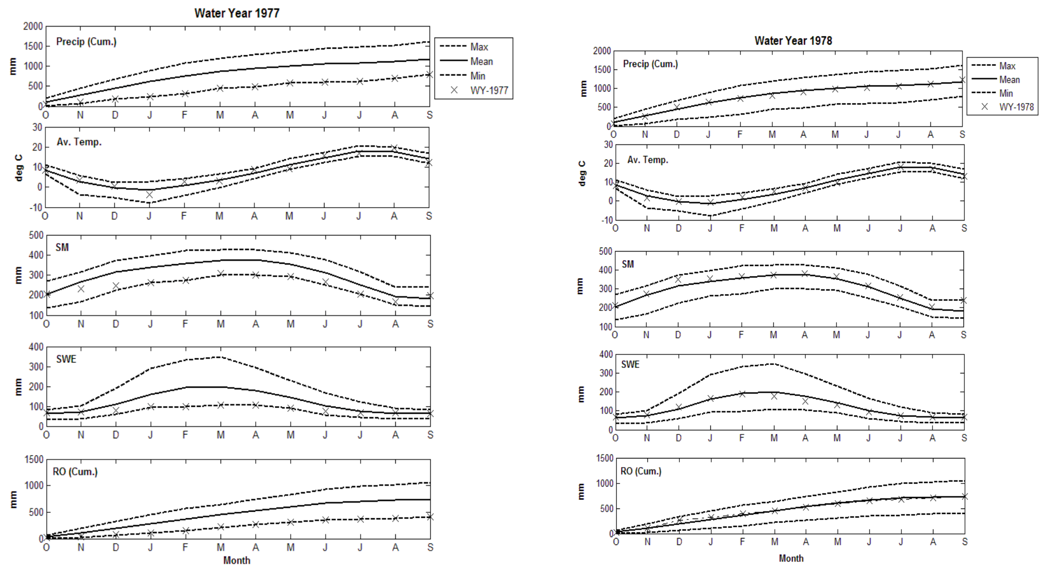
Figure 2.3: Number of WRIA under drought severity class 3 or more severe drought classes 1925-2006 according to DMS indicators.

To provide an assessment of drought onset and recovery that is relevant to state drought decision-making, we perform additional analyses using DMS indicators, following Steinemann and Cavalcanti (2006). We define drought onset as the last month of any three-month period for which an indicator has a continuous drought severity of class 3 or higher. We define drought recovery as the last month of the next four-month period for which that indicator has a continuous drought severity of class 2 or lower (less severe). The onset of the next drought is then defined as the last month of the next three-month period for which the indicator again has a continuous drought severity of class 3 or higher. Results are provided for the Yakima River Basin in Tables 2.2(b), 2.3(b), 2.4(b), and 2.5(b), where drought onset is indicated by bold italic font, and drought recovery is indicated by bold regular font. The drought onset criterion of three consecutive months with a drought severity of class 3 or higher, and the drought recovery criterion of four consecutive months with a drought severity of class 2 or lower, strives to provide early warning, but guard against premature declarations of drought onset ("false alarms") or drought recovery ("false assurances"), respectively, as described in Steinemann and Cavalcanti (2006).

In order to assess statewide occurrences of drought, we extend this analysis by defining the onset of statewide drought as when 50% or more of the WRIAs (i.e., 31 or more of the 62 WRIAs) have a drought severity of class 3 or higher for three consecutive months, and by defining the recovery from statewide drought when fewer than 50% of the WRIAs have a drought severity of class 2 or lower for four consecutive months. Results are provided in Tables 2.2(a), 2.3(a), 2.4(a), and 2.5(a), where drought onset and recovery are again indicated by bold italic and bold regular fonts, respectively. Tables 2.2–2.5 also indicate the months of the state's official drought declaration and recovery for each of the four droughts with bold italic and bold regular fonts in the left hand columns. Finally, to provide a more specific evaluation of these indicators and to offer comparisons with real-time drought declarations, we examine the evolution of the four drought events and the results from the DMS in the following sections.

3.1 1976-1977 Drought

Lack of precipitation during the fall (SON) of 1976, combined with record-low snowpack in the winter of 1977, resulted in a severe drought during Water Year (WY) 1977. Figure 2.4 shows the major water balance components (precipitation, temperature, SM, SWE, and runoff), spatially aggregated across the state, as they evolved during WYs 1977 and 1978. Although WY 1976 ended with normal conditions, it was followed by a dry fall in the beginning of WY 1977. Considerably below-normal precipitation began to affect SM by late November. Record-low snowpack during the winter further exacerbated these conditions, leading to extremely low SM and a significant drop in runoff in the spring. Furthermore, the spring of 1977 was relatively warm, resulting in an early melt of the abnormally low snowpack. On April 1, 1977, SWE ranged from 30-71% of normal (King 1978).



(a) (b)

Figure 2.4: Statewide cumulative precipitation (Precip (Cum.)), average temperature (Av. Temp), soil moisture (SM), snow water equivalent (SWE) and cumulative runoff (RO (Cum.)) during WY 1977 (a) and 1978 (b) shown against 1950-2005 mean climatology, maximum and minimum values for each month.

Due to the combined effects of the low winter snowpack and warm spring, little snow remained by the end of June, resulting in extremely low summer streamflows in most of the state's watersheds. The official drought recovery was attained in December 1977.

Table 2.2(a) shows the number of WRIAs with a drought severity of class 3 or higher as calculated by the SMP and SPI/SRI-3, -6, -12, -24, and -36 in 1976. In January 1977, SMP, SPI-3, SRI-3, SPI-6 met this criterion. At the time of the official drought declaration in March 1977, all indicators except SPI/SRI-24 and -36 were, by our definition, already in statewide drought.

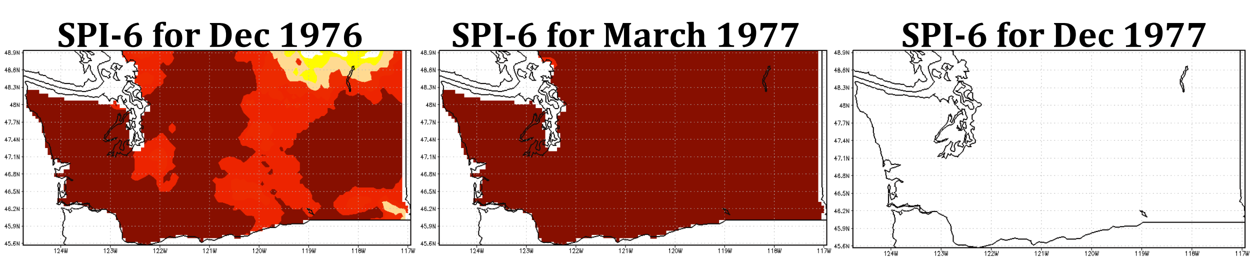
Table 2.2 (a) Number of WRIAs under class 3 or more severe drought according to DMS indicators during the 1976-77 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jan-76	0	1	0	0	0	0	0	0	0	0	0
Feb-76	0	0	0	0	0	0	0	0	0	0	0
Mar-76	1	0	1	0	0	0	0	0	0	0	0
Apr-76	0	0	3	0	0	0	0	0	0	0	0
May-76	4	25	4	0	0	0	0	0	0	0	0
Jun-76	0	37	4	3	0	0	0	0	0	0	0
Jul-76	0	3	3	2	0	0	0	0	0	0	0
Aug-76	0	0	0	0	3	0	0	0	0	0	0
Sep-76	0	0	0	3	0	0	0	0	0	0	0
Oct-76	11	8	7	13	3	3	0	0	0	0	0
Nov-76	52	61	55	58	30	10	0	0	0	0	0
Dec-76	61	61	61	59	41	59	17	0	0	1	0
Jan-77	***61***	***61***	***61***	***61***	53	61	38	30	1	13	0
Feb-77	61	61	61	61	***61***	***61***	41	50	3	20	0
Mar-77	57	61	61	61	61	61	***49***	50	10	24	3
Apr-77	61	61	61	61	61	61	54	***53***	18	44	12
May-77	55	19	60	61	61	61	58	45	22	38	15
Jun-77	53	50	61	61	61	61	61	52	26	***39***	19
Jul-77	56	4	55	56	61	61	61	49	31	54	23
Aug-77	53	0	52	8	59	61	61	49	34	33	22
Sep-77	22	0	34	2	57	61	61	30	***34***	19	23
Oct-77	22	0	28	1	50	61	61	58	44	16	20
Nov-77	23	**0**	21	**1**	39	61	61	60	53	13	21
Dec-77	**2**	0	1	0	18	9	56	61	56	**5**	17
Jan-78	8	0	**1**	0	6	2	50	61	60	14	18
Feb-78	8	5	2	1	1	0	44	61	61	20	15

Mar-78	21	55	23	9	**1**	**2**	42	61	59	32	17
Apr-78	8	37	29	2	2	0	29	61	60	18	15
May-78	0	5	31	5	4	2	19	61	61	12	19
Jun-78	6	0	22	41	28	1	11	61	61	17	20

Figure 2.5 depicts the spatial distribution of drought severity during three months of the drought, highlighting its statewide impact in terms of SPI/SRI-6, -12, and SMP. In March 1977, virtually the entire state had a drought severity of class 5 or 6 in terms of SPI-6, -12, and SRI-6.

We defined the recovery from statewide drought as the last month of a four-month period for which an indicator had a drought severity of class 3 or higher in less than 31 of the WRIAs. As shown in Table 2.2(a), SPI-3 met this criterion in November 1977, while SPI-6 met it in December 1977. As noted above, the official drought recovery declaration came in December 1977, but by then, according to DMS, these two indicators were the only ones that showed any real sign of recovery. This number increased to five by March 1978. The decision to declare drought recovery, however, also depends on the status of the snowpack (Anderson et al., 2005). As shown in Figure 6, SWE percentiles during the winter of 1978 were mostly normal or above normal.



(a)

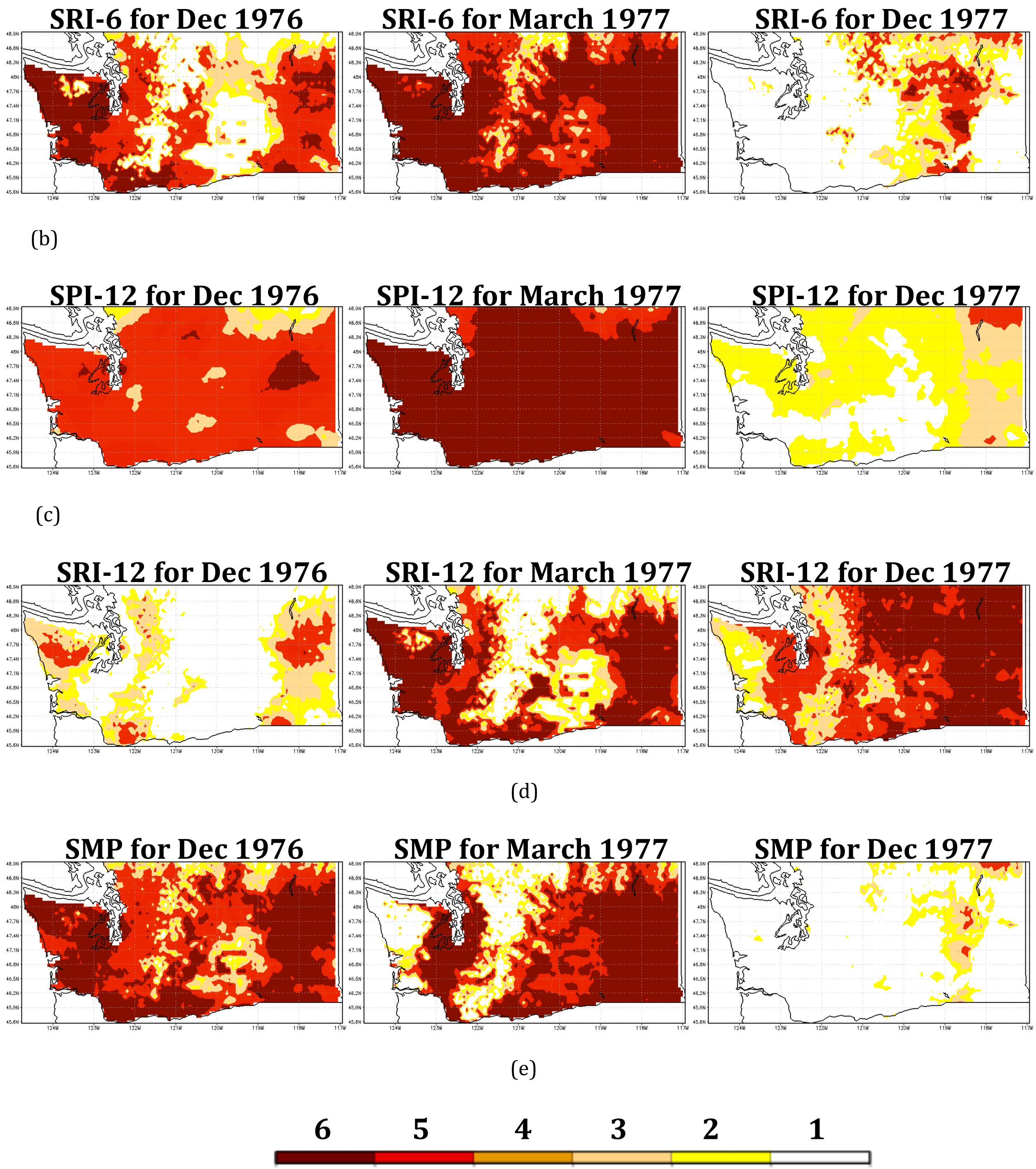


Figure 2.5: Spatial depiction of 1976-77 drought severity according to DMS indicators (a) SPI-6 (b) SRI-6 (c) SPI-12 (d) SRI-12 (e) SMP.

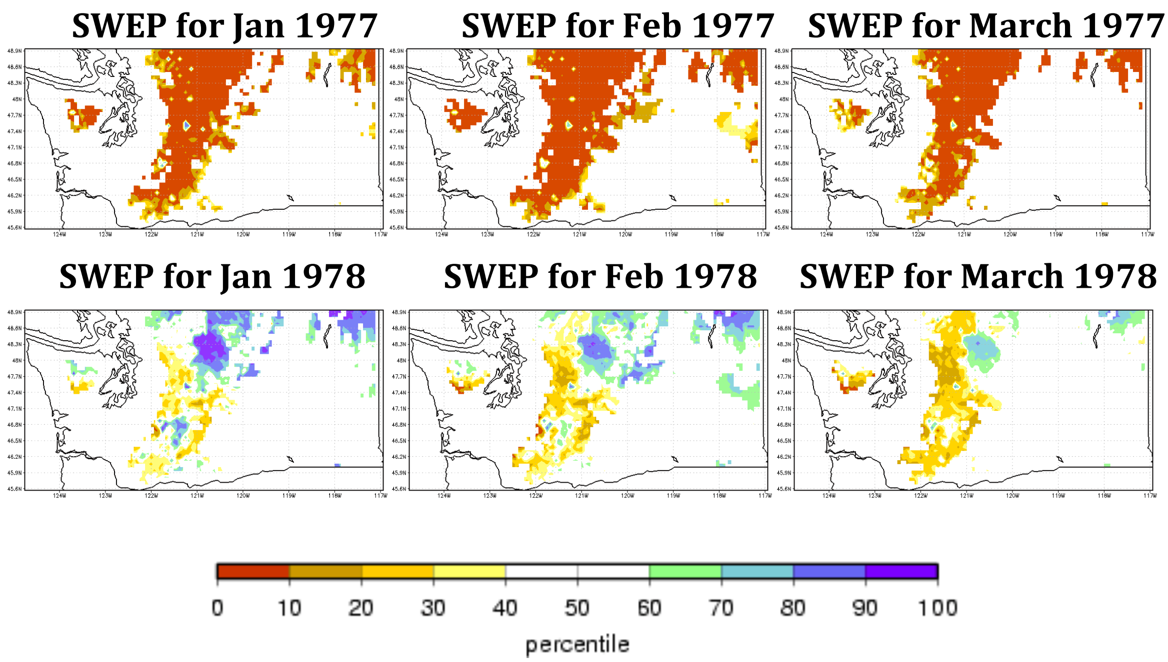


Figure 2.6: Model simulated snow water equivalent percentiles (SWEP) during January, February and March 1977 and 1978.

Table 2.2(b) shows the monthly progression and recession of drought severity in the Yakima River Basin during 1976 and 1977. By January 1977, the onset of basin-wide drought was indicated by SMP, SPI-3, SRI-3, SPI-6. By March 1977, when drought was officially declared, SRI-6, -12 and SPI-12, -24 also indicated basin-wide drought. By the time the drought was officially declared over in December 1977, the indicators that showed sign of recovery were SPI-3, (October) SPI-6 (November), SMP, SRI-3 and SPI-36 (December). By March 1978, SRI-6, and SPI-12 had also recovered.

Table 2.2 (b) Drought severity classes according to DMS indicators in the Yakima River Basin during the 1976-77 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jan-76	1	1	1	1	1	1	1	1	1	1	1
Feb-76	1	1	1	1	1	1	1	1	1	1	1

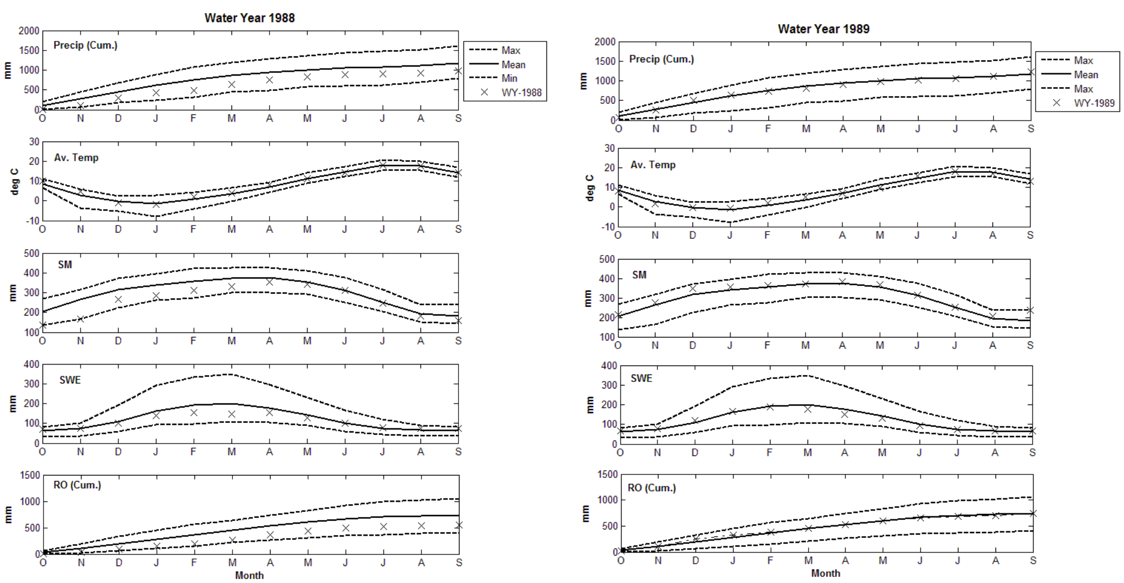
Mar-76	1	1	1	1	1	1	1	1	1	1	1
Apr-76	1	1	2	1	1	1	1	1	1	1	1
May-76	1	3	2	1	1	1	1	1	1	1	1
Jun-76	1	3	1	1	1	1	1	1	1	1	1
Jul-76	1	1	1	1	1	1	1	1	1	1	1
Aug-76	1	1	1	1	1	1	1	1	1	1	1
Sep-76	1	1	1	1	1	1	1	1	1	1	1
Oct-76	1	2	1	2	1	1	1	1	1	1	1
Nov-76	4	6	4	4	1	1	1	1	1	1	1
Dec-76	5	6	6	6	3	4	2	1	1	1	1
Jan-77	***6***	***6***	***6***	***6***	6	6	3	3	1	2	1
Feb-77	6	6	6	6	***6***	***6***	4	3	1	2	1
Mar-77	6	6	6	6	6	6	***5***	***3***	1	2	1
Apr-77	6	4	6	6	6	6	5	3	1	3	1
May-77	6	1	6	6	6	6	6	3	2	3	1
Jun-77	6	3	6	6	6	6	6	3	2	***3***	2
Jul-77	6	1	6	3	6	6	6	3	3	3	2
Aug-77	4	1	4	1	5	6	6	3	3	3	2
Sep-77	1	1	2	1	5	6	6	2	***3***	2	2
Oct-77	1	**1**	1	1	4	6	6	3	3	2	2
Nov-77	1	1	1	**1**	2	4	6	3	3	1	2
Dec-77	**1**	1	**1**	1	1	2	3	3	3	**1**	1
Jan-78	1	1	1	1	1	1	3	4	3	2	1
Feb-78	1	1	1	1	**1**	1	2	5	4	2	2
Mar-78	2	4	3	2	1	**1**	2	5	4	3	2
Apr-78	2	3	3	1	1	1	2	5	4	2	2
May-78	1	2	3	2	1	1	**1**	4	4	2	2
Jun-78	1	1	3	4	3	1	1	4	4	2	2

3.2 1987-1989 Drought

The 1987-89 drought resulted primarily from below-normal rainfall and hence snow accumulation during the fall of 1987 and winter of 1988 (EWEC 1988). An extended dry spell that lasted from summer 1987 into winter 1988 was attributable in part to El Niño. Seattle, which normally receives about 20 cm (8 inches) of rain from June to October, had only 4.5 cm (1.8 inches) of rain during that period in 1987. Consequently, a serious water supply situation resulted for the City of Seattle and its customers in late summer and fall of 1987 (Lettenmaier et al., 1990). Anomalously low precipitation, combined with warm temperatures in the following winter of 1988, led to below-normal snow accumulation and early snowmelt in spring 1988, which extended the drought into 1988. On March 7, 1988, the United States Bureau of Reclamation (USBR) announced, "*a water supply shortage is likely this summer*" (EWEC 1988). Normal precipitation and snow accumulation during fall 1988 and winter 1989 brought an end to the drought.

As shown in Figure 2.7(a), precipitation and snowfall were below normal statewide during WY 1988. Throughout the fall of 1987 and much of 1988, SM and cumulative runoff were also below normal. During WY 1989 (Figure 2.7 (b)) the precipitation and snowfall returned to normal.

WY 1988 began as a dry year with all indicators showing signs of ongoing drought by November (Table 2.3 (a)). Although it is not known exactly when statewide drought was declared, we do know that by the late fall of 1987, water supply and hydropower production for the City of Seattle were significantly affected (Lettenmaier et al., 1990). By July 1988, SPI-3 and SPI-6 were in recovery; by then, the number of WRIAs with a drought severity of class 3 or higher for these indicators had been less than 31 for four months, an improvement that could be attributed to a spring storm. Nevertheless, none of the other indicators showed signs of recovery, and the statewide drought persisted through the fall of 1988. Although we were unable to obtain information as to how long the official statewide drought declaration remained in effect, indications from the DMS are that SMP, SPI-12, and SRI-3, -6, -12 showed recovery in January, February and June 1989, respectively.



(a) (b)

Figure 2.7: Statewide cumulative precipitation (Precip (Cum.)), average temperature (Av. Temp), soil moisture(SM), snow water equivalent (SWE) and cumulative runoff (RO (Cum.)) during WY 1988 (a) and 1989 (b) shown against 1950-2005 mean climatology, maximum and minimum values for each month.

Table 2.3 (a) Number of WRIAs under class 3 or more severe, according to DMS indicators, during the 1987-88 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jan-87	15	14	11	21	12	7	8	51	51	42	38
Feb-87	6	61	36	23	8	43	11	49	47	47	39
Mar-87	8	13	14	31	12	22	23	36	***39***	***43***	***40***
Apr-87	36	9	16	20	15	25	20	33	36	46	49
May-87	45	0	22	52	34	28	27	29	36	53	50
Jun-87	***49***	32	48	39	27	24	30	36	40	56	54
Jul-87	46	14	52	7	25	19	31	22	40	53	54
Aug-87	41	39	***50***	0	30	11	30	26	39	52	55
Sep-87	58	39	45	41	56	54	36	45	42	54	56
Oct-87	61	***61***	61	57	61	60	44	60	47	60	58
Nov-87	61	61	61	***61***	***61***	***61***	***59***	***61***	51	61	59
Dec-87	52	56	56	51	57	57	59	49	47	61	59
Jan-88	58	37	48	60	59	57	59	56	51	60	59
Feb-88	54	44	39	61	54	57	60	61	54	60	58
Mar-88	58	49	61	61	60	59	61	61	61	60	60
Apr-88	48	5	39	26	59	55	61	61	61	55	60
May-88	42	0	28	1	56	54	61	61	61	54	60
Jun-88	17	0	25	5	57	48	60	56	61	54	60
Jul-88	23	**0**	29	**1**	44	59	61	59	61	51	60
Aug-88	36	33	33	0	32	61	61	59	61	56	60
Sep-88	56	17	43	0	26	57	61	61	61	58	60
Oct-88	26	32	43	22	37	35	61	61	61	61	60
Nov-88	2	0	2	0	11	0	50	59	61	58	59
Dec-88	17	3	14	12	27	10	52	59	61	47	58
Jan-89	**6**	1	1	11	11	8	45	58	61	54	58
Feb-89	37	57	46	22	31	**1**	51	56	61	61	60

Mar-89	12	4	24	6	18	0	30	50	60	55	61
Apr-89	6	7	12	4	7	2	24	45	59	56	60
May-89	27	0	2	28	24	9	19	43	58	55	60
Jun-89	34	18	**6**	9	**11**	12	**20**	44	57	53	60

Analysis of the spatial extent of the drought (not shown here) depicted that at the time of its onset, the drought was more pronounced in western Washington, especially in the vicinity of Seattle, than in the eastern part of the state. However, as the water year progressed, the drought continued to spread across eastern Washington.

Table 2.3(b) indicates the drought severity classes from January 1987 to June 1989 for the Yakima basin. By December 1987 all the DMS indicators had met the criteria for the onset of drought in the basin. There were no signs of recovery until the following year, when drought recovery was finally attained by January 1989, in terms of SPI-3, -6, -12 and SRI -3, -6.

Table 2.3 (b) Drought severity classes according to DMS indicators in the Yakima River Basin during the 1987-89 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jan-87	3	2	2	2	2	2	2	3	4	3	3
Feb-87	2	4	3	2	2	3	2	3	3	3	3
Mar-87	1	2	1	2	1	2	2	***3***	2	***3***	***3***
Apr-87	2	1	1	2	1	2	2	2	2	3	3
May-87	3	1	1	3	2	2	2	2	2	4	3
Jun-87	4	3	3	3	2	2	2	3	3	4	4
Jul-87	3	3	4	2	2	2	2	2	3	4	4
Aug-87	***4***	***5***	***4***	2	2	2	2	3	***3***	4	4

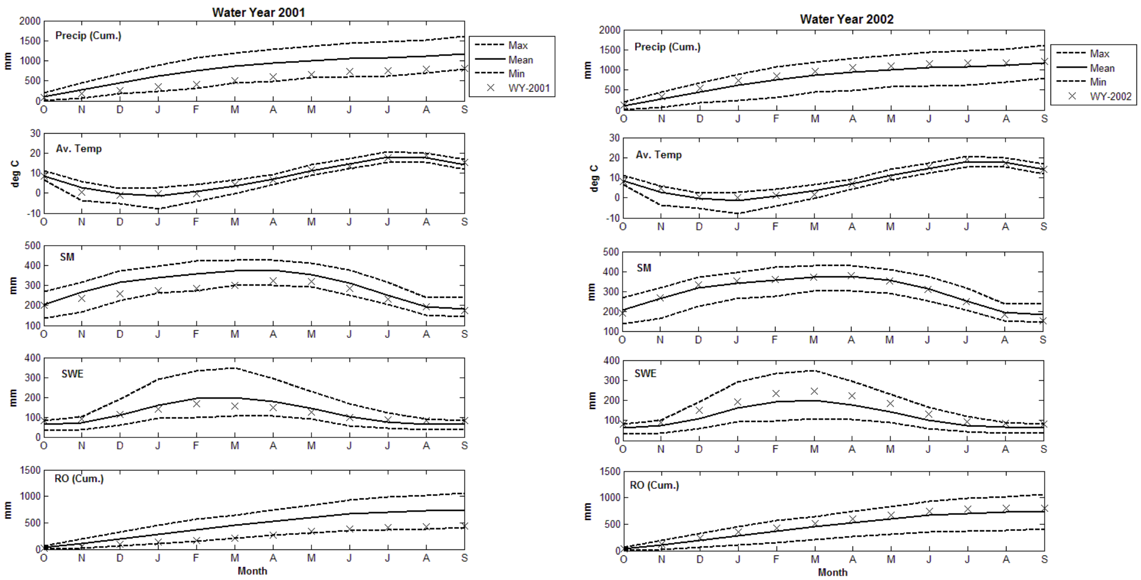
Sep-87	5	4	5	4	4	3	2	3	3	4	4
Oct-87	6	6	6	6	5	4	3	4	3	5	4
Nov-87	6	6	6	***6***	***6***	***6***	4	5	3	6	5
Dec-87	4	4	4	5	5	4	***3***	3	3	5	4
Jan-88	5	3	4	5	5	5	4	4	3	4	4
Feb-88	4	3	3	5	5	5	4	5	4	4	4
Mar-88	4	3	4	4	4	5	5	4	4	4	4
Apr-88	3	1	2	2	3	4	5	4	4	4	4
May-88	3	1	1	1	3	4	4	3	4	3	4
Jun-88	1	1	1	1	3	4	4	3	3	4	4
Jul-88	2	**1**	2	**1**	2	4	4	4	3	3	4
Aug-88	2	2	2	1	1	4	4	3	3	3	4
Sep-88	4	2	3	1	1	3	4	4	3	4	4
Oct-88	3	3	3	2	**2**	2	3	4	3	4	4
Nov-88	1	1	1	1	1	1	2	4	4	3	3
Dec-88	2	1	2	2	2	2	3	3	4	3	3
Jan-89	2	1	2	2	2	**1**	2	3	3	3	3
Feb-89	3	4	4	2	3	1	3	4	4	4	4
Mar-89	3	2	3	2	3	1	3	3	4	3	4
Apr-89	1	2	2	2	2	2	2	4	4	3	4
May-89	3	1	1	3	3	2	2	4	4	3	4
Jun-89	3	3	1	3	2	2	2	4	4	3	4

3.3 2000-2001 Drought

WY 2001 began as a normal year. Although the fall of 2000 was drier and cooler than normal, wetter-than-normal weather for the Pacific Northwest was predicted for the winter months. The prediction, however, was not realized, and the dry spell persisted throughout the winter of 2001. Between November 2000 and March 2001, most of the state's precipitation and snowpack totals were approximately 60 percent of normal. Considerably below-normal precipitation and snowpack led to a severe statewide drought. A statewide drought emergency was declared on March 14, 2001 (Hart et al., 2001), and the drought declaration remained in effect until December 2001.

Figure 2.8 shows spatially aggregated water balance components as they evolved during WYs 2001 and 2002. Although statewide precipitation and SWE were normal throughout WY 2000, precipitation dropped below normal at about the beginning of WY 2001. The significantly below-normal SWE worsened conditions and resulted in far below-normal SM and runoff.

Table 2.4(a) shows the number of WRIAs with a drought severity of class 3 or higher from January 2000 to June 2002. None of the indicators showed signs of drought until January 2001, when SMP, SPI-3, -6, -12 and SRI-3, -6 met the criteria for the onset of drought. This highlights an important feature of the 2000–2001 drought: it developed very quickly, much more so than the other droughts we analyzed. Statewide drought was declared on March 10, 2001 (Hart et al., 2001), by which time SRI-12 and SPI-24 had also met the criteria for the onset of statewide drought.



(a) (b)

Figure 2.8: Statewide cumulative precipitation (Precip (Cum.)), average temperature (Av. Temp), soil moisture(SM), snow water equivalent (SWE) and cumulative runoff (RO (Cum.)) during WY 2001 (a)and 2002 (b)shown against 1950-2005 mean climatology, maximum and minimum values for each month.

The statewide drought persisted through December 2001 in terms of most of the indicators except SPI-3, which started showing signs of recovery as early as August 2001. By November 2001, SPI-6 also indicated recovery from statewide drought. Despite the continuation of drought among all other indicators, the drought declaration was lifted by the governor on December 31, 2001. Precipitation since the beginning of WY 2001 was well above normal, contributing to an optimistic outlook for the winter snowpack (Hart et al., 2001). The simulated SWE conditions (not shown here) confirm that the state had well above normal snowpack during the winter of 2002. The combination of a good winter snowpack, normal precipitation during the fall of 2001, and indications of recovery by SPI-3 and SPI-6 would have supported the drought management decision.

Table 2.4 (a) Number of WRIAs under class 3 or more severe according to DMS indicators during the 2000-2001 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jan-00	0	0	0	0	0	0	0	0	0	0	0
Feb-00	7	0	0	0	0	7	0	0	0	0	0
Mar-00	1	9	11	0	0	0	0	0	0	0	0
Apr-00	11	12	9	0	0	0	0	0	0	0	0
May-00	0	5	10	0	0	0	0	0	0	0	0
Jun-00	0	0	3	2	6	0	0	0	0	0	0
Jul-00	2	1	2	6	9	0	0	0	0	0	0
Aug-00	17	30	4	7	8	0	0	0	0	0	0
Sep-00	18	29	14	1	6	0	0	0	0	0	0
Oct-00	13	16	28	5	3	0	0	0	0	0	0
Nov-00	48	46	53	54	36	31	7	0	0	0	0
Dec-00	58	61	61	60	59	43	30	0	0	0	0
Jan-01	***61***	***61***	***61***	***61***	***61***	***53***	35	31	1	2	0
Feb-01	61	61	61	61	61	59	44	55	21	10	0
Mar-01	61	61	61	61	61	61	***57***	***55***	27	10	0
Apr-01	61	44	61	61	61	59	60	50	33	2	0
May-01	52	7	56	61	61	61	61	51	38	10	2
Jun-01	47	0	52	59	61	61	61	49	***45***	4	3
Jul-01	44	0	50	25	61	61	61	49	49	3	3
Aug-01	34	**0**	48	0	57	61	61	54	50	1	3
Sep-01	36	38	52	0	54	61	61	54	50	3	4
Oct-01	43	0	37	**0**	46	61	61	47	50	0	4
Nov-01	20	0	15	0	36	58	61	48	53	3	5
Dec-01	9	0	12	0	27	30	59	47	53	14	14
Jan-02	7	0	7	0	13	0	45	48	54	14	20
Feb-02	**13**	2	**8**	0	12	0	33	53	55	51	36

Mar-02	14	4	3	0	**8**	**0**	31	54	57	48	43
Apr-02	1	16	9	1	4	1	30	54	57	***41***	***41***
May-02	16	3	8	4	5	2	23	57	57	38	43
Jun-02	22	1	12	6	5	0	15	57	58	44	43

Table 2.4(b) shows how drought severity varied in the Yakima River Basin from January 2000 to June 2002 in terms of DMS indicators. SMP, SPI-3, -6, -12 and SRI-3, -6 indicated the onset of drought by January 2001. By the time statewide drought was officially declared, all of DMS indicators except SPI-36, SRI-24, -36 met the criteria for the onset of drought. For a major part of the rest of the year, many of the indicators continued to have a drought severity of class 3 or more. The first indicator to show signs of recovery was SPI-3 in August 2001. None of the other indicators except SPI-3 and SPI-6 recovered before the statewide drought was officially declared over in December, suggesting that the drought may have indeed persisted in the Yakima River Basin.

Table 2.4 (b) Drought severity classes according to DMS indicators in the Yakima River Basin during the 2000-2001 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jun-00	1	1	1	2	2	1	1	1	1	1	1
Jul-00	1	1	2	2	2	1	1	1	1	1	1
Aug-00	2	2	2	2	2	1	1	1	1	1	1
Sep-00	3	3	3	1	2	1	1	1	1	1	1
Oct-00	2	2	3	1	2	1	1	1	1	1	1
Nov-00	4	3	***4***	4	3	3	2	1	1	1	1
Dec-00	5	6	6	6	5	4	4	2	1	1	1
Jan-01	***6***	***6***	6	***6***	***6***	***6***	5	3	2	2	1

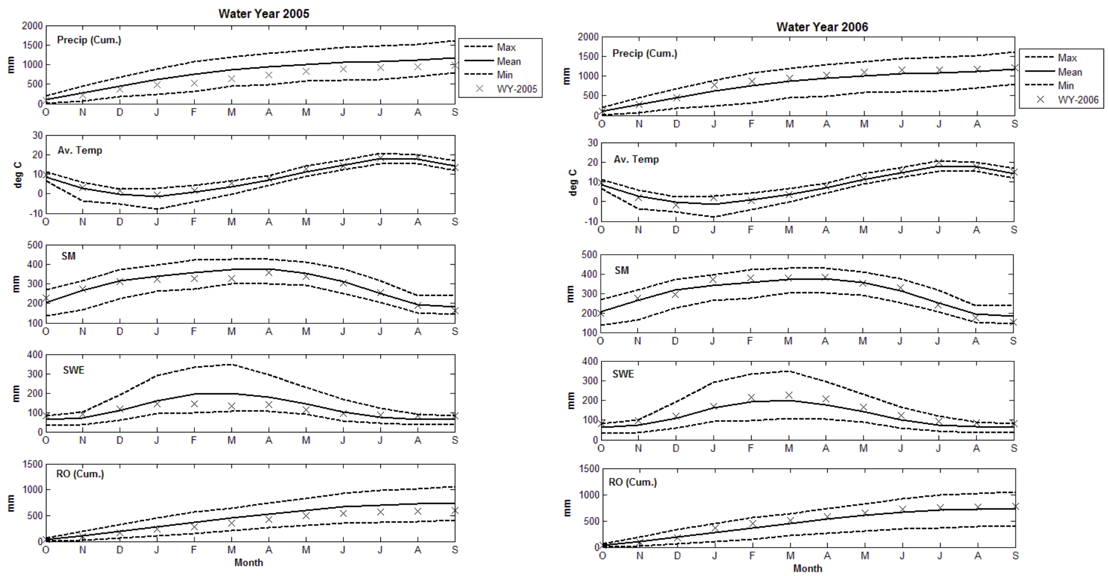
Feb-01	6	6	6	6	6	6	***5***	5	3	2	2
Mar-01	6	6	6	6	6	6	6	***5***	3	2	2
Apr-01	6	4	6	6	6	6	6	4	***3***	2	2
May-01	5	1	5	6	6	6	6	4	3	2	2
Jun-01	5	1	4	5	6	6	6	4	4	2	2
Jul-01	3	1	4	3	6	6	6	4	4	2	2
Aug-01	2	**1**	4	1	5	6	6	4	4	2	2
Sep-01	2	3	4	1	4	6	6	4	4	2	2
Oct-01	3	1	3	1	4	6	6	4	4	2	2
Nov-01	2	1	1	**1**	2	4	6	4	5	2	2
Dec-01	1	1	1	1	1	2	4	4	5	2	2
Jan-02	1	1	1	1	1	1	3	3	4	2	3
Feb-02	**1**	1	**1**	1	**1**	1	2	4	4	3	3
Mar-02	1	1	1	1	1	**1**	2	3	4	3	***3***
Apr-02	1	1	1	1	1	1	1	3	4	***3***	3
May-02	1	1	1	1	1	1	**1**	4	4	3	3
Jun-02	1	2	1	1	1	1	1	4	4	3	3

3.4 2004-2005 Drought

WY 2005 began with normal to below-normal precipitation in October for all but the north Puget South region. The dry spell started in November 2004, and a relatively warm winter in 2005 resulted in low snowpack accumulation and early melt. One major feature of the 2005 drought was that, like the 2000–2001 drought, it developed quickly. This rapid change in conditions was attributed to a record low snowpack in February and March 2005, due in part to a mid-January storm (a so-called “Pineapple Express”) that removed much of the accumulated snowpack (Anderson et al., 2005). Statewide drought was declared in March and recovery from drought was officially declared on December 31, 2005 (Anderson et al., 2005).

Spatially aggregated water balance components (Figure 2.9) show that three important factors led to the 2004-2005 drought: (i) less than normal precipitation in the fall of 2004, (ii) record low snowpack, and (iii) above normal temperatures. Higher temperatures that were attributed to El Niño conditions resulted in little snow accumulation during the winter and brought about earlier snowmelt. SM was below normal throughout the year, resulting in adverse impacts on state agriculture.

Table 2.5(a) shows the number of WRIAs with a drought severity of class 3 or higher from January 2004 to June 2006 for the various DMS indicators. WY 2004 started out dry, and by June 2004, SMP, SPI-3, -6, -12, -24 and SRI-6, -12, 24, 36 had all met the criteria for statewide drought. Although six of these indicators (SMP, SPI-3, -6, -12, 24 and SRI-3) showed signs of recovery by December 2004, low fall precipitation and winter snowpack caused SMP, SPI -3, -12, -24 to again fall into drought by the time of the state's declaration on March 10, 2005 (Anderson et al., 2005). As such, DMS indicators were in line with the official drought declaration. Due largely to spring storms in western Washington, SPI-3 and SPI-6 met the criteria for statewide drought recovery in August and October 2005, respectively. However, none of the other indicators showed signs of recovery by the time the drought was declared over in December 2005. As with the 2000–2001 drought, this decision may have been influenced by an above normal winter snowpack outlook. Simulated SWE conditions (not shown here) confirm that the snowpack during the winter of 2006 was well above normal.



(a) (b)

Figure 2.9: Statewide cumulative precipitation (Precip (Cum.)), average temperature (Av. Temp), soil moisture (SM), snow water equivalent (SWE) and cumulative runoff (RO (Cum.)) during WY 2005 (a) and 2006 (b) shown against 1950-2005 mean climatology, maximum and minimum values for each month.

Table 2.5(b) shows the progression of drought in the Yakima River Basin in terms of the severity classes of DMS indicators. By March 2005, all the DMS indicators met criteria for the onset of drought. Although both SPI-3 and SPI-6 indicated drought recovery by December 2005 when the statewide drought recovery was officially declared, none of the other indicators showed signs of recovery until then.

Table 2.5 (a) Number of WRIAs under class 3 or more severe according to DMS indicators during the 2004-05 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jan-04	43	0	26	3	26	17	31	50	44	22	54
Feb-04	29	36	39	0	26	12	29	51	48	16	46
Mar-04	44	39	27	16	23	42	46	***59***	***43***	20	***41***

Apr-04	54	***61***	***40***	50	43	59	59	58	48	35	42
May-04	***57***	34	36	39	46	***57***	***56***	49	50	21	40
Jun-04	32	32	49	***37***	***44***	42	55	49	53	32	41
Jul-04	52	7	44	44	46	31	54	47	53	34	40
Aug-04	35	0	31	12	37	0	50	42	51	17	37
Sep-04	0	0	12	2	38	0	47	26	49	6	31
Oct-04	2	**0**	3	0	24	12	49	12	45	10	32
Nov-04	3	4	13	**0**	30	**29**	52	4	40	42	46
Dec-04	**22**	52	**28**	7	31	27	50	**8**	41	48	51
Jan-05	34	56	25	28	23	43	42	48	51	***53***	52
Feb-05	43	***61***	41	56	42	49	44	53	53	58	53
Mar-05	***48***	61	47	57	45	***43***	51	***55***	53	55	53
Apr-05	40	57	***51***	***57***	46	35	50	55	55	55	54
May-05	38	0	39	50	51	36	51	52	55	45	54
Jun-05	21	0	31	35	52	30	50	41	55	44	54
Jul-05	19	0	32	13	54	24	49	37	54	44	55
Aug-05	22	**3**	34	0	39	40	50	34	54	43	55
Sep-05	42	13	36	0	35	43	51	35	54	41	55
Oct-05	22	1	28	**0**	32	42	52	39	54	40	54
Nov-05	8	0	18	3	35	31	51	39	54	28	52
Dec-05	43	0	15	1	25	25	50	34	53	29	51
Jan-06	0	0	**0**	0	4	0	21	16	40	4	46
Feb-06	1	0	0	0	2	0	18	16	36	**3**	38
Mar-06	8	0	0	0	**2**	**0**	15	11	38	29	50
Apr-06	**9**	38	15	0	1	0	**14**	**5**	32	31	49
May-06	17	26	25	0	0	0	11	9	32	25	48
Jun-06	0	6	11	0	0	0	3	6	31	19	43

Table 2.5 (b) Drought severity classes according to DMS indicators in the Yakima River Basin during the 2004-2005 drought.

Month	SMP	SPI-3	SRI-3	SPI-6	SRI-6	SPI-12	SRI-12	SPI-24	SRI-24	SPI-36	SRI-36
Jan-04	3	1	2	1	2	1	2	3	2	2	3
Feb-04	2	2	2	1	2	1	2	3	2	2	3
Mar-04	3	2	2	2	2	2	3	***3***	3	2	***3***
Apr-04	4	6	2	3	2	3	3	4	3	2	2
May-04	***4***	4	3	3	3	3	***3***	3	***3***	2	3
Jun-04	3	***3***	3	***3***	3	***3***	3	4	3	2	2
Jul-04	4	1	***3***	5	***3***	3	3	4	3	3	2
Aug-04	3	1	3	2	3	1	3	3	3	2	2
Sep-04	1	1	2	1	3	1	2	3	3	2	**2**
Oct-04	1	**1**	1	1	3	2	3	2	3	2	2
Nov-04	1	2	2	**1**	3	3	3	2	3	3	3
Dec-04	**2**	4	**2**	2	3	3	3	2	3	3	3
Jan-05	3	5	3	3	2	4	3	3	3	***4***	3
Feb-05	4	***6***	4	5	3	5	4	3	4	4	3
Mar-05	***5***	5	***4***	***5***	4	4	4	4	4	4	4
Apr-05	4	4	4	5	4	4	4	4	4	4	4
May-05	4	1	3	4	4	4	4	4	4	4	4
Jun-05	2	1	3	3	5	3	4	3	4	4	4
Jul-05	1	1	4	2	5	3	4	3	4	4	4
Aug-05	1	**1**	4	1	4	4	4	3	4	4	4
Sep-05	3	2	4	1	4	4	4	3	4	4	4
Oct-05	2	1	2	**1**	4	4	4	3	4	3	4
Nov-05	1	1	1	1	3	3	4	3	4	3	4
Dec-05	3	1	1	1	2	2	4	3	4	3	4
Jan-06	1	1	**1**	1	1	1	2	2	3	2	3
Feb-06	1	1	1	1	1	1	1	2	3	2	3

Mar-06	2	1	1	1	**1**	**1**	1	2	3	3	3
Apr-06	**2**	4	2	1	1	1	**1**	**2**	3	3	3
May-06	3	3	3	1	1	1	1	2	3	3	3
Jun-06	1	1	1	1	1	1	1	2	3	2	3

4. Summary and Conclusions

Washington State has experienced several major droughts, and substantial associated economic losses, over the last three decades. Because the state's water resources are strongly dependent on winter snow accumulation, they are susceptible to droughts resulting from dry winter conditions, warm winter conditions, or both. In addition, as the climate warms, the sensitivity of the state to drought is likely to increase due to reductions in mean snow accumulation. This vulnerability emphasizes the need for proactive drought management and the potential value of a drought monitoring system. We have described how such a system, which is based on the SPI, SRI, and SMP as indicators of drought, would have performed during four major droughts over the study period.

In this paper, a daily data set covering the period 1915–2006 was aggregated to monthly data over the major Water Resource Inventory Areas (WRIAs) of the state. Simulated SM data were used to estimate monthly SMP, and monthly precipitation and model-generated runoff data were used to estimate SPI-3, -6, -12, -24, -36 and SRI-3, -6, -12, -24, -36. We used these indicators to reconstruct 4 major drought events during the last four decades (1976–77, 1987–89, 2000–2001, and 2004–2005), based on 6 drought severity classes, for each of the 62 WRIAs in the state. We also performed an analysis of the progression, persistence, and recession of drought according to these indicators. We additionally used gridded precipitation, SM, and runoff data to depict the spatial pattern of all four drought events.

Our main findings are as follows:

(1) For drought onset, DMS indicators, primarily SPI-3, -6, -12, SRI-3, -6, and monthly SMP, showed the onset of statewide drought at least 0 to 2 months before the state's official declarations of the 1976–1977, 2000–2001, and 2004–2005 droughts.

(2) For drought recovery, DMS indicators, primarily SPI-3, and -6, showed recovery from statewide drought at least 0 to 4 months before the state's official declarations in the 1976–1977, 2000–2001, and 2004–2005 droughts.

(3) For the Yakima basin, DMS indicators, primarily SPI-3, -6, -12, SRI-3, -6, and monthly SMP, showed drought onset at least 0 to 2 months before the state's official declarations of the 1976–1977, 2000–2001, and 2004–2005 droughts.

(4) For the Yakima basin, DMS indicators, primarily SPI-3 and SPI-6, showed drought recovery at least 0 to 4 months before the state's official declarations in the 1976–1977, 2000–2001, and 2004–2005 droughts.

These results suggest that a DMS can provide a method for early detection of the onset, duration, severity, and recovery from drought, and an approach that would allow for finer-scale resolution of drought declaration. The DMS approach also provides a scientific basis for indicators and triggers that can assist in drought management decisions for Washington State and other regions. There are a number of obvious extensions to the approach we have outlined that will make it useful in real-time drought assessments and decision making. For instance, a DMS at national scale (www.hydro.washington.edu/forecast/monitor) based on the approach described by Wood and Lettenmaier (2006) is currently used as one of the NOAA Climate Prediction Center's inputs to the U.S. Drought Monitor. A similar system for Washington State (www.hydro.washington.edu/forecast/sarp) is currently made available to state and regional water managers.

III. SEASONAL HYDROLOGIC PREDICTION IN THE UNITED STATES: UNDERSTANDING THE ROLE OF INITIAL HYDROLOGIC CONDITIONS AND SEASONAL CLIMATE FORECAST SKILL

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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 Seasonal Drought Outlook, the University of Washington's Surface Water Monitor (SWM; Wood and Lettenmaier, 2006; Wood, 2008) and Princeton University's drought forecast system (Wood and Lettenmaier 2006; Wood 2008) 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 Seasonal Drought Outlook derives drought prediction skill from knowledge of initial hydrologic conditions (IHCs) taken from the U. S. Drought Monitor (Svoboda et al. 2002) and from weather/climate forecasts at various time scales ranging from 6-10 days to 3 months. Alternatively, SWM and the Princeton University systems obtain the IHCs by forcing one or more land surface models (LSMs) with observed gridded station data up to the time of the forecasts, and then continue the LSM runs using either gridded climate data randomly resampled from a retrospective period (SWM) or seasonal climate forecasts over the forecast period downscaled for use by the LSMs (Princeton University system). 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 LSM's prediction skill and forcings over the recent past; and (2) climate forecast skill (FS) over the forecast lead time. Thus, 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 FS), which presumably vary depending on location, forecast lead time, and time of year.

Numerous attempts have been made by the hydrologic and climate communities to reduce the uncertainties associated with the aforementioned factors. For example, various researchers have investigated methods for assimilating snow water equivalent (SWE) 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 also been made in parallel to improve FS (Krishnamurti et al. 1999; Stefanova and Krishnamurti 2010).

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 FS to the skill (Wood and Lettenmaier, 2008; Li et al., 2009). For example, assimilating observed data to improve the IHCs is valuable mainly for 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 FS can most improve seasonal hydrologic forecasts where atmospheric forcings play a more significant role in influencing future SM and runoff than the IHCs. Depending on factors such as SM variability at the time of forecast initialization, the seasonal cycle, and the variability of precipitation and topology of the hydrologic regime, the contribution of IHCs and FS to seasonal hydrologic forecast skill can vary significantly (Hayes et al. 2005a).

Previous studies have identified the major sources of hydrological predictability. Wood et al., (2002) assessed the role of IHCs and FS in seasonal hydrological forecasts for the southeastern United States during the drought of 2000 and found that dry IHCs dominated FS, whereas for the same region in the case of El Niño conditions from December 1997 to February 1998, both IHCs and FS contributed to hydrologic predictability. Maurer and Lettenmaier (2003) evaluated the predictability of runoff throughout the Mississippi River basin spatially, by season and prediction lead time using a multiple regression technique to relate runoff and climate indices (El Ninõ-Southern Oscillation and the Arctic Oscillation) and components of the IHCs (SM and SWE). They found that initial SM was the dominant source of runoff predictability at lead-1 in all seasons except in June-July-August (JJA) in the western mountainous region, where SWE was most important. Maurer et al., (2004) used Principal Component Analysis to examine contributions to North American runoff variability of climatic teleconnections, SM, and SWE 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 up to 4.5 months of lead time. They found statistically significant correlations between March 1 SWE and March-April-May (MAM) runoff over parts of the western U.S. and Great Lakes regions and between March 1 SWE and June-July-August (JJA) runoff over the Pacific Northwest (PNW), the Far West, and the Great Basin. According to Maurer et al., (2004), even in regions where runoff variability is dominantly related to climate, SM could be a valuable predictor for seasonal lead times. Wood and Lettenmaier, (2008) used an Ensemble Streamflow Prediction (ESP)-based framework to conduct ESP and reverse-ESP experiments to partition the role of the IHCs and FS in seasonal hydrologic prediction in two western U.S. basins. They noted that the skill derived from the IHCs is particularly high during the transition from wet to dry seasons, and that climate forcings dominate most during the transition from dry to wet seasons. Li et al., (2009) used a similar approach to quantify the relative contributions of IHCs and FS in the Ohio River basin and the southeastern U.S. They found that relative errors are primarily controlled by the IHCs at a short lead time (~1 month); however, at longer lead times FS dominates.

In a recent study Koster et al., (2010) used a suite of LSMs to evaluate the importance of model initialization (SWE and SM) for seasonal hydrologic forecasts skill in 17 river basins, mostly in the western U.S. They concluded that SWE and SM initialization on January 1st, individually contribute to March-April-May-June-July streamflow forecast skill at a statistically significant level across a number of western U.S. river basins. The contribution from SWE is especially important in the northwestern U.S., whereas SM tends to be important in the southeast. Mahanama et al., (2011) expanded this work to 23 basins across the CONUS, for multiple forecast initialization dates, throughout the year. They observed that SWE (mainly during the spring melt season) and SM (during the fall and winter seasons) provide statistically significant skill in streamfow forecast. Furthermore, they found the skill levels to be related to the ratio of standard deviation of initial total water storage to the standard deviation of forecast period precipitation (which they termed *k;* see section 2.5).

The studies reviewed above have used a variety of methods to assess the relative contributions of IHCs and FS to seasonal hydrologic forecast skill. Aside from the 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). This framework is applicable over large spatial scales (e.g. continental) and is similar to operational seasonal hydrological forecast approaches, hence we used it to address explicitly the relative contributions of IHCs and FS to hydrologic forecast skill across the entire CONUS for forecast lead times up to 6 months. Specifically, we seek in this study 1) to quantify the contributions of IHCs and FS to seasonal prediction of cumulative runoff (CR) and SM during each month of the year, and 2) to identify the months and sub-regions within CONUS, where improvement in simulating the IHCs and/or FS can have the greatest impact on seasonal hydrologic forecast skill.

2. Approach

We conducted paired ESP and reverse-ESP experiments 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 continental U.S. 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) model; a macroscale hydrology model (Cherkauer et al. 2003; Liang et al. 1994) that has been extensively used over the CONUS and globally (e.g. (Maurer et al., 2001; Nijssen et al., 2001; Adam et al., 2007; Wang et al., 2009). VIC was applied over the CONUS at a spatial resolution of ½ degree latitude and longitude. We then spatially aggregated the forecasts generated by each experiment to the scale of 48 hydrologic sub-regions across the CONUS (Table 3.1 and Fig. 3.1). These 48 sub-regions were created by merging the 221 U.S. Geological Survey (USGS) hydrologic sub-regions. Each sub-region is named after the water resources region in which it is located (Table 3.1). We compared the spatially aggregated forecasted cumulative runoff (CR) and mean monthly SM with the corresponding observations (section 2.2) for each sub-region and lead time over the reforecast period. We then estimated a forecast evaluation score (section 2.4) and quantified the contributions of the IHCs and FS 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

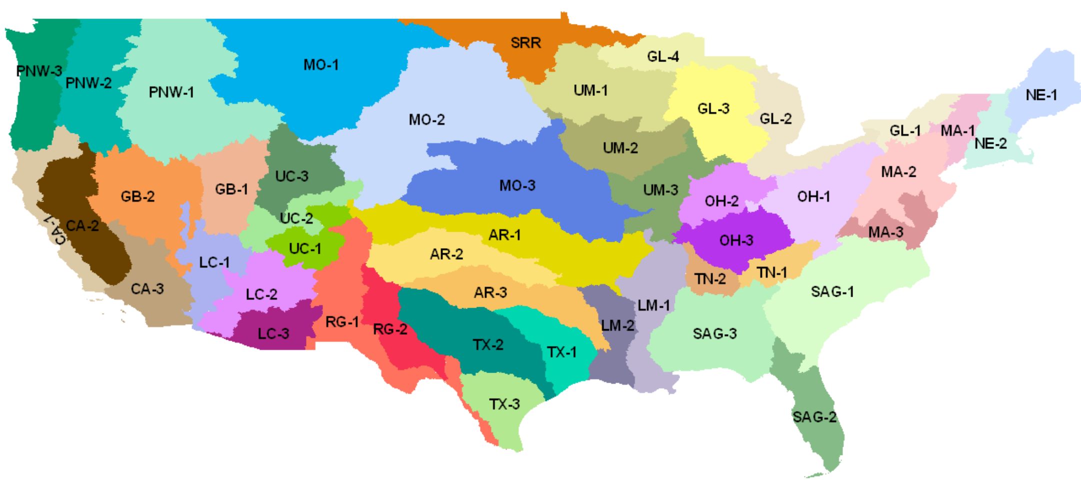


Figure 3.1: 48 hydrologic sub-regions of the CONUS used in this study, based on aggregation of 221 USGS sub-regions.

Table 3.1: 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 (MO)
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)

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 energy flux 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-hour time step. The ½ degree parameters (i.e. vegetation, soils, elevation and snow band parameters) used in this study are the same as in Andreadis et al., (2005), which were aggregated from the North America Land Data Assimilation System parameters used in Maurer et al. (2002). The three VIC soil layers had typical depths of ~0.10 m for the first layer, 0.2 to 2.3 m for the second layer, and 0.1 to 2.5m for the third layer. Additional details of the model setup are included in Maurer et al. (2002) and Andreadis et al., (2005).

2.2 Synthetic truth data set

For purposes of evaluating forecast skill, we used 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 set of about 2100 precipitation and temperature stations across the CONUS that have relatively little missing data over our period of analysis. As in (Maurer et al., 2002), we used surface wind from the lowest level of the National Centers for Environmental Protection/National Center for Atmospheric Research reanalysis (Kalnay et al. 1996). Other model forcing variables (downward solar and longwave radiations, humidity) were derived from daily temperature and temperature range as in (Maurer et al., 2002). We first ran the model for the period 1916-1969 starting from a prescribed initial state and saved the IHCs at the end of the simulation. Using those IHCs, generated after 53 years of spin-up, we initialized the control run simulation over 1970-2003. The same IHCs were also 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 CR (i.e. sum of surface runoff and baseflow) and SM (i.e. sum of soil moisture of all three layers) to monthly values and spatially aggregated them to the 48 hydrologic sub-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 SM and streamflow well 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 (section 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 hour of the day *i*/01/01 and ran the model with forcings from *j*/01/01 to *j*/07/01 of each year *j* between 1971-2001. Fig. 3.2 (b) 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 the forecast on 01/01 of any year *i*, we used IHC at the 00:00 hour of the day *j*/01/01 of each year *j* between 1971-2001, and forced the model with gridded observations for the period *i*/01/01 to *i*/07/01. As shown in Fig. 3.2 (c), 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.

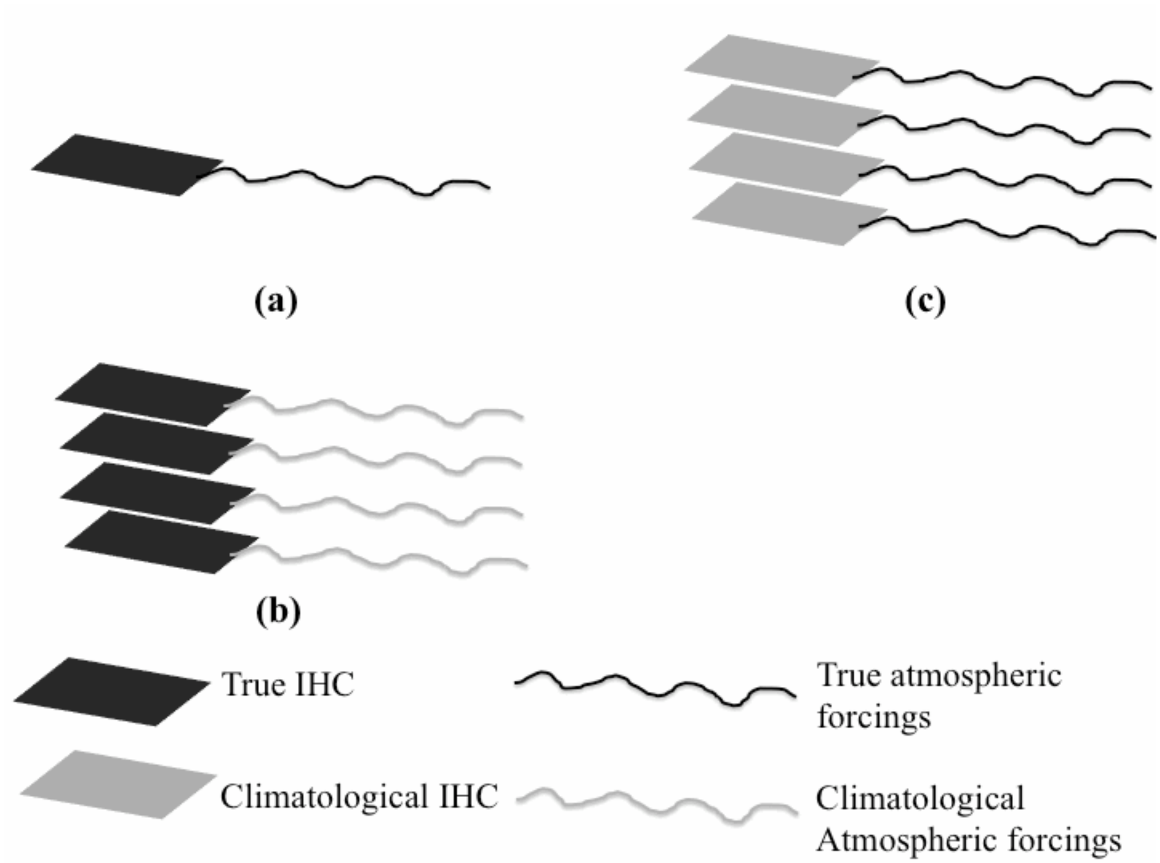


Figure 3.2: Schematic diagram of (a) Observational analysis (b) ESP and (c) reverse-ESP experiments.

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-region. Let *N* be the total number of IHC or forcing ensembles (1971-2001), and *M* be the number of years (1971-2003) for which the reforecasts were generated. We designate E_{ijk} as the CR or SM generated by the ESP experiment using the IHC of year *i* and forcing of year *j* at a lead time *k*. Let O_{ik} be the observed CR or SM obtained from the baseline run as the synthetic truth for year i and lead time *k*.

$RMSE_{ESP}$ is then:

$$RMSE_{ESP} = \sqrt{\frac{1}{M}\left[\sum_{i=1}^{M}\frac{1}{N}\sum_{j=1}^{N}\left(O_{ik} - E_{ijk}\right)^2\right]} \qquad (1)$$

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

$$RMSE_{revESP} = \sqrt{\frac{1}{M}\left[\sum_{i=1}^{M}\frac{1}{N}\sum_{j=1}^{N}\left(O_{ik} - R_{ijk}\right)^2\right]} \qquad (2)$$

We then calculated, the ratio of RMSE of each experiment [Eq. 3].

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

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 FS dominates.

2.5 *k* parameter

Mahanama et al., (2011) introduced a parameter, k, which is the ratio of the standard deviation of the historical values of initial moisture (i.e. sum of the soil moisture and snow water equivalent on the forecast initialization date) (s_W) to the standard deviation of the historical precipitation total during the forecast period (i.e. 1 month, 3 months and 6 months since the start of the forecast period) (s_P) [Eq 4]. High k values correspond to high total moisture variability at the time of forecast initialization relative to precipitation variability during the forecast period and vice versa. k is basically a measure of the hydrologic predictability derived solely from knowledge of the IHCs at the start of the forecast period.

$$k = s_W / s_P \tag{4}$$

3. Results

In this section we examine the variation of relative contributions of the IHCs and FS in the CR and SM forecast with each forecast initialization date (i.e. day 1 of each month) for lead times of 1 to 6 months across the CONUS. We also highlight the sub-regions and forecast periods for which improvement in knowledge of IHCs or FS 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. 3.3 (a) 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 1.0 indicate that the relative forecast error due to uncertainties in the FS 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. 3.3). The IHCs strongly dominate CR forecasts during winter and spring (March and April mainly) months over GL, SRR, UM, and MO-1 sub-regions. The dominance of the IHCs in CR prediction over MO-1 sub-region, almost throughout the year is an observation made by Maurer and Lettenmaier

(2003) as well.

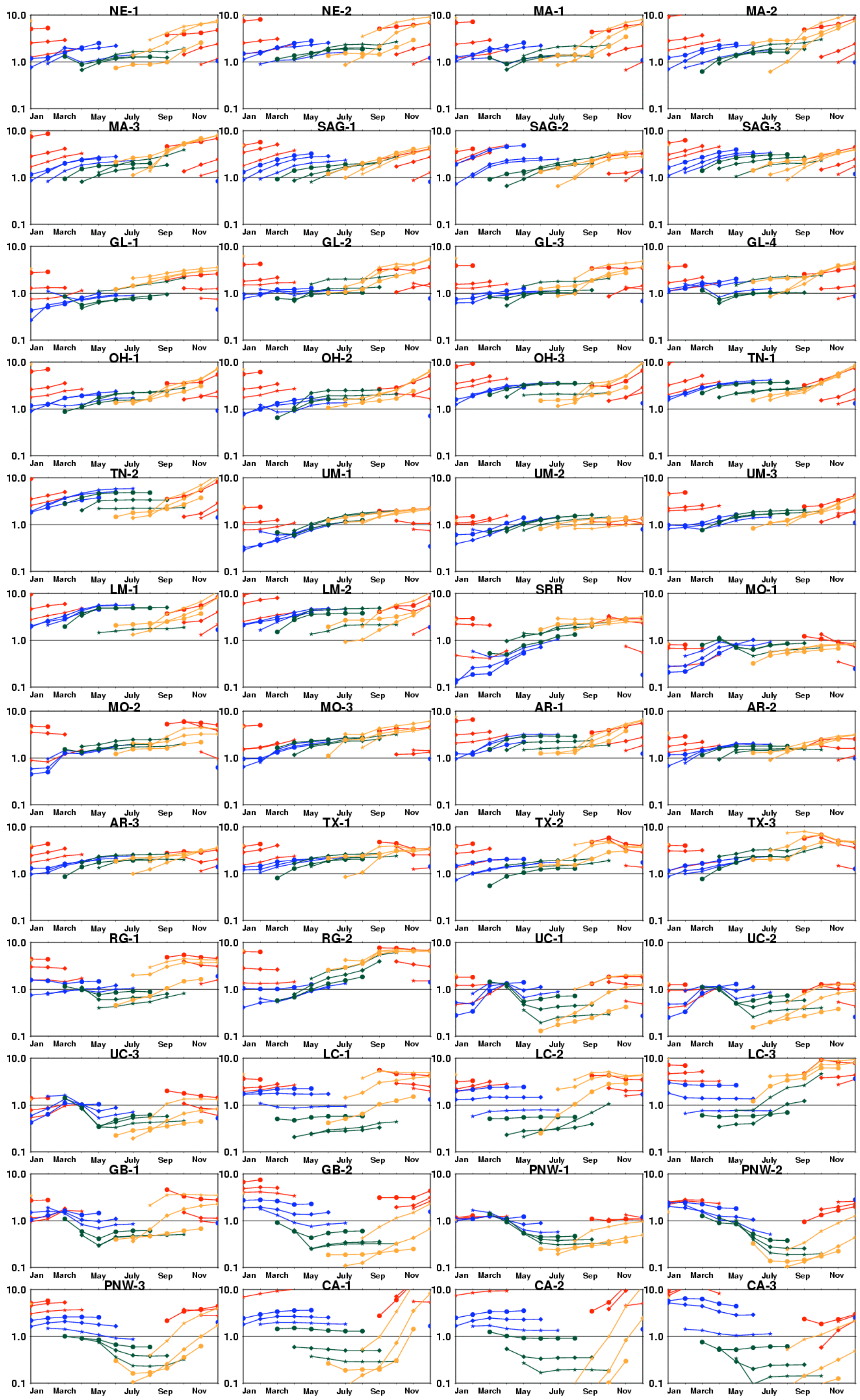


Figure 3.3: Variation of RMSE ratio ($RMSE_{ESP}/RMSE_{revESP}$) with lead time over 48 hydrologic sub-regions, for the CR forecasts at lead 1-6 months, initialized on the beginning of each month. (DJF: blue, MAM: green, JJA: light brown and SON: red)

In the western U.S., 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. Wood and Lettenmaier (2008) also found dominance of the IHCs in the seasonal runoff forecast during winter/spring transition months over two western U.S. basins. This finding suggests that runoff forecasts in the above-mentioned sub-regions and forecast periods could benefit substantially from improvements in knowledge of the IHCs. For sub-regions in the eastern U.S. 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, for CR forecasts initialized during winter (December-January-February (DJF)) and spring month (March and April, mainly). This finding is in agreement with Li et al. (2009) who noted that the IHCs dominate the streamflow (and SM) forecasts made during January and July, over Ohio and southeastern U.S. sub-regions, up to lead 1 month. These sub-regions as well could potentially benefit from improvements in estimates of the IHCs during these seasons. Aside from those months and locations, FS 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 in those sub-regions improved hydrologic forecasts must, for the most part, await improvements in FS.

There is also a clear difference between the variations of RMSE ratio initialized from wet vs dry IHCs. For example, in most 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 (also shown by Wood and Lettenmaier, 2008 and Li et al., 2009) for forecasts initialized during summer months. 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, FS may well be important in improving seasonal hydrologic forecasts.

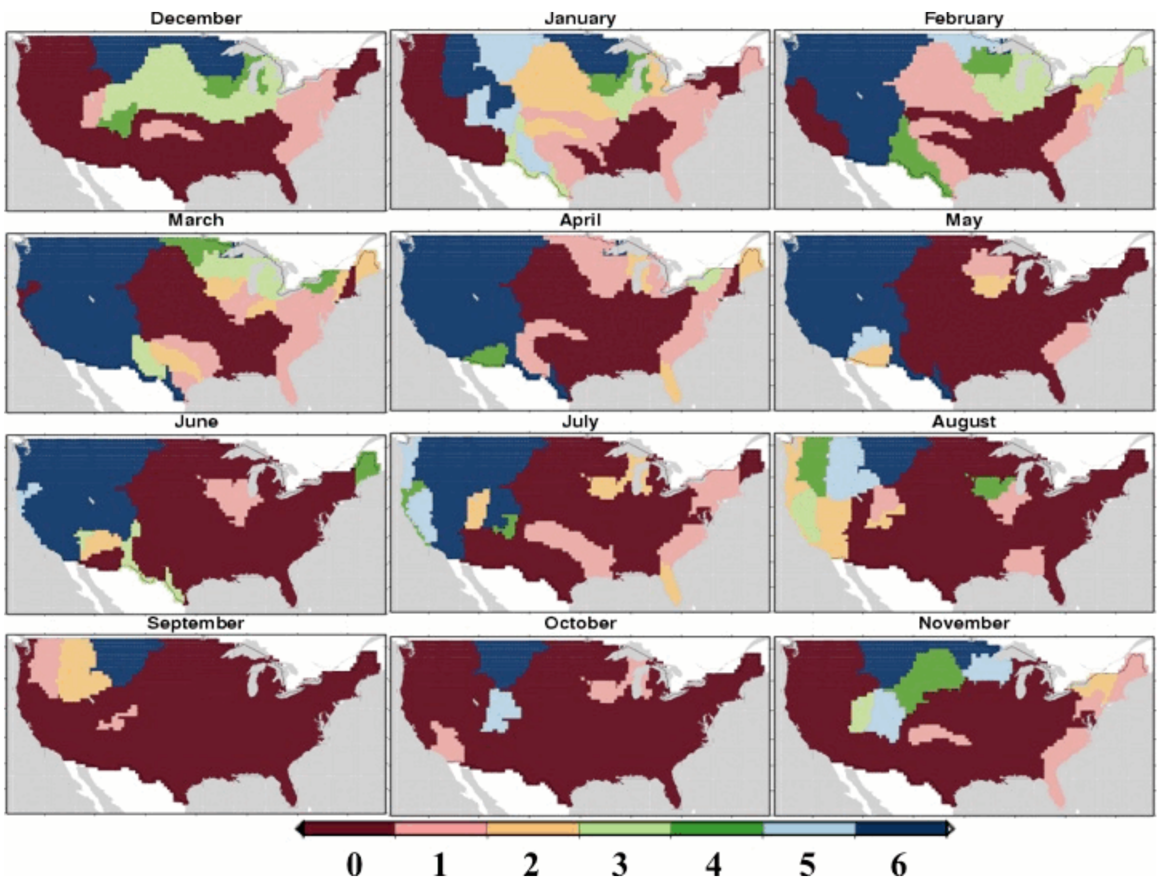


Figure 3.4: Plot of the maximum lead (in months) at which RMSE Ratio is less than 1, for CR forecasts, initialized on the beginning of each month.

Fig. 3.4 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 FS. Beyond this lead, FS dominates the CR forecast skill; hence improvement in the FS would lead to higher forecast skill. For the most part, the sub-regions in northeastern and southeastern U.S. would benefit most from improvements in FS throughout the year because the IHCs dominate up to lead-2 only. In the mountainous west and Pacific Coast sub-regions FS dominates mainly during fall and winter. On the other hand, IHCs dominate in those sub-regions during spring and summer for up to 6 months lead time. GL, SRR, and UM sub-regions overall would benefit most from improvement in knowledge of IHCs during winter and spring months (mainly March) and FS during summer months.

3.2 Soil moisture forecasts

SM is a key hydrologic state variable, and a natural indicator of agricultural drought. Fig. 3.5 shows 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 6^{th} 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 improvement in FS will be required to improve SM forecasts beyond lead-1. This pattern for SM forecasts was also shown by Li et al. (2009) in the Ohio and southeastern regions. Conversely, in the majority of the sub-regions in the Midwestern U.S., such as GL-1, -2, -3; SRR, UM, and the western U.S. show strong IHC influence for SM forecasts up to lead-5, when the forecast is initialized in winter or spring months. In snowmelt-dominated sub-regions in the western U.S., 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 U.S., in particular during spring and summer months.

Following the same criterion as we used for CR forecasts, Fig. 3.6 shows the maximum lead time at which the RMSE ratio is below 1 for mean monthly SM forecasts. In general most of the sub-regions have some SM forecasts skill derived by the IHCs, at least up to lead-1 (including sub-regions in northeastern and southeastern U.S.). This means that the relative contribution of the IHCs in the SM forecasts is more extensive than in the CR forecasts during the first month of the forecast period (i.e. lead-1). The spatial contrast between the sub-regions and forecast periods with high and low values of maximum lead time, where IHCs significantly influence the SM forecasts skill, is similar to CR forecasts.

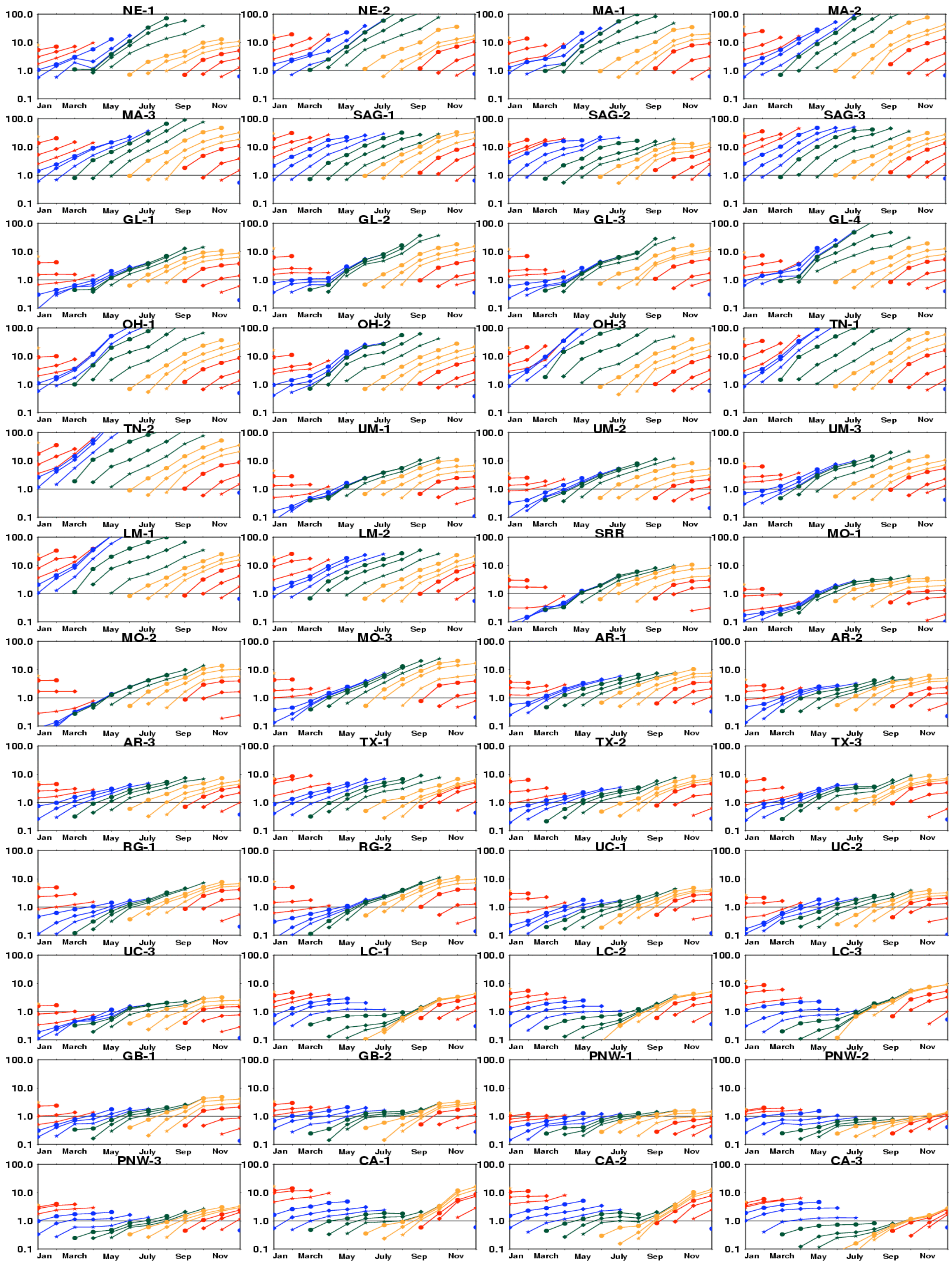


Figure 3.5: Variation of RMSE ratio (i.e. $RMSE_{ESP}/RMSE_{revESP}$) with lead time over 48 hydrologic sub-regions, for the SM forecasts at lead-1 to 6 months, initialized on the beginning of each month. (DJF: blue, MAM: green, JJA: light brown and SON: red)

3.3 Controls on hydrologic forecast skill

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 k. Following their analogy we expect a first order relationship between the inverse RMSE ratio (i.e. $RMSE_{revESP}/RMSE_{ESP}$) and k. Namely, we expect that $RMSE_{ESP}$ should be smaller for sub-regions and forecast periods with higher k. Scatter of the inverse RMSE ratio and k are shown for forecast periods of 1, 3, and 6 months in Figs. 3.7a, b, and c,

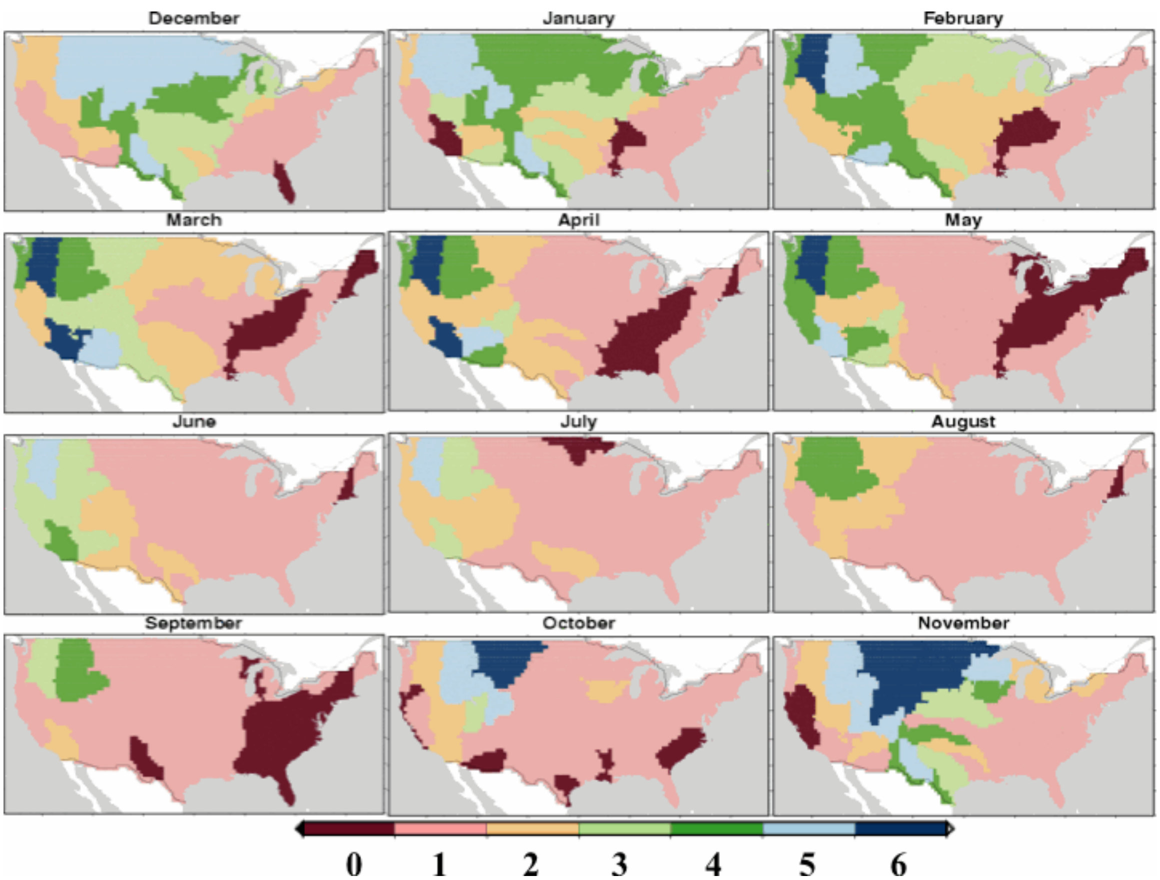
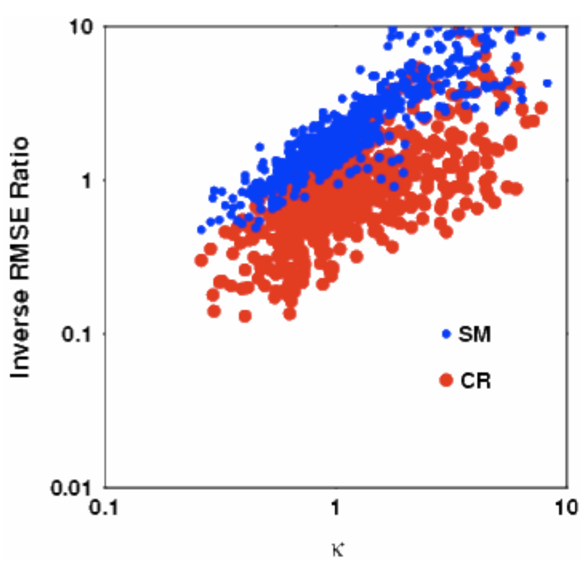
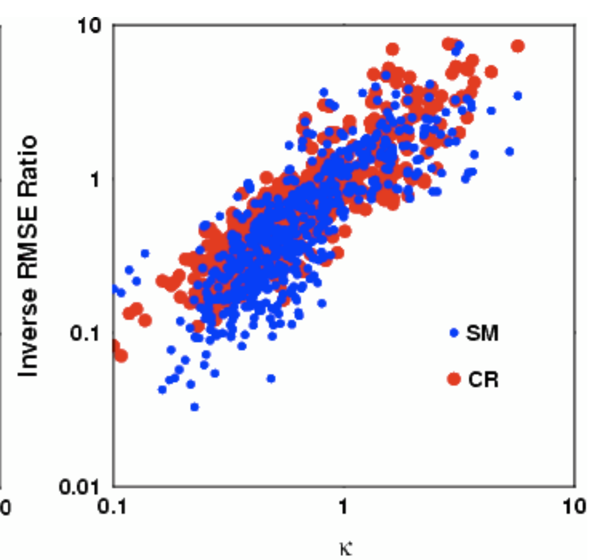


Figure 3.6: Plot of the maximum lead (in months) at which RMSE Ratio is less than 1, for mean monthly SM forecasts, initialized on the beginning of each month.

respectively. Red circles and blue circles show the inverse RMSE ratio estimated across all the hydrologic sub-regions and forecast initialization dates for the forecast of CR and mean monthly SM at lead-1, lead-3, and lead-6. (Figs. 3.7a, b, and c, respectively) The values of *k* vary for different forecast periods, and in general, the number of hydrologic sub-regions and forecast periods with $k>1$ decreases as the lead time increases. First order relationships between the inverse RMSE ratio and *k* clearly exist at each lead time. The range of inverse RMSE ratios for a given *k* value seems to be higher for CR at lead-1 than for SM (Fig. 3.7(a)). 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 lead-3 forecast (Fig. 7 (b)). The inverse RMSE ratio for lead-6, CR forecast is generally higher than its corresponding values for SM forecasts at lead-6 (Fig. 3.7 (c)).



(a)



(b)

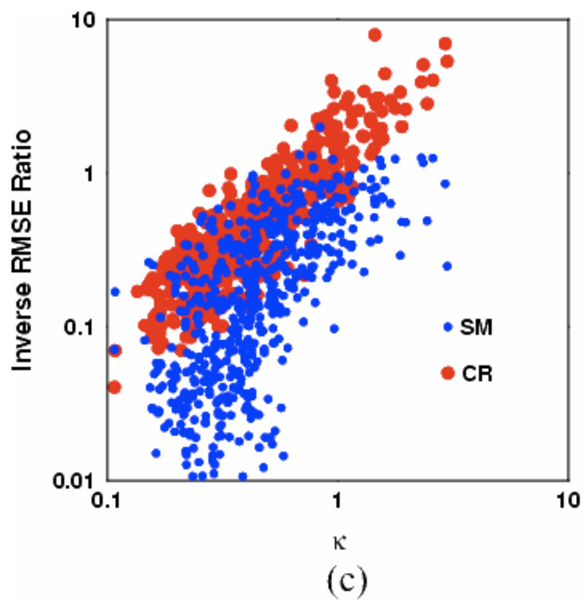


Figure 3.7: Inverse RMSE ratio (i.e. $RMSE_{revESP}/RMSE_{ESP}$) of CR and mean monthly SM forecasts at (a) lead-1 (b) lead-3, and (c) lead-6 plotted against κ parameter of each forecast period (i.e. 1 month, 3 months, and 6 months respectively)

4. Summary and conclusions

The two key factors influencing seasonal CR and SM forecast skill are IHCs and FS. 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 -- ESP and reverse-ESP -- in which the hydrologic prediction skill exploits knowledge of IHCs and FS respectively to quantify the relative contributions of each factors and to identify the sub-regions and forecast periods which can benefit most from improvements in the FS 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 U.S.

(3) FS dominates CR and SM forecast skill beyond lead-1 mainly over the northeastern and southeastern U.S. throughout the year. For the rest of the CONUS, FS generally dominates CR and SM forecasts during fall and early winter months.

(4) The relative contributions of IHCs and FS 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.

While the ESP-based framework used in this study allows a consistent estimation of the contribution of the IHCs and FS over large spatial scale (e.g. continental scale) and long time period, it is important to understand the limitations of the study design. The distribution of FS (in the ESP experiment) and IHCs (in the reverse-ESP experiment) is unconditional (i.e. climatological distribution) and we assume that IHCs (in the ESP experiment) and FS (in the reverse-ESP experiment) are perfect, hence our results arguably provide an upper bound on the contributions of the IHCs and FS to seasonal hydrologic prediction skill. Furthermore since we do not route the runoff through the stream network and rather use spatially aggregated values, there will be some difference in the spatial extent and lead time of the contribution of IHCs (mainly snow-melt) in streamflow based on the time of concentration of a given basin, although this effect can be expected to be limited, for the most part, to about a month.

We believe the findings of this study could have important implications for the improvement of seasonal hydrologic and drought prediction in the CONUS. We identified the sub-regions and forecast periods during which improvement in the knowledge of IHCs and FS could result in the most improvement in seasonal hydrologic prediction skill. For those river basins and forecast periods which have a substantial contribution of IHCs to seasonal hydrologic prediction skill, for instance, skill improvements might be derived by improving the IHCs - for example through the assimilation of ground based or remote sensing data. Another possible way of improving seasonal hydrologic forecasts with relatively short leads may be to exploit the skill of medium range weather forecasts over the first 1-2 weeks of the forecast period.

IV. VALUE OF MEDIUM RANGE WEATHER FORECASTS IN THE IMPROVEMENT OF SEASONAL HYDROLOGIC PREDICTION SKILL

This chapter has been submitted in its current form and currently in review in the journal Hydrology and Earth System Sciences: Shukla, S., N. Voision, and D. P. Lettenmaier. 2012. Value of medium range weather forecasts skill in seasonal hydrologic prediction. *Hydrol. Earth Syst. Sci.* 9, 1827-1857, doi:10.5194/hessd-9-1827-2012

1. Introduction

Droughts are among the most expensive natural disasters (Ross and Lott 2003). Proactive risk-based approaches to drought management that include better monitoring, early warning and prediction, are essential for mitigating drought losses (Schubert et al. 2007). Seasonal hydrologic and drought prediction systems, such as the NOAA Climate Prediction Center's seasonal drought outlook, derive their skill from knowledge of initial hydrologic conditions (IHCs) and weather/climate information during the forecast period. The contribution of IHCs and climate forecast skill in seasonal hydrologic prediction varies seasonally, spatially and with lead-time. Over the Conterminous United States (CONUS), (Shukla and Lettenmaier 2011) found that IHCs generally dominate at short leads (i.e. 1-2 months) while climate forecast skill dominates for longer leads, although IHCs can account for a substantial part of the total hydrologic forecast skill under some conditions for leads of as long as 6 months. .

Macro-scale land surface models (LSMs) provide a reasonably accurate estimate of IHCs at the time of forecast initialization for seasonal hydrologic prediction. For example, seasonal hydrologic/drought prediction systems, such as The National Centers for Environmental Prediction's (NCEP) drought monitor (*http://www.emc.ncep.noaa.gov/mmb/nldas/forecast/TSM/prob/*) and the University of Washington's Surface Water Monitor (*http://www.hydro.washington.edu/forecast/monitor/outlook/index.shtml*), use IHCs generated by LSMs. Within the multi-institutional North American Land Data Assimilation System project (Mitchell et al. 2004, 1999), a suite of large scale hydrologic models have been developed and tested over the CONUS for their ability to simulate various hydrometeorological processes (Cosgrove et al. 2003; Luo et al. 2003; Pan et al. 2003; Sheffield et al. 2003; Schaake et al. 2004; Xia et al. 2011a; b)

Simultaneously, major strides have been made toward understanding the sources of predictability of seasonal precipitation and temperature in the U.S. (Higgins et al. 2000) and improving climate forecasts (O'Lenic et al. 2008). Statistical and physical modeling approaches can exploit predictability in the climate system primarily via the thermal inertia present in sea-surface temperatures (Barnston et al. 1999), especially during strong El Niño/La Niña-Southern Oscillation years. Otherwise, precipitation forecast skill beyond a month or so is quite limited (Quan et al. 2006; Wilks 2000). Precipitation forecast skill is generally lower than the skill of forecasts for temperature or atmospheric circulation patterns for the same location and time (Wilks and Godfrey 2002; Gong et al. 2003; Lavers et al. 2009; Barnston et al. 2010). Since precipitation is the major driver of drought conditions, seasonal drought prediction skill is severely limited by the lack of precipitation forecast skill under most conditions. The difficulty of forecasting rainfall, mainly during summer, has been a major stumbling block for the CPC's seasonal drought outlook as well (Hayes et al. 2005).

Due to limited seasonal climate forecast skill, seasonal hydrologic prediction skill comes in substantial part from IHCs (Lettenmaier and Wood 2009). One potential means for improving seasonal hydrologic prediction is to better exploit medium range weather forecasts (MRWFs) for the first 14 days of a seasonal forecast period. MRWFs have greatly improved in the last two decades as increased computer power and more integrated observation systems have allowed general circulation models to run at finer resolutions with improved initializations (Pappenberger et al. 2005). MRWFs have been coupled with LSMs to provide flood and streamflow forecasts for lead times of up to 2 weeks, using both deterministic and probabilistic approaches (Clark and Hay 2004b; Werner et al. 2005; Hou et al. 2009; Thielen et al. 2009; Voisin et al. 2011) . Werner et al. (2005) found that incorporating 14-day precipitation and temperature forecasts from a MRWF model into the National Weather River Forecast System's traditional ESP forecast system generally improved the streamflow forecast skill for up to 18 days. Hou et al. (2009) evaluated the Global Ensemble Forecast System of NCEP coupled with the Noah LSM for its ability to provide useful streamflow forecast skill. They concluded that the coupled system has some positive streamflow forecast skill at lead times varying from 1-3 days for smaller basins and more than 7-10 days for large river basins.

The use of MRWFs has been mostly limited to up to two weeks in lead-time and their value in improving hydrologic prediction at seasonal scale is largely unexplored so far. By merging MRWFs (~14 day lead) with seasonal climate forecasts, seasonal hydrologic prediction skill could potentially be i) improved at short lead times (~1-2 months) and ii) extended in time beyond what is derived solely from the IHCs; particularly in those cases when climate forecasts at even short lead times have skill that is no better than climatological.

The goal of this study is to assess the contribution of MRWFs in seasonal hydrologic prediction. Specifically, we evaluate the potential of MRWFs to improve seasonal hydrologic forecast skill relative to that achievable by the Ensemble Streamflow Prediction (ESP) approach. ESP (Day 1985; Franz et al. 2003) is a method that involves running an LSM up to the forecast initialization date using observed forcings, and then producing ensembles by resampling time sequences of forcings from years in the historic record. Hence, its skill is derived solely from knowledge of IHCs. We evaluate the additional forecast skill derivable from MRWFs in the context of hydrologic ensembles of monthly runoff and mean monthly soil moisture (SM) at leads from one to several months.

2. Approach

Three ESP-based experiments were conducted. The basic framework for each experiment was the same: IHCs were derived by running an LSM using observed meteorological forcings until the date of forecast initialization, i.e. on the first of each month in the 1980-2003 period. In forecast mode, the LSM was forced with 6-month long observed meteorological forcings resampled from the historical period (23 ensemble members in the 1980-2003 period when the year of the forecast was excluded) and starting on the day of the forecast, i.e. on the first of each month. The experiments differed in the forcings for the first 14 days of the forecasts period as follows:

- The first experiment (hereafter referred to as *ESP*) used the conventional ESP framework (Fig. 4.1a) as in Wood and Lettenmaier 2006; 2008; Wood et al. 2002; Li et al. 2009), and Shukla and Lettenmaier, 2011). It defines the baseline seasonal hydrologic prediction skill.

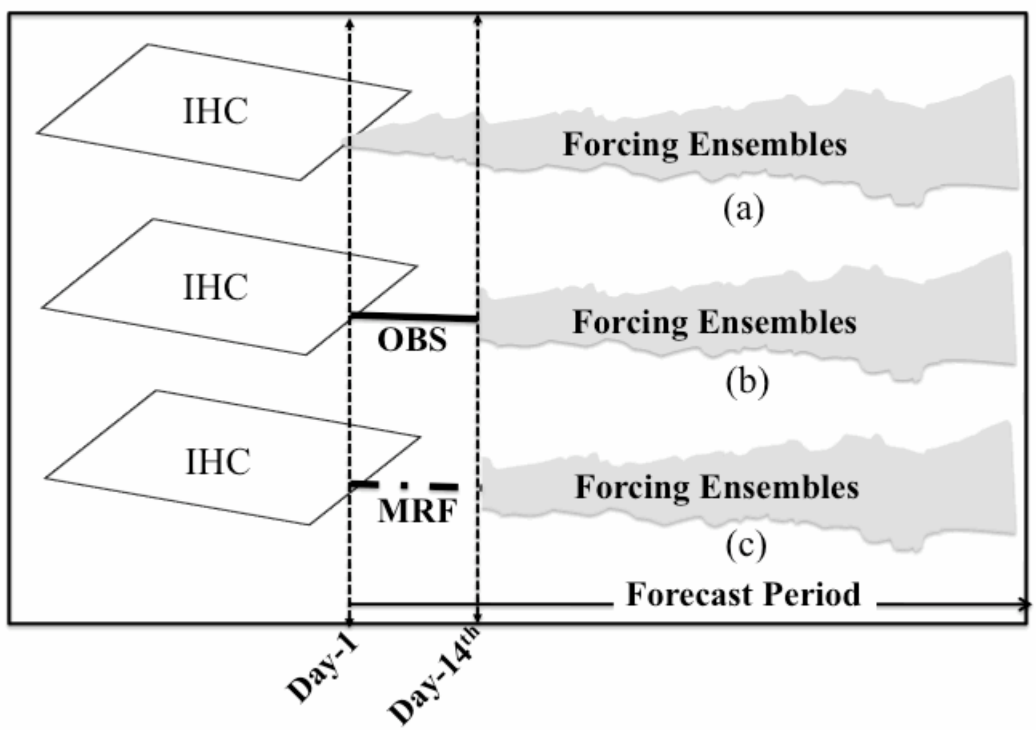


Figure 4.1: Schematic showing the climate forecast framework for (a) Experiment-1 (*ESP*) (b) Experiment-2 (*OBS_Merged_ESP*) and (c) Experiment-3 (*MRF_Merged_ESP*).

- In the second experiment (hereafter referred to as *OBS_Merged_ESP*), the first 14 days of each *ESP* ensemble member were replaced with observations (i.e. perfect MRWF). For example, as shown in Fig. 1b, the forcings used for days 1 to 14 were the observations during that period (deterministic perfect forecast), beyond which the forecast ensemble members were the same as in *ESP*. *OBS_Merged_ESP* defines the maximum improvement in seasonal hydrologic prediction skill that can be obtained if perfect knowledge of the LSM forcings could be extended to 14 days in the future.

- The third experiment (hereafter referred to as *MRF_Merged_ESP*) is similar to the second experiment, but observations for the first 14 days in each ensemble member were replaced with a deterministic MRWF (Fig. 4.1c). This experiment defines the actual improvement in seasonal hydrologic prediction skill that can be derived from use of realistic weather forecasts over those 14 days. The skill contributed by these forecasts may also be limited by the need to downscale the MRWF to the spatial resolution of the hydrologic model (one-half degree in the case of our experiments).

The skill of each experiment was estimated with respect to the "simulated observed" values (hereafter referred to as reference values) of runoff and SM, which were treated as surrogates for observations. The reference runoff and SM were obtained from a consistent long-term (1980-2003) simulation of the Variable Infiltration Capacity (VIC) LSM (section 2.1.1) forced with observed gridded station data (see section 2.1.2).

2.1 LSM and forcing data

2.1.1 The Variable Infiltration Capacity (VIC) model

The VIC macro-scale hydrology model (Liang et al. 1994; 1996; Cherkauer et al. 2003) was run at a daily time step and ½ degree latitude-longitude spatial resolution. The VIC model includes a parameterization for spatial variability of the infiltration capacity (and hence variability of runoff) and evaporation from different vegetation types, as well as bare soil evaporation. It provides for non-linear dependence of the partitioning of precipitation into infiltration and direct runoff as determined by soil-moisture in the upper layer and its spatial heterogeneity. The subsurface is partitioned into three layers. The first layer has a fixed depth of ~10 cm and responds quickly to changes in surface conditions and precipitation. Moisture transfers between the first and second, and second and third soil layers are governed by gravity drainage, with diffusion from the second to the upper layer allowed in unsaturated conditions. Base flow is a non-linear function of the moisture content of the third soil-layer (Todini 1996; Liang et al. 1994). The model was run in water balance mode; which means that the surface temperature is assumed equal to the surface air temperature, and is not iterated for energy balance closure (this also implies zero ground heat flux). The VIC model represents the snowpack as a two-layer medium (a thin surface, and a thick deeper layer), and solves an energy and mass balance as part of its computation of pack ablation (Andreadis et al. 2009).

2.1.2 Retrospective simulation (Control Run)

Arguably observed discharge could be used as reference in order to evaluate forecasted monthly runoff. However, there is no such proxy available for evaluation of forecasted monthly mean soil moisture, and we therefore chose to use an historic reference simulation as the basis for evaluation of both runoff and soil moisture. A consistent data set of runoff and mean monthly SM over the analysis period (1980-2003) to be used as the reference was generated by forcing the VIC model with observed gridded meteorological forcings over the analysis period. This simulation also included a >50 years model spinup. The model forcings (daily precipitation, and maximum (Tmax) and minimum (Tmin) temperature) were taken from Cooperative Observer Program stations, and gridded using methods outlined in Maurer et al. (2002). Additional model forcings (downward solar and longwave radiation, and humidity) were estimated from the daily air temperature and temperature range following methods outlined in Maurer et al. (2002). Surface wind was taken from the lowest level of the NCEP/NCAR reanalysis (Kalnay et al. 1996). The IHCs for each forecast initialization day used in the experiments were provided by this control run.

2.1.3 Weather forecasts

We used the 1979-2005 15-day 12-hourly 2.5-degree NCEP/Climate Diagnostics Center (CDC) Medium Range Forecast (MRF) reforecast dataset of (Hamill et al. 2006). The Hamill et al. (2006) data set uses a fixed version (1998) of the NCEP global forecast model and hence should have nearly consistent (aside from some differences in the data that were available for assimilation) forecast skill over the period of analysis. The reforecasts were downscaled from their native resolution (2.5 degree) to the 0.5-degree scale of the hydrology model and bias corrected to be consistent with the meteorological forcings used in the LSM spinup and reference simulation. The downscaling was performed by first aggregating the 12-hourly ensemble mean forecasts to 14 days, then interpolating the ensemble averages using an inverse squared distance interpolation scheme (Shepard 1984; Voisin et al. 2010). Figs. 4.2 and 4.3 show the Spearman rank correlation between the observed and downscaled forecasts (at ½ degree resolution) of 14-day accumulated precipitation and 14-day mean average daily temperature. The downscaled and accumulated 14-day weather forecasts were subsequently bias corrected by rescaling so that the long term 14-day accumulated mean precipitation and average Tmax and Tmin matched the corresponding values from the observed gridded forcings over the 1980-2003 period. The 14-day downscaled and bias corrected forecasts were then temporally disaggregated to a daily time scale by multiplying [adding] the non-bias corrected 14 days daily forecasts with the ratio [shift] of 14-day bias corrected and non bias corrected total precipitation [average temperature] values. More elaborate "weather pre-processors" could have been used (e.g., Schaake et al., 2007; Voisin et al., 2010);

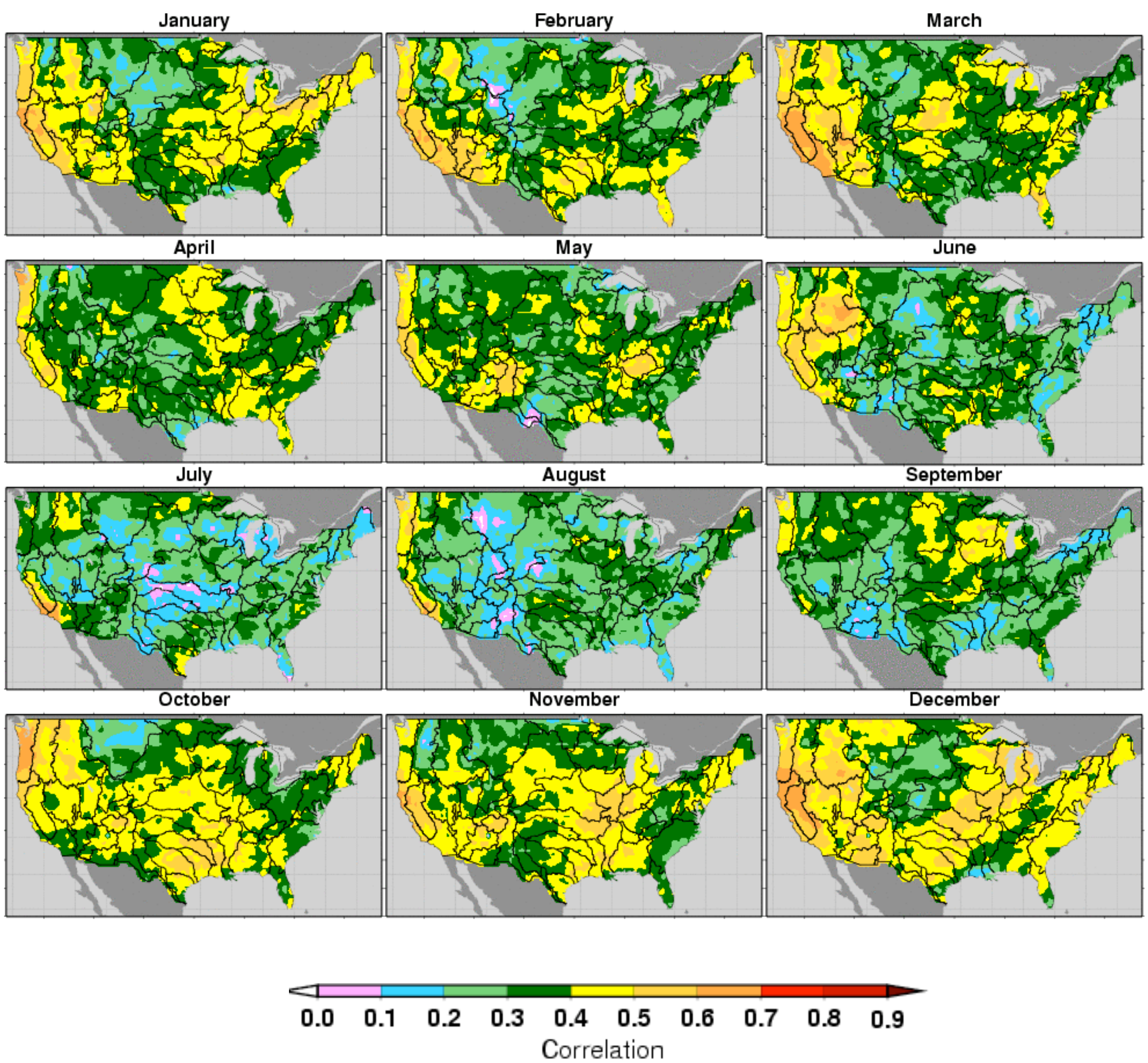


Figure 4.2: Correlation between observed and forecasted (MRF) 14-day accumulated precipitation during each month.

however, we focus here on the implications of weather forecasts of the first 14 days on seasonal hydrological forecasts.

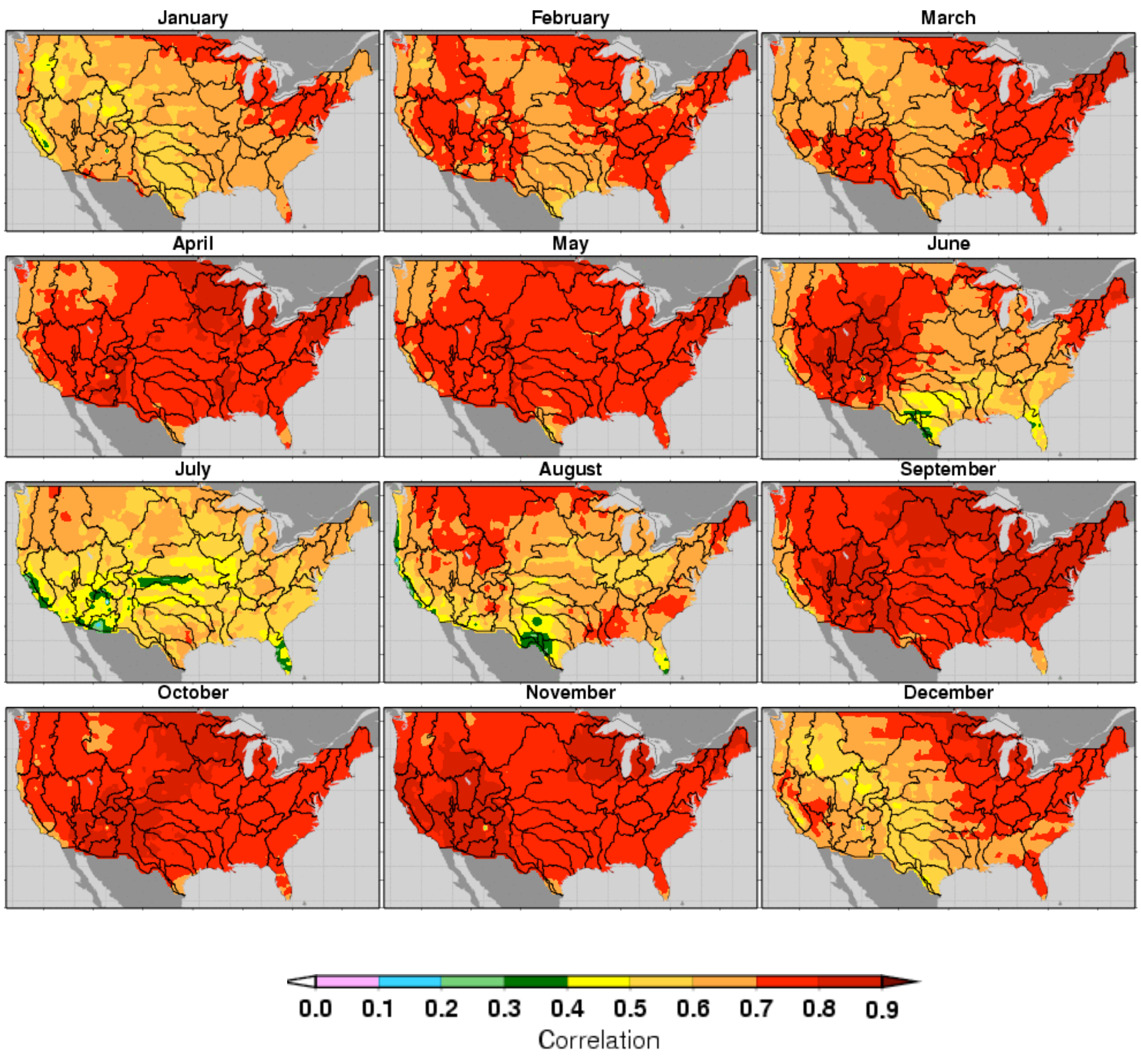


Figure 4.3: Correlation between observed and forecasted (MRF) 14 days mean average daily temperature during each month.

Although the daily sequencing of events is less important than the aggregate quantities for this analysis, rescaling the MRF daily values to match the 14 day precipitation total [average temperature] preserves the daily variability of the precipitation [temperature] in the MRF weather forecast dataset and also insures that the daily variability over the first 14 days of each *MRF_MERGED_ESP* ensemble experiment is preserved for a given forecast period.

Merging the 14-day ensemble mean forecasts, rather than each ensemble member, into the ESP forecasts avoids complications in merging the ensemble members (Clark et al. 2004) and limits the impact of the calibration and downscaling approaches on the ensemble forecast skill. The bias correction and spatial disaggregation approach in general reduces or eliminates biases, but does not preserve probabilistic information inherent in the forecasts (Voisin et al., 2010). Here we evaluate the potential improvement in seasonal hydrologic prediction from merging MRF with *ESP*, assuming that the information in the MRF ensemble is not calibrated and only the ensemble mean forecast is useful for our application.

2.2 Forecast skill score

For simplicity, daily spatially distributed runoff and SM forecasts and reference values (obtained from the control run) were aggregated in time to monthly accumulations or averages, and to the spatial scale of 48 hydrologic sub-regions across the CONUS domain (Table 1). These sub-regions are the same as the sub-regions used in Shukla and Lettenmaier (2011) and were created by merging the 221 USGS hydrologic sub-regions. Each of the sub-regions is named after the water resources region in which it is located (Table 4.1).

Table 4.1: 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 (MO)
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)

To evaluate the forecast skill of each experiment we estimated Spearman rank correlation coefficients (Wilks 2006) between the ensemble mean forecasts (over years) and the reference simulations. Spearman rank correlation is a measure of monotonic associations between forecasts and observations (Jolliffe and Stephenson 2003). The skill (rank correlation) of the *ESP* experiment is considered to be the “Baseline skill”. We considered the difference between the skill of *OBS_Merged_ESP* and the *ESP* experiment as the potential improvement and the difference between the skill of *MRF_Merged_ESP* and the *ESP* experiment as the actual improvement in baseline skill.

3. Results

We present the results for a forecast period of 2 months only (Figs. 4.4, 4.5, 4.6, 4.7, 4.8 and 4.9). Although in a few cases we observed improvements in seasonal hydrologic prediction skill due to use of MRWFs for three-month lead, generally the improvement in skill was limited to lead-1 and lead-2.

First we show the baseline skill (skill of the *ESP* experiment). The sub-regions where the baseline skill is not significant at 95% significance level have been masked and are shown in dark grey (the critical value of the Spearman rank correlation was estimated using the table given in Zar (1972)). We then show the potential improvement in the baseline skill (difference between the skill of OBS_*Merged_ESP* and *ESP* experiments). Again the improvement is shown over those sub-regions where the skill of OBS_*Merged_ESP* is significant at the 95% level. Finally, we show the ratio of the actual improvement in skill (difference between the skill of MRF_*Merged_ESP* and *ESP* experiment) and the potential improvement in skill, to highlight the level of the improvement in skill actually recovered by using realistic MRWFs. We show the actual improvement in skill over those sub-regions only where the potential improvement in skill is > 0.1 and the skill of OBS_*Merged_ESP* is significant at the 95% level.

3.1 Monthly runoff forecasts

The correlations of ensemble mean monthly runoff forecasts from *ESP* initialized (baseline skill) on day 1 of each with the reference runoff at leads 1 to 2 months are shown in Fig. 4.4. In general the baseline skill is highest at lead-1. Overall, across the CONUS, the baseline skill for runoff forecasts is highest during forecast periods starting in winter months (e.g. December-January-February, (DJF)) and lowest during forecast periods starting in fall months (mainly September and October). During forecast periods starting in spring (March-April-May) and early summer months (June and July), the western U.S. stands out with relatively high runoff forecast skill up to lead-2 (and beyond, not shown here). This is mostly attributable to the effects of snow, which provides substantial IHC-related forecast skill for forecast periods starting in late winter to early summer.

Fig. 4.5 shows the potential improvement in baseline skill of monthly runoff forecasts (i.e. difference between the skill score of runoff forecasts from *OBS_Merged_ESP* and *ESP*). Not surprisingly the greatest improvement in runoff forecast skill is at lead-1, and the effect decreases with lead-time. The largest improvement in skill for any given sub-region at lead-1 is generally in those cases where the first month of the forecast period is climatologically wet. This is the case, for example, for sub-regions in the Great Plains, Midwest and LM sub-regions for forecasts starting in April through October, and for the Pacific coastal sub-regions for forecast periods starting in November through the winter months (e.g., DJF). On the other hand, the improvement in skill at lead-1 is small for sub-regions for which the first month of the forecast period is climatologically dry or the initial moisture variability is much higher than the precipitation variability during the forecast period (small κ values according to the convention of Mahanama et al. (2011)); such conditions lead to high baseline skill.

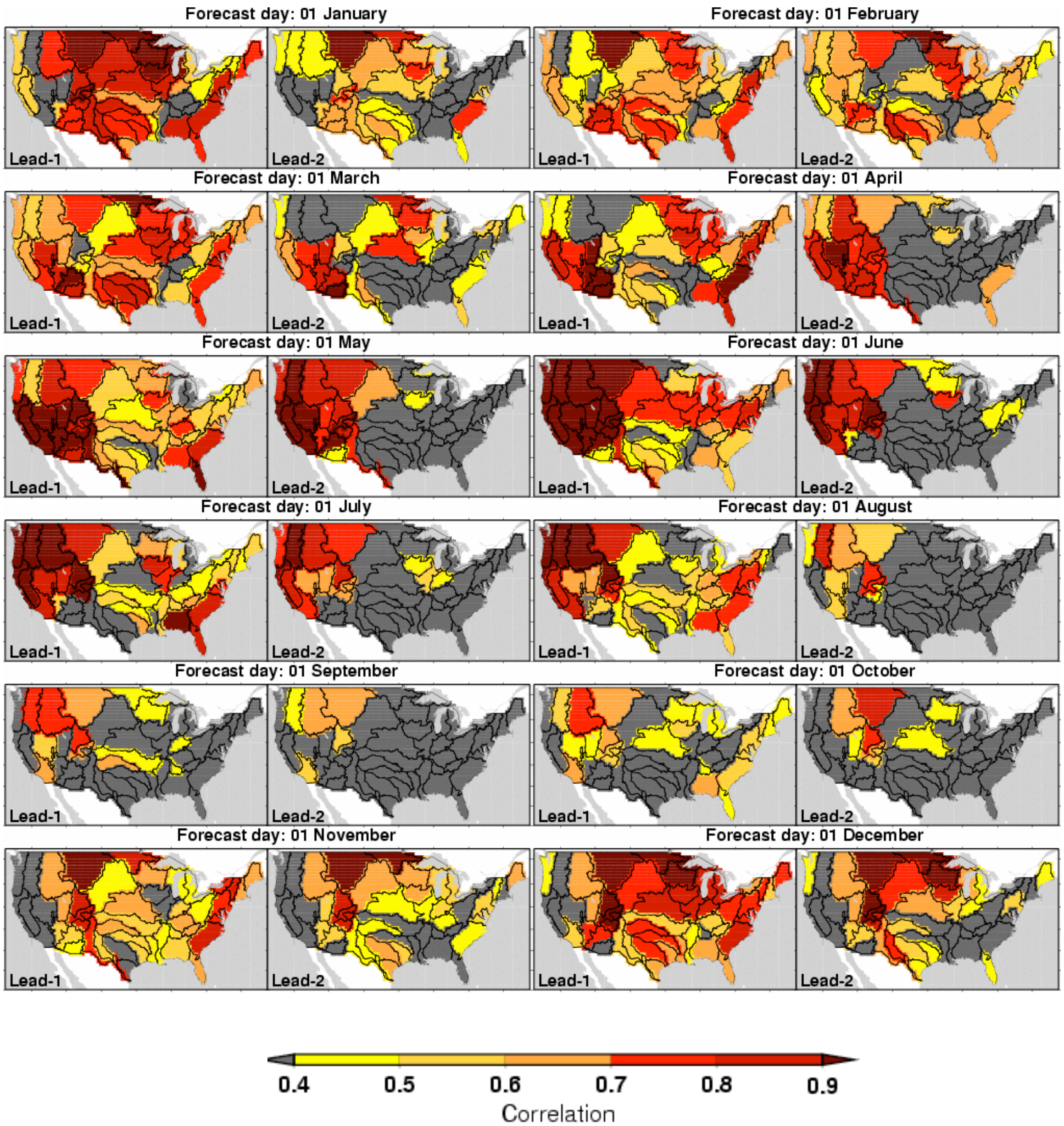


Figure 4.4: Baseline skill (i.e., skill of *ESP* experiment) for runoff forecasts at leads 1-2 months. (Dark grey color shows the sub-regions where the baseline skill is not significant at 95% significance level.)

This is the case for instance in the interior of the Western U.S. during spring and summer months.In some cases, the improvements in skill due to use of perfect MRWFs persists into leads-2 and -3 (not shown). These cases likely correspond to better knowledge of IHCs at the end of the 14 days in *OBS_Merged_ESP* experiment than in the *ESP* experiment.

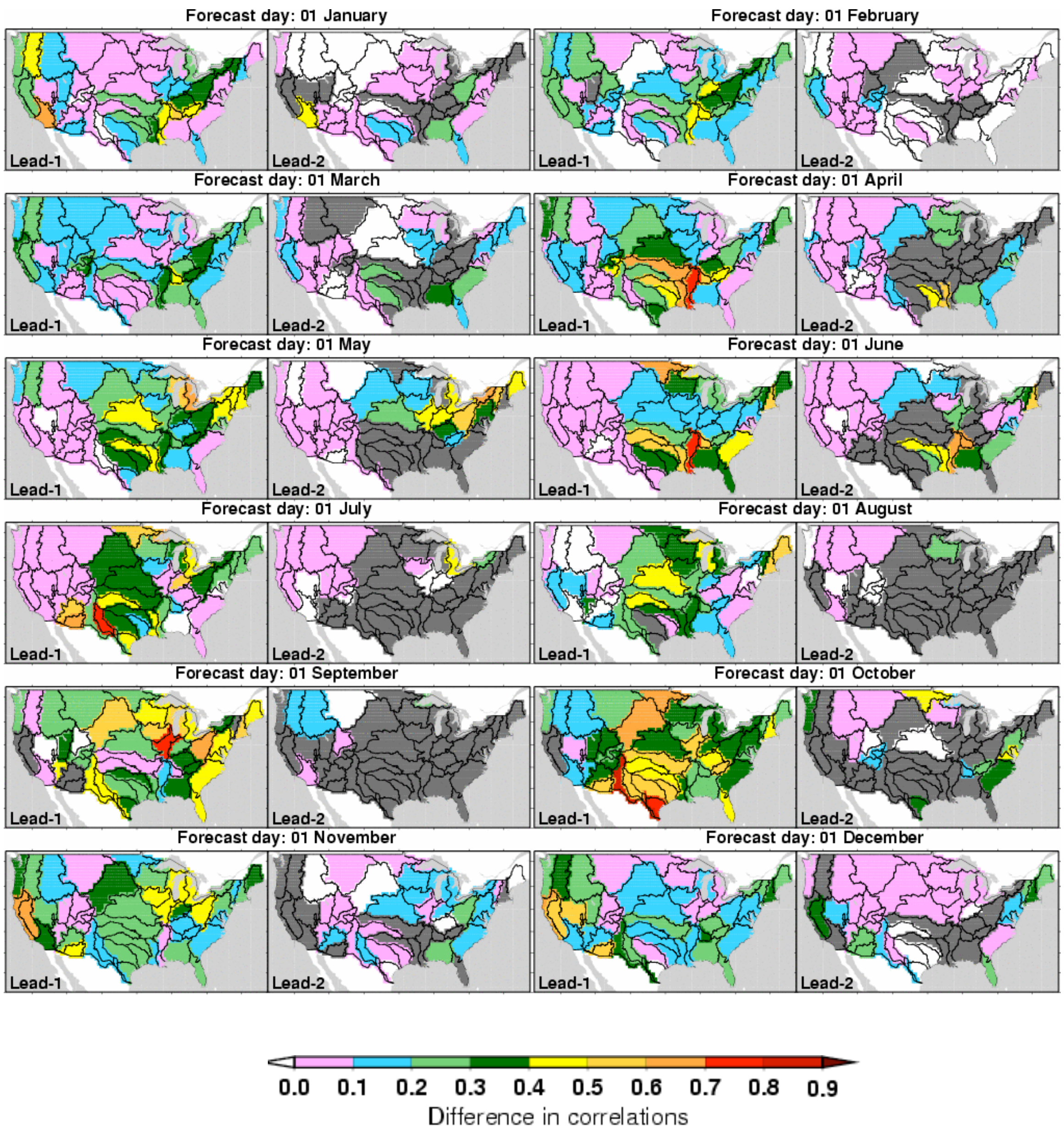


Figure 4.5: Potential improvement in runoff forecast skills at leads 1-2 months. (Dark grey color shows the sub-regions where the skill of *OBS_Merged_ESP* is not significant at 95% significance level.)

The potential improvement in skill shown in Fig. 4.5 clearly is optimistic relative to what is achievable in practice because weather forecast skill is imperfect even for the smallest (e.g., one day) leads, and declines thereafter throughout the 14-day MRWF period.

Fig. 4.6 shows the ratio of actual improvement in skill (differences in correlations for runoff forecasts derived by *MRF_Merged_ESP* and *ESP*) to potential improvement in skill (as discussed above) and indicates the improvement in runoff forecast skill that can be achieved realistically by using MRF medium range weather forecasts for the first 14 days of the forecast period. (It should be noted that these results may be slightly pessimistic as the MRF model has been retired, and MRWF skill for current generation weather forecast models may be slightly higher. However, the MRF reforecast data set is unique in providing a consistent set of reforecasts appropriate for the type of analysis we have performed; a newer version of this data set is planned but has not yet been released). Two main factors control the actual improvement in runoff forecast skill: (i) the potential improvement in skill (as shown in Fig. 4.5, derived from the use of perfect MRWFs) and (ii) the forecast skill of the MRWFs themselves. In other words, the improvement in skill due to use of MRWFs will be highest when both the potential improvement in hydrologic forecast skill and the MRWF skill (primarily for precipitation) are high. Therefore in Fig. 6, we show the actual improvement over those sub-regions only where the skill of *OBS_Merged_ESP* is significant at 95% level and the potential improvement in baseline skill is greater than 0.1.

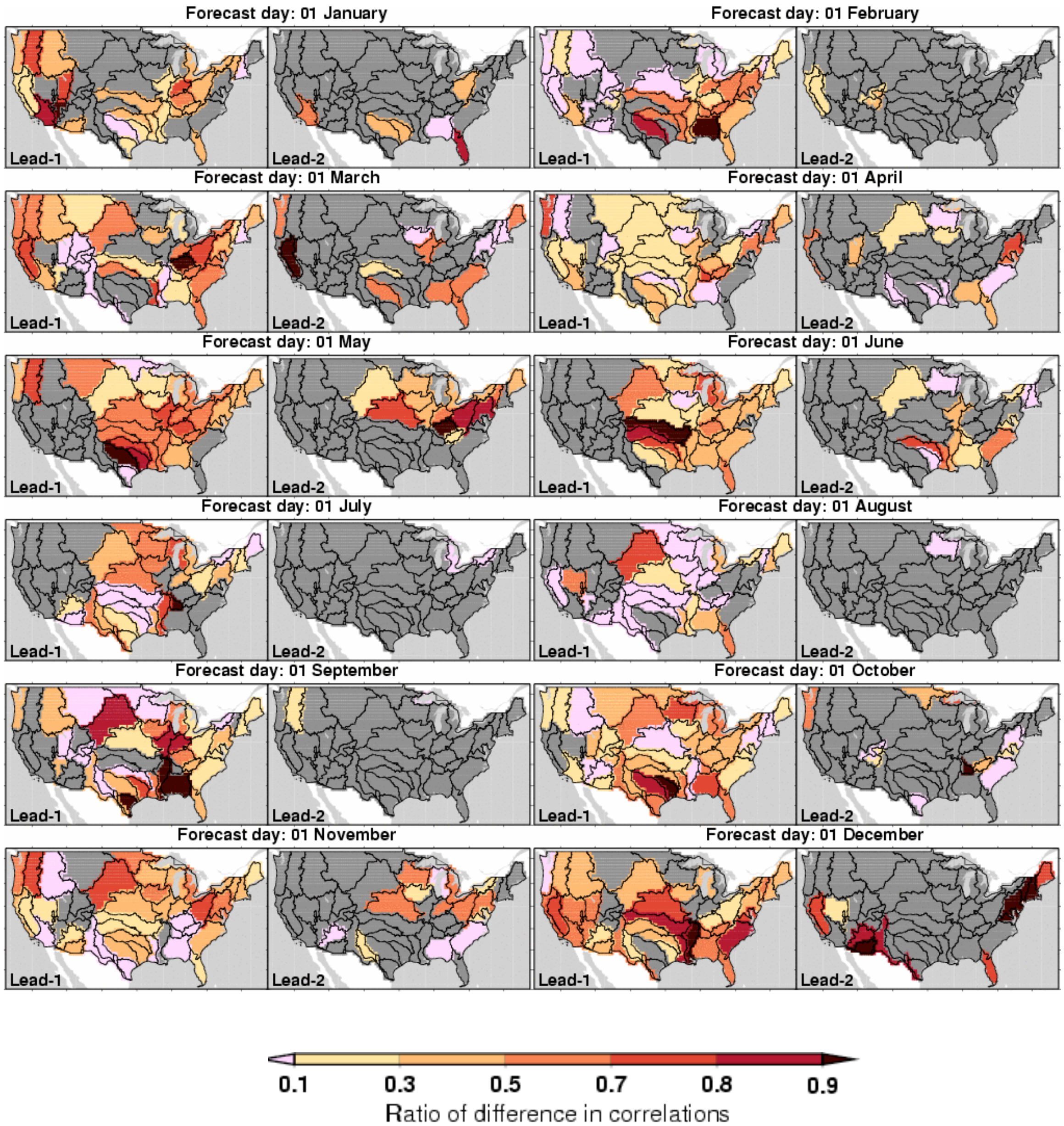


Figure 4.6: The ratio of actual improvement and potential improvement in baseline runoff forecast skill at leads 1-2 months. (Dark grey color shows the sub-regions where either the potential improvement in skill is < 0.1 or the skill of *OBS_Merged_ESP* is not significant at 95% significance level.)

In general, Fig. 4.6 shows that the actual improvement in skill due to use of the MRF forecasts is highest for those sub-regions and times of the year where the first month is climatologically wet. Overall the actual improvement in skill is extensive over the Great Plains, Midwest, Texas-Gulf and parts of the Northern and Southeastern U.S. at lead-1 during the forecast periods starting in spring (mainly April and May), summer (mainly June and July) and fall (SON, September-October-November) months. Over the mountainous West sub-regions the actual improvement in skill is highest during the forecast period initialized on 01 November, December and January. Again those are also the forecast periods when the baseline skill is low over those regions (Fig. 4.4), whereas during the forecast periods starting in spring and summer months (when the baseline skill is high) both the potential and actual improvement in skill is generally negligible (Fig. 4.5 and Fig. 4.6). The sub-regions shown in white during each forecast period show potential improvement but little or no actual improvement; likely due to limited MRF precipitation forecast skill.

3.2 Soil moisture (SM) forecasts

Fig. 4.7 shows the baseline skill for SM forecasts for lead-1 and lead-2. In general, the baseline skill for SM is much higher than for runoff (Figs. 4.5 and 4.7). Shukla and Lettenmaier (2011) also showed that at lead-1 IHCs generally dominate SM forecast skill.

Similar to the case of runoff forecasts across the CONUS, baseline skill for SM is generally highest during forecast periods starting in the winter, with higher skill over the western as compared with the eastern U.S. The baseline skill at leads-2 (and -3, not shown here) is high over the interior of the Western U.S. for forecast periods starting on day 1 of spring (March-April-May, MAM) and summer (June-July-August, JJA) months.

The potential improvement in the baseline skill of SM forecasts for each forecast period is shown in Fig. 4.8. Overall, the potential improvement in SM forecast skill at lead-1 is lower than the corresponding values for monthly runoff forecast skill (Figs. 4.5 and 4.8).

This appears to be a result of the high baseline skill for SM at lead-1 (i.e., high contribution of IHCs in SM forecast skill), hence leaving less room for improvement than for the case of runoff (since the maximum correlation value or the value of skill is 1). As for runoff, the greatest potential improvement in skill is for sub-regions and forecast periods where the lead-1 month is climatologically wet. Improvements at lead-1 are mostly limited to the Southwestern and Eastern U.S. (and Great Plains in a few cases) where the contribution of IHCs to SM forecast skill is lower than for the Western U.S. Mainly in the forecast periods starting in April, May and June and fall months (September and October) relatively large potential improvements can be seen over those regions. The potential improvement in skill at lead-2, however, seems more extensive in the case of SM forecasts than runoff. There could be a few explanations for this pattern. First, more sub-regions show significant levels of *OBS_Merged_ESP* skill at lead-2 in the case of SM forecasts skill than in that of runoff skill (therefore fewer regions are shown in dark grey at lead-2 in Fig. 4.8 than Fig. 4.5). Second, the baseline skill for SM forecasts (i.e., skill of *ESP* experiments) at lead-2 is smaller than at lead-1 leaving more room for improvement in skill. Finally, the improvement in SM forecast skill at lead-2 could be a result of persistence of the contribution of MRWF skill at lead-1. Once again the potential improvement in SM forecasts skill at lead-2 is generally prominent over the eastern half of the country.

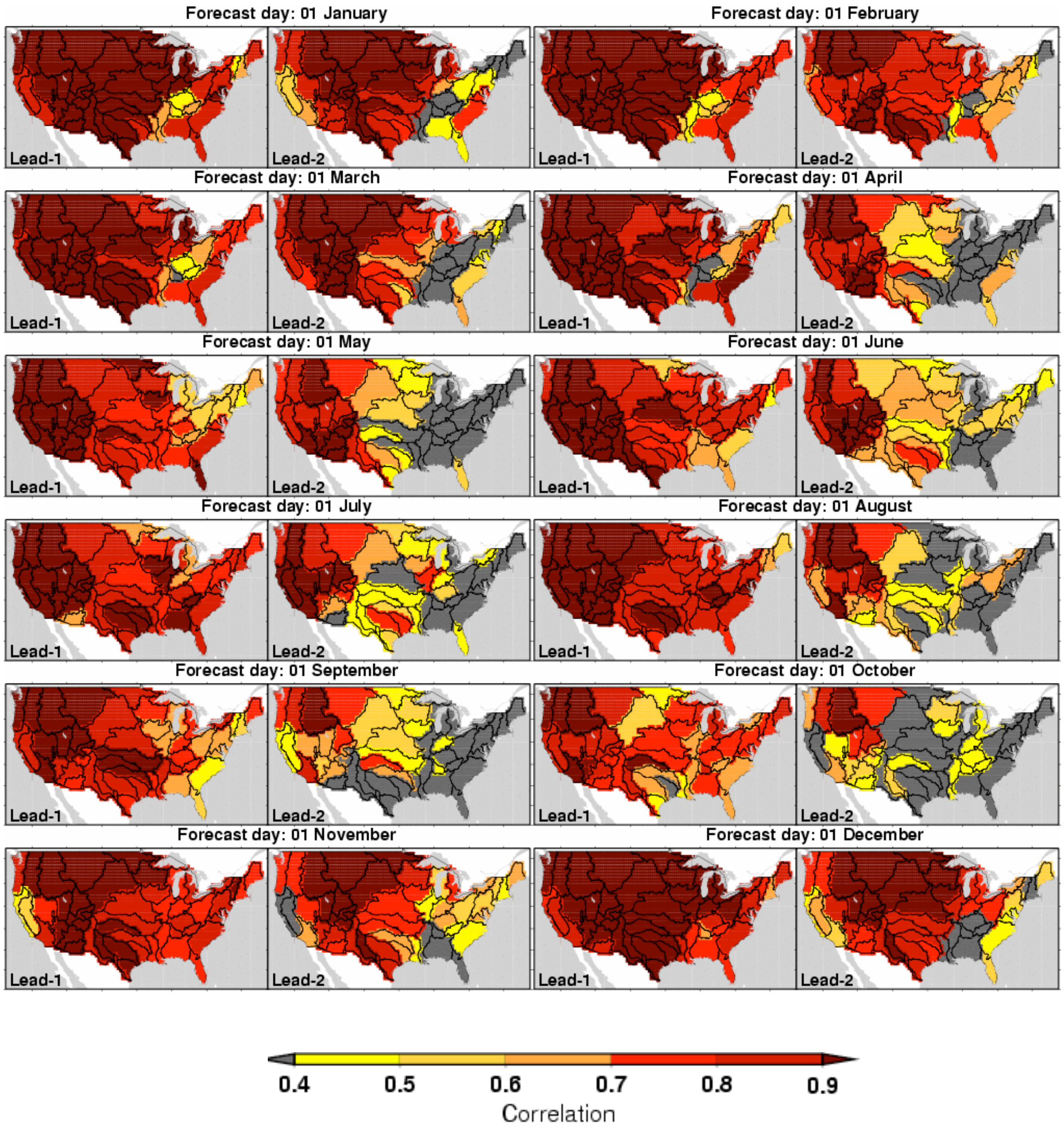


Figure 4.7: Baseline skill (i.e., skill of *ESP* experiment) for SM forecasts at leads 1-2 months. (Dark grey color shows the sub-regions where the baseline skill is not significant at 95% significance level.)

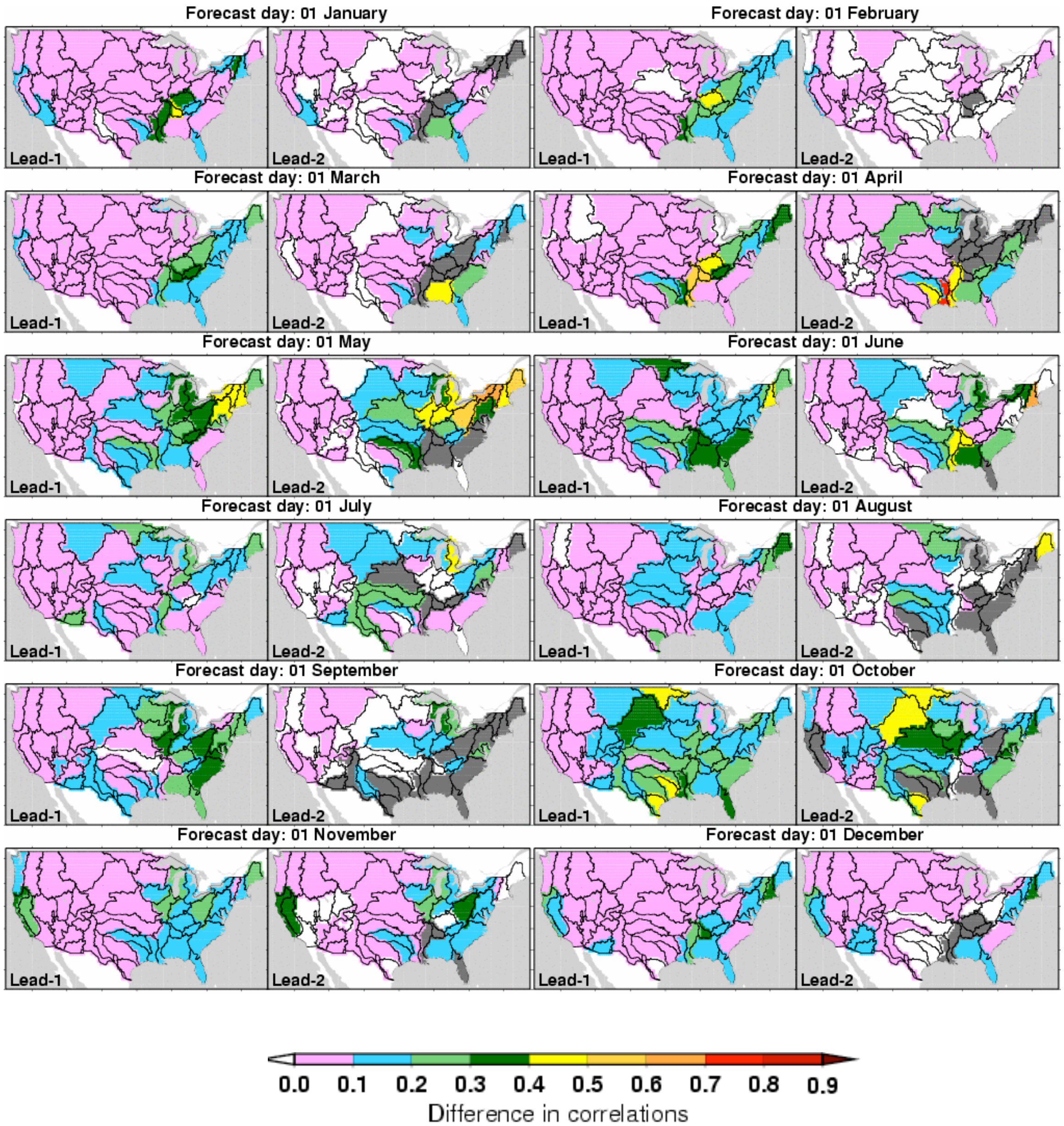


Figure 4.8: Potential improvement in SM forecast skills at leads 1-2 months. (Dark grey color shows the skill of *OBS_Merged_ESP* is not significant at 95% significance level.)

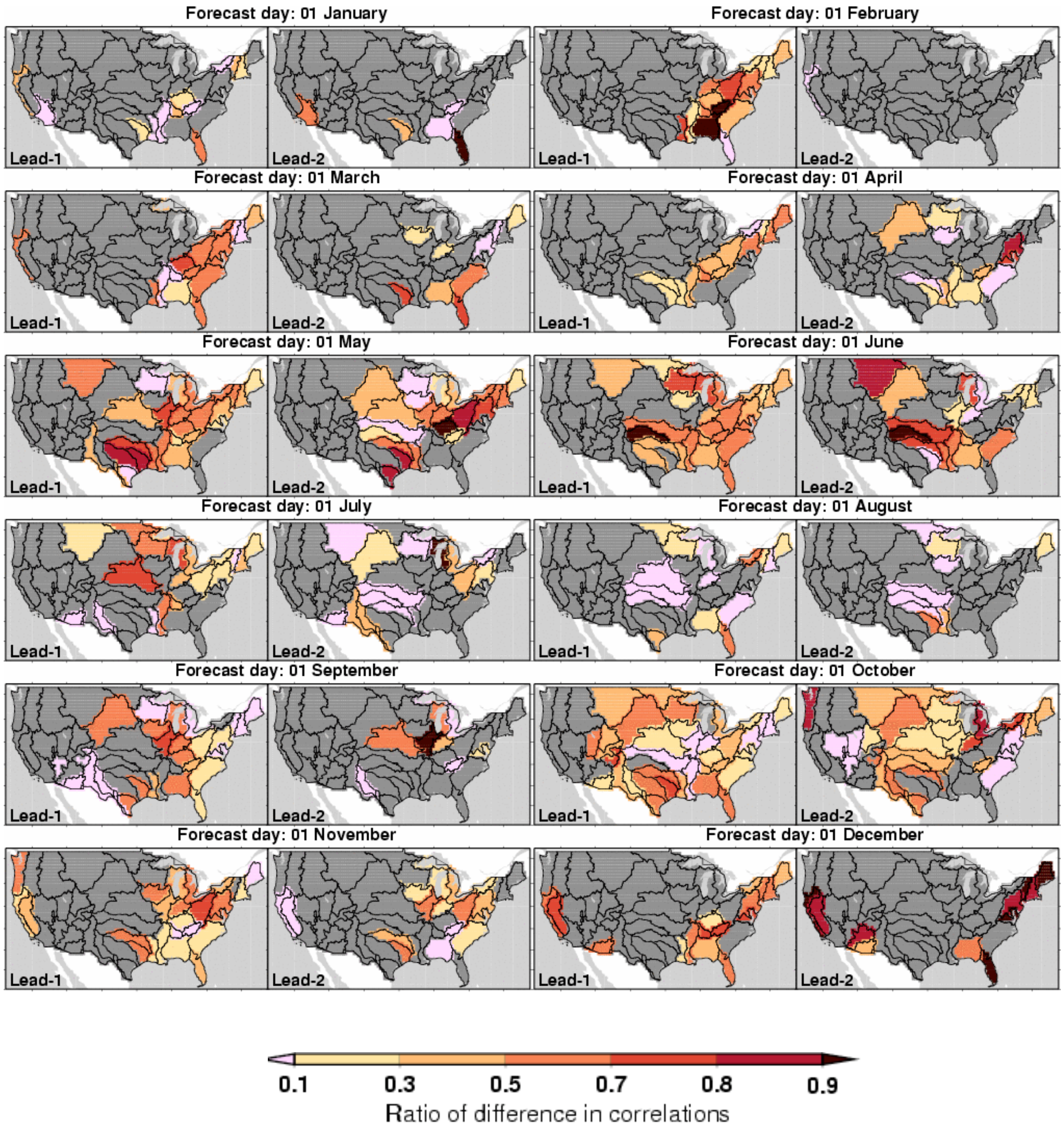


Figure 4.9: The ratio of actual improvement and potential improvement in baseline SM forecast skill at leads 1-2 months. (Dark grey color shows the sub-regions where either the potential improvement in skill is < 0.1 or the skill of *OBS_Merged_ESP* is not significant at 95% significance level.)

The ratio of actual to potential improvement in SM forecast skill is shown in Fig. 4.9. The actual improvement in skill is shown only over the regions where potential improvement in SM forecasts skill is greater than 0.1 and the skill of *OBS_Merged_ESP* is significant at the 95% level. Since the baseline skill of *ESP* (and hence skill of *OBS_Merged_ESP*) is generally significant across the CONUS at lead-1, the sub-regions shown in grey in Fig. 4.9 are mostly those regions where the potential improvement in skill is lower than 0.1. Overall for the most part the actual improvement in skill is limited to the sub-regions in the eastern half of the U.S., mostly during the forecast periods starting in April, May, June, September and October. Actual improvement in skill, however, can be seen over Pacific coastal regions at lead-1 for forecast periods starting in November and December. Again following the pattern of potential improvement, actual improvement at lead-2 in SM forecast skill also seems more extensive than in runoff forecast skill. This could be due to the persistence of the contributions of MRWFs at lead-1.

4. Discussion

Not surprisingly, perfect MRWFs show the greatest improvement in skill while MRF forecasts show smaller or no improvement. However, further improvement in MRWF skill will presumably lead to improvement in seasonal hydrologic prediction skill in those sub-regions and forecast periods where the use of perfect medium range weather forecasts yields most improvement in seasonal hydrologic prediction skill. For example during summer months (JJA), when the potential improvement for interior Western U.S. regions and much of the Eastern U.S. is greater than 0.2, the actual improvement is limited due to the limited MRWF skill (Figs. 2 and 3).

We used a simple bias correction and disaggregation approach in the *MRF_Merged_ESP* experiment. Our focus was on the removal of bias in the 14-day accumulated forecast.

Our analyses were performed at the monthly time scale for each grid cell (not routed) and as such the daily sequencing should not change the monthly results significantly.

5. Conclusions

Our analysis indicates the following:

(1) There is potential to improve monthly runoff and SM forecast skill beyond the IHC effect at lead-1 (and up to 3 months in a few cases) by exploiting MRWF skill. In general the Great Plain regions, Midwest, parts of the Southwestern U.S. (sub-regions in Texas) and Eastern U.S. would benefit most during forecast periods starting in April through November. On the other hand, sub-regions in the mountainous Western U.S. would benefit most during forecast periods starting in November and the winter months (DJF).

(2) The potential (and actual) improvement in runoff forecasts skill as contrasted with SM skill is larger at lead-1, mostly due to high baseline skill for SM (i.e. stronger IHC effect in SM), whereas the improvement at lead-2 is more extensive for SM forecasts than for runoff.

(3) Potential improvement in baseline skill for runoff forecasts generally varies from 0 to 0.8, whereas for SM it varies from 0 to 0.5. However, the space-time patterns of improvements are similar for runoff and SM.

(4) The actual improvement in skill due to use of MRF forecasts is limited by modest forecast skill for precipitation. The ratio of actual skill to potential skill improvement generally varies from 0 to 0.8. Sub-regions in the Great Plains, Midwest, Texas, and

Northeastern and Southeastern U.S. could potentially benefit most from improvement in MRF skill during forecast periods starting in the summer months (JJA, June-July-August).

Our findings could have significant implications for the improvement of seasonal hydrologic predictions at short lead-time (i.e. lead-1 to -3 months). Present protocols for generation of ensemble hydrologic forecasts from seasonal climate forecasts (e.g., Luo et al. 2007) make use of climate forecast ensembles that are generated through use of temporal offsets. The temporal offsets are mainly used to exploit predictability from different initial SST conditions. For example real-time operational seasonal climate forecasts such as the International Research Institute (IRI) seasonal climate forecasts are generated using seven atmospheric global circulation models (forced by the predicted global tropical SSTs). However, the forecast integration occurs 3-4 weeks in advance of the seasonal forecast period, hence the models do not exploit the skill from the observed atmospheric initial conditions (as well as the land surface conditions) at the beginning of the forecast period (Barnston et al. 2010). Likewise the Climate Forecast System (CFS) (Saha et al. 2006) real-time seasonal forecasts make use of initial conditions of the last 30 days. As a result, the effects of MRWFs at the beginning of forecast period are not reflected in the seasonal climate forecasts. This could be resolved either by a) use of shorter temporal offsets or (b) merging deterministic weather forecasts for the first 14 days (or perhaps shorter, given that most forecast skill comes from the first 5 days or so) with seasonal climate model forecasts thereafter.

Finally, improvement in drought prediction skill at short lead-times could potentially help with decisions that involve identification of regions with the potential for drought recovery. This often occurs over much shorter lead times than drought onset, hence better use of weather forecasts could provide practical benefits in this arena as well.

V. MULTI-RCM ENSEMBLE DOWNSCALING OF NCEP CFS SEASONAL FORECASTS: EVALUATION OF IMPLICATIONS FOR SEASONAL HYDROLOGIC FORECAST SKILL

This chapter will be submitted to the Journal of Geophysical research in its current format: Shukla, S., and D. P. Lettenmaier. 2012. Multi-RCM Ensemble Downscaling of NCEP CFS Seasonal Forecasts: Evaluation of Implications for Seasonal Hydrologic Forecast Skill. *J. Geophy. Res.*

I. Introduction

Improved seasonal climate forecasts offer one of the best mechanisms by which climate-related risks to water and drought management can be mitigated (Hamlet et al. 2002; Wood et al. 2002; Steinemann 2006; Voisin et al. 2006). Major strides have been made in improving the scientific underpinnings of seasonal climate forecasts over the past two decades, notably through the evolution of coupled global atmosphere-ocean models (Goddard et al. 2001; Palmer et al. 2004; Barnston et al. 2003; Saha et al. 2006b). It remains to be demonstrated, however, that these modeling advances improve climate forecast accuracy (especially of precipitation, the key hydrologic driver), and in turn seasonal hydrologic forecast accuracy. One of the major challenges in using seasonal climate forecasts for hydrologic prediction is their coarse resolution, which results in a mismatch in the scale of hydrologic models, and requires some form of spatial (and sometimes temporal) downscaling (Wood et al. 2002; Diez et al. 2005b; Wood et al. 2005; Wood and Lettenmaier 2006; Luo et al. 2007).

Two methods of downscaling global climate model outputs are commonly used: (i) statistical downscaling (Wood et al. 2002, 2005; Vrac et al. 2007; Maurer and Hidalgo 2008a; Zorita and Von Storch 2010; Yoon et al. 2011), and (ii) dynamical downscaling (Nobre et al. 2001; Diez et al. 2005a; Castro et al. 2007; Diez et al. 2009). Statistical downscaling methods take advantage of the observed relationships between the climate at finer resolution and coarser resolution and use that relationship to translate global climate model output to finer resolution (Wood et al. 2002; Maurer and Hidalgo 2008b). In dynamical downscaling, regional climate models (RCMs) are nested in the global model over a regional domain, with lateral boundary conditions taken from the global model (Castro et al. 2005, 2007; Pielke Sr and Wilby 2012). RCMs provide higher detail in both topographic variations and areas of strong contrast in land cover, such as coastal zones or urban areas, and also allow description of smaller-scale atmospheric processes, which lead to the formation of mesoscale weather phenomena (Feser et al. 2011; Leung et al. 2003).

Dynamical downscaling clearly is more physically based than statistical downscaling. It therefore is arguably applicable in global climate change scenario analysis when the assumption of climate stationarity inherent in statistical methods may not be valid (Hay and Clark 2003). However, dynamical downscaling is much more computationally demanding than statistical downscaling. The computational time required to generate climate forecasts is critically important for medium range to seasonal hydrological forecasts that are made at daily, weekly and bi-weekly intervals, and there are questions as to whether computational resources are better allocated to increasing the spatial resolution of the global model relative to the RCM.

Several recent studies have evaluated the value of dynamically downscaled medium range to seasonal climate forecasts relative to statistically downscaled forecasts in terms of potential improvement in precipitation, temperature and hydrologic forecast skill (Kidson and Thompson 1998; Wilby et al. 2000; Hay and Clark 2003; Schmidli et al. 2007). Hay and Clark (2003) evaluated runoff forecast skill in three snowmelt-dominated basins in the western U.S. using dynamically and statistically downscaled output from the NCEP/NCAR reanalysis (Kalnay et al. 1996). They concluded that even dynamically downscaled climate model output needs to be bias-corrected, and runoff forecasts based on statistically downscaled climate forecasts were at least as skillful as those based on dynamical downscaling in all three basins. Other studies, such as (Wilby et al. 2000; Wood et al. 2004), also came to similar conclusions.

The Multi-RCM Ensemble Downscaling (MRED) of National Centers for Environmental Prediction (NCEP) Climate Forecast System CFS Seasonal Forecasts (MRED) was undertaken to answer a central question: "*Do RCMs add significant regional skill to current global model forecasts?*" In the MRED project, CFS winter (December through April) seasonal (re)forecasts for 1982 to 2003+, were downscaled using seven RCMs. Ten CFS ensemble members, initialized at 00UTC on Nov. 21-25 and Nov. 29-Dec. 3 were downscaled by each of the RCMs. Yoon et al. (2012) evaluated the dynamically downscaled MRED forecasts and concluded that dynamical downscaling of forecasts does produce fine scale features in the climatology and anomalies of precipitation and temperature that are missing in the CFS forecasts due to their inherent coarse spatial resolution. They also observed that the skill of the dynamically downscaled forecasts was somewhat higher than in CFS, mainly over the Northwest and north-central U.S.

In this study we evaluate the value of multi-RCM ensembles in terms of their implications for seasonal hydrologic forecast skill. We quantify the skill of multi-RCM ensembles (dynamically downscaled) in comparison with statistically downscaled (using Bias Correction and Spatial Downscaling (BCSD); Wood et al., 2002) CFS forecasts used to produce similar hydrologic forecasts. Our specific objectives are to (1) estimate the forecast skill of runoff (RO), soil moisture (SM) and snow water equivalent (SWE) obtained via the dynamically downscaled MRED CFS forecasts in comparison with hydrologic forecasts that are based on statistical downscaling of the same CFS reforecasts used in MRED; and (2) evaluate whether multi-RCM ensembles improve hydrologic forecast skill relative to the use of single RCM ensembles.

2. Methods, data and hydrologic model

In this section we provide a brief description of the MRED project (section 2.1), the statistical downscaling method (section 2.2), the hydrologic model (section 2.3), the observed forcings data set and observational analysis (section 2.4), the experimental design (section 2.5), and the forecast evaluation metrics (section 2.6). Fig. 5.1 summarizes the approach we used. We statistically downscaled both CFS forecasts (from their native resolution of T62) as well as dynamically downscaled MRED forecasts (from 0.375 degrees latitude-longitude) to 0.125 degree to force the hydrologic model and generate hydrologic forecasts.

2.1 Dynamical downscaling

Dynamical downscaling of winter season (December - April) CFS forecasts was undertaken by the MRED project. The RCMs used by MRED to dynamically downscale CFS forecasts are: (1) The Regional Spectral Model (RSM)-NCEP (Juang et al. 1997); (2) The Regional Spectral Model (RSM)-ECPC (Roads et al. 2010); (3) The Advanced Research WRF (WRF-ARW) (Skamarock et al. 2005); (4) Mesoscale Model 5 (MM5-ISU) (Anderson et al. 2007); (5) Climate-Weather Research and Forecasting (CWRF) (Liang et al. 2005); (6) Eta (Xue et al. 2007); and (7) Regional Atmospheric Modeling System (RAMS) (Cotton et al. 2003).

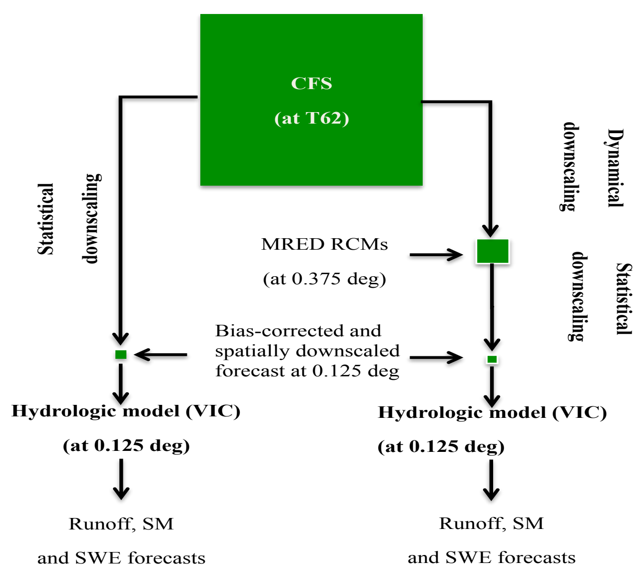


Figure 5.1: Schematic diagram of approach used in this study.

Each RCM was forced with CFS lateral boundary conditions. Initial conditions for the 10 common CFS ensemble members used in this study were taken from 21-25 Nov. and 29 Nov. – 3 Dec., for the years 1982-2003. The forecast period was from 1st December through 30th April of each forecast year. The spatial resolution of each RCM was 0.375 degree latitude-longitude. The hydrologic model (section 2.3) we used for this study was implemented at 0.125 degree, hence the multi-RCM ensembles had to be further downscaled from their original resolution of 0.375 degrees. We used BCSD method (section 2.2) to bias-correct and then spatially and temporally downscale monthly means of Precipitation (P), Surface temperature maximum (Tmax) and Surface temperature minimum (Tmin) for each of the multi-RCMs ensembles to daily time step. Further details about the MRED project and the experimental setup used to dynamically downscale CFS forecasts is reported in Yoon et al. (2012).

2.2 Statistical Downscaling

We used the Bias Correction and Spatial Downscaling (BCSD) (Wood et al. 2002, 2005) method to downscale CFS forecasts from their native resolution (T62) and multi-RCM forecasts from 0.375 degrees – in both cases to 0.125 degrees latitude-longitude (the spatial scale of the hydrologic model). The BCSD method has been widely used to downscale global climate model output to finer resolution for hydrologic simulation purposes (Maurer and Hidalgo 2008b; Wood et al. 2002, 2005). The method as used in this study can be summarized in the following steps (see Wood et al. 2002, 2005 for details).

(i) The monthly values of CFS and RCM P, Tmax and Tmin output for each month were bias-corrected relative to the observed monthly climatology of those variables (section 2.4) at their respective native resolutions, using a quantile mapping approach (Panofsky and Brier 1968) on a grid cell by grid cell basis. The CFS and RCM climatologies for each grid cell were taken from hindcast simulations, and included all values from the 10 ensemble members for the 1982 to 2003 period (we did not include the forecast ensembles and observations from the target year in the climatologies used for bias-correction). Therefore the number of values in the forecast and observed climatologies for any given target year was 210 (21 years ×10 ensembles) and 21, respectively.

(ii) Following bias-correction we spatially interpolated the forecast anomalies (multiplicative anomalies in case of P and additive anomalies in case of Tmax and Tmin) to 0.125-degree spatial resolution.

(iii) Finally, we disaggregated downscaled monthly anomalies to daily values of P, Tmax and Tmin following a random resampling approach as described in (Wood et al. 2002).

The statistical downscaling was performed separately for each ensemble member from CFS and each of the seven RCMs, resulting in 10 ensembles of daily P, Tmax, Tmin values for the 1st December to 30th April forecast period for each model for the period 1982-2003. Performing BCSD on P, Tmax and Tmin and using those downscaled forecasts to run a hydrologic model (such as VIC) to simulate hydrologic variables arguably is a better strategy than performing BCSD directly on the hydrologic outputs from the RCMs or CFS, because: (1) bias corrections of inputs (i.e. P, Tmax and Tmin) to the hydrologic model, in turns reduce biases in each of the energy and water balance components and (2) it avoids having to perform separate BCSD on each of hydrologic variables obtained from RCMs or CFS (thus reduces the computational time). Furthermore, differences in the soil layer depth (i.e. moisture storage) among RCMs and

CFS could pose challenges in bias-correcting their hydrologic output relative to the VIC output. (3) it is also possible that depending on how well the land surface processes have been represented in the RCMs or CFS the skill (e.g. correlation) of hydrologic variables such as SM and RO could be lower than the skill of P, Tmax and Tmin when compared with corresponding observations.

2.3 Variable Infiltration Capacity (VIC) model

The VIC model is a semi-distributed macroscale hydrologic model (Liang et al. 1994). It parameterizes major surface, subsurface, 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. 1996a; b). It provides for non-linear dependence of the partitioning of precipitation into infiltration and direct runoff as determined by soil-moisture in the upper layer and its spatial heterogeneity. The subsurface is usually partitioned into three layers. The first layer has a fixed depth of ~10 cm and responds quickly to changes in surface conditions and precipitation. Moisture transfers between the first and second, and second and third soil layers are governed by gravity drainage, with diffusion from the second to the upper layer allowed in unsaturated conditions. Baseflow is a non-linear function of the moisture content of the third soil-layer (Liang et al. 1994; Todini 1996). The model was run in water balance mode, which means that the surface temperature is assumed equal to the surface air temperature and is not iterated for energy balance closure (this also implies zero ground heat flux). The snow accumulation and ablation algorithm (Cherkauer et al. 2003; Andreadis et al. 2009) module of the VIC model was run at a 3-hourly time step. The vegetation, soil, elevation and snow band parameters used in this study were the same as in (Maurer et al. 2002). As mentioned in section 2.4, we used the Maurer et al. 2002 precipitation and temperature forcings data set. Other forcings, such as shortwave and longwave radiation, specific humidity, etc., were determined using the daily temperature range (difference between Tmax and Tmin) following the methods of (Kimball et al. 1997; Bohn et al. 2012)

2.4 Gridded observations

To estimate the hydrologic forecast skill derived from the use of the alternate forcing approaches, a consistent long-term data set of RO, SM and SWE is needed. Due to scarcity of SM and SWE observations (and to a lesser extent runoff), we created long-term VIC model (section 2.3) output for these variables by forcing the model with high quality gridded forcings of P, Tmax, Tmin and wind speed. These gridded data were taken from (Maurer et al. 2002), extended from 2000 to 2010 following essentially the same methods as in (Maurer et al. 2002) (see *http://www.engr.scu.edu/~emaurer/gridded_obs/index_gridded_obs.html*). This data set was also used as the observational climatology for the bias-correction and spatial downscaling of the CFS and RCM output (section 2.2). The soil, vegetation and snow band parameters used to run VIC model were the same as in (Maurer et al. 2002). Daily values of RO, SM and SWE obtained from the VIC simulations were used to calculate total runoff (surface + baseflow) and mean SM and SWE at monthly time steps for each month during the forecast period (December to April).

2.5 Forecast evaluation

We calculated the hydrologic prediction skill for each variable (runoff, SM and SWE) by calculating a simple Pearson Product-moment correlation (Wilks 2006) between the ensemble mean forecasts of those variables with the corresponding values obtained from the observational analysis (section 2.4). We focus here on those regions and lead-times at which the correlation coefficient (forecast skill) was statistically significant at 90% confidence level. For a sample size of 21 years (1982-2002), statistical significance is achieved for sample correlations r with $|r| > 0.37$.

We also identified the regions and leads at which the difference between the hydrologic forecast skill derived by using statistically as contrasted with dynamically downscaled CFS forecasts is significant at 95% and 90% confidence levels. We did so by transforming each of the correlation values (say r_1 and r_2) into standard normal deviates (say Z_1 and Z_2) by using Fisher's Z transformation method (Eq. 1)

$$Z_{1[2]} = 0.5 \times \log_e \left(\frac{1 + r_{1[2]}}{1 - r_{1[2]}} \right) \tag{1}$$

We then estimated critical Z values using Z_1 and Z_2 (Eq. 2), where n is the sample size (i.e. 21)

$$Z = \frac{Z_1 - Z_2}{\sqrt{1/(n-3)}} \tag{2}$$

For the correlation values to be statistically different at 95%[90%] confidence level the value of Z should be greater or equal to 1.96[1.66].

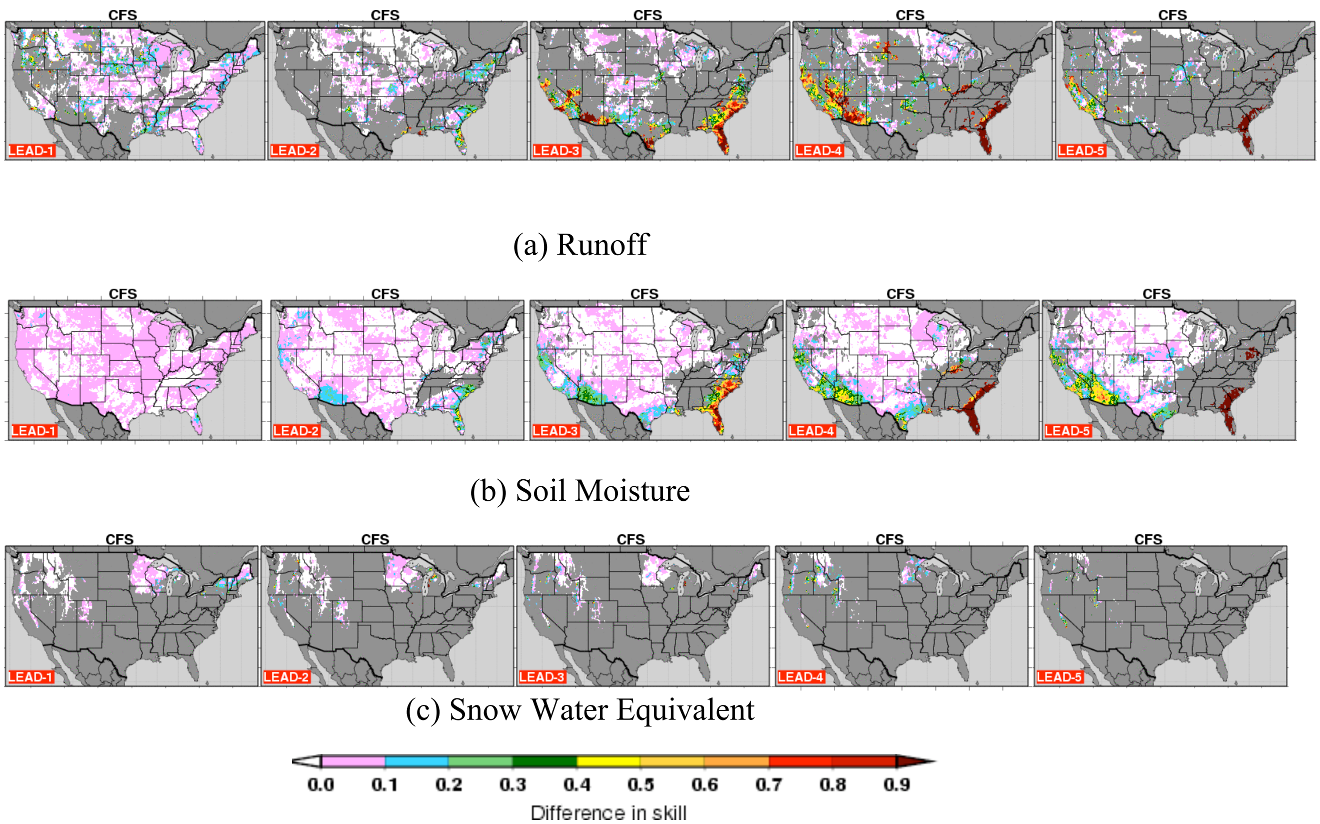
3. Results

In this section, we first present the difference in the hydrologic forecast skill resulting from VIC forced with statistically downscaled CFS precipitation and temperature forecasts relative to ESP forecasts made with VIC. The ESP method derives its hydrologic forecast skill solely from knowledge of the initial hydrologic conditions (IHCs), hence the difference between ESP and downscaled CFS skill provides a basis for estimating the value of CFS for hydrologic forecast applications. We then assess how dynamical downscaling of CFS via multi-RCMs compares with statistical downscaling of CFS in terms of hydrologic forecast skill. In all cases, we assert hydrologic forecast skill improvements only when the results are statistically significant (for differences from the benchmark ESP) at 90% confidence level. We also highlight those regions and lead-times for where the hydrologic forecast skill derived from using statistically (or dynamically) downscaled CFS forecasts is statistically different than the skill derived from the ESP method. We also compare the skill of each individual RCM against the multi-RCM ensemble average (Multimodel) and the RCMs that displays the highest hydrologic forecasts skill for any given grid cell and lead-time (Best Model).

3.1 Statistically downscaled CFS-based vs. ESP hydrologic forecast skill

3.1.1 Runoff (RO) forecasts:

Fig. 5.2 (a) shows the difference between the forecast skill of monthly total RO derived from statistically downscaled CFS forecasts and the ESP method, at lead times of one to five months. For the regions in grey, hydrologic forecast skill derived from the use of CFS is not statistically significantly (90% confidence interval) different from ESP.



(a) Runoff

(b) Soil Moisture

(c) Snow Water Equivalent

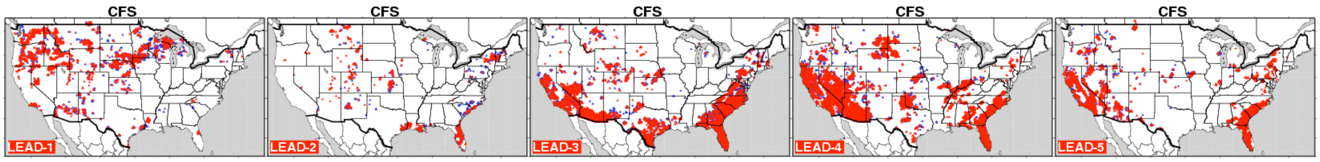
Figure 5.2: The difference in (a) runoff (b) soil moisture and (c) snow water equivalent forecast skill (measured as correlation between ensemble mean forecast and observations) derived from statistically downscaled CFS forecasts and the ESP method. Only those regions where the skill of hydrologic forecasts derived from CFS is significant at 90% confidence level are shaded. The regions in white indicate degradation of skill in downscaled CFS forecasts relative to ESP and non-white colors show improvement in skill relative to ESP method. Gray areas indicate no statistically significant skill derived from CFS forecasts.

Regions in white color show degradation of hydrologic forecast skill for CFS relative to ESP, whereas non-white colors depict improvement in skill relative to ESP. As shown in *Yoon et al.*, [2012], the CFS precipitation forecast skill (of the ensemble mean forecast) at lead-1 month is significant mainly only over the southwestern, north, southeastern, and parts of the north-central U. S., whereas the temperature forecast skill at lead-1 is significant over the entire northern part of the country. However, significant improvements in runoff forecast skill at lead-1 are sparse and generally limited to the mountainous western U.S. and north central U. S. (Fig. 5.2 (a) and Fig. 5.3 (a)). Improvements in runoff forecast skill using CFS are most apparent at leads of 3, 4 and 5 months over major parts of California, the southwestern mountainous regions, and the Southeastern U. S. (Fig. 5.2 (a)). In most cases those improvements in skill are significant at the 90% confidence level (Fig. 5.3 (a)). The improvement in runoff forecast skill at relatively long leads can be attributed to CFS precipitation skill "rebound" (Guo et al. 2011, 2012) (also shown in (Yoon et al. 2012)) as well as to the low ESP skill at longer lead time (leaving more room for improvement in RO forecast skill at higher lead times than at short lead times).

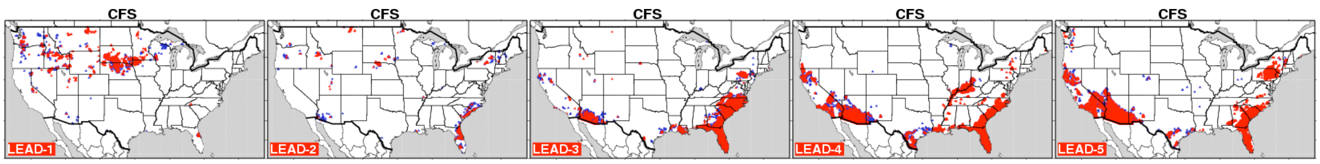
3.1.2 Soil Moisture (SM) forecasts:

Figs. 5.2 (b) and 5.3 (b) show the differences and their significance levels in the SM forecast skill derived by using statistically downscaled CFS and ESP methods. There are no regions in grey at lead-1 month, which indicates that CFS results in significant skill improvements across the CONUS (probably in part due to lower natural variability of soil moisture relative to runoff). However as observed in (Shukla and Lettenmaier 2011), this significant SM forecast skill across the CONUS, at short lead time (e.g. lead-1 to -2 months) is mainly derived from the knowledge of the IHCs (particularly in winter and spring months). This feature results in small room for improvement in skill through use of CFS, which is why the differences in SM forecast skill derived from CFS and ESP are nominal (< 0.1), even if statistically significant, at 1 month lead, across the country (Fig.

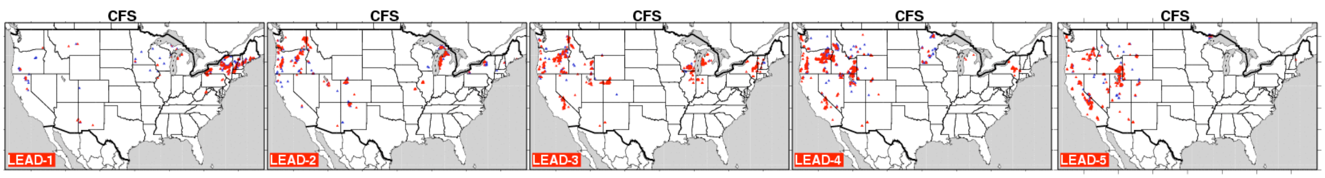
5.2 (b)). Nonetheless, there are some regions in mountainous northwestern U. S. and



(a) Monthly Runoff



(b) Soil Moisture



(c) Snow Water Equivalent

Figure 5.3: Significance levels of the difference in (a) runoff (b) soil moisture and (c) snow water equivalent forecast skill derived from statistically downscaled CFS forecasts relative to ESP method (measured as correlation between ensemble mean forecast and observations). Significance levels are shown only for those regions where the hydrologic forecast skill derived by statistically downscaled CFS forecast is significant at 90% confidence level. (Red color shows 95% significance whereas blue color shows 90% significance)

North central U. S. where the difference between the SM forecast skill derived from CFS and ESP, at 1-month lead is significant at 90 and 95% confidence level (Fig 5.3 (b)). Similar to the case of runoff forecast skill, the improvement in SM forecast skill for CFS relative to ESP method is also high (Fig. 5.2 (b)) and significant (Fig. 5.3 (b)) at leads-3, -4 and -5 months over the southwestern and southeastern U.S. Again this improvement in skill is the result of both the CFS precipitation forecast skill and low ESP skill.

3.1.3 Snow Water Equivalent (SWE) forecasts:

Figs. 5.2 (c) and 5.3 (c) show the improvement in forecast skill of SWE derived by using statistically downscaled CFS forecasts and the ESP method. In this case we focus on those regions only where the long term mean SWE is greater than 10 mm. Aside from some parts of the Northeast, for most regions the difference in SWE forecast skill at 1-month lead is either < 0 (degradation in skill) or nominal (<0.1). Nevertheless, at leads -3, -4 and -5 months there are some regions in the mountainous western U. S. where the improvement in SWE forecast skill is significant (Fig. 5.3 (c)). This improvement in SWE forecast skill at the end of the spring could be important for water supply during summer months over the mountainous western U.S.

3.2 Hydrologic forecast skill using dynamically vs .statistically downscaled CFS

In this section we evaluate the difference in hydrologic forecast skill derived from dynamically downscaled and bias-corrected multi-RCM forecasts and the statistically downscaled CFS forecasts (Fig. 5.4-5.9). We show the relative improvement in hydrologic forecast skill for individual RCMs as well as multi-RCM ensemble averages (Multimodel) and the skill of the RCMs with the highest skill (Best Model)

3.2.1 Runoff forecasts

Fig. 5.4 shows the difference in the runoff forecast skill derived from bias-corrected dynamically downscaled relative to statistically downscaled CFS forecasts. The difference in skill for each individual RCM is shown in top seven rows in the figure (for leads 1-5 months) and the eighth row shows the skill difference for Multimodel; the final row shows the highest skill among each individual RCMs. The regions shown in grey do not have statistically significant skill differences at 90% confidence level (that is, the hydrologic forecast skill derived from dynamically downscaled CFS forecasts is not significant at 90%). Fig. 5 shows those regions where the runoff forecast skill derived from dynamically downscaled CFS forecasts is statistically different from the statistically downscaled CFS forecasts at 95% (red colors) and 90% (blue colors) confidence level.

Where there is an improvement in dynamically relative to statistically downscaled CFS-derived forecasts, the improvement is mostly nominal (generally less than 0.2). Although overall most RCMs are in general agreement, a few RCMs do stand out with local improvements in skill as large as about 0.5 relative to statistically downscaled CFS. The hydrologic forecasts skill obtained from Multimodel is generally higher than the skill of statistically downscaled CFS (Fig. 5.4), hence there are fewer regions shown in white (degradation of skill) (compare row 8 of Figure 5.4 with rows 1-7 of the same figure). Additionally the highest skill among all the individual RCMs (Best Model) is almost always equal to or higher than the Multimodel skill. For example, at lead-1 over the Southwestern U. S., Best Model shows an improvement in runoff forecast skill of as much as 0.5 relative to statistically downscaled CFS forecasts, whereas the Multimodel-based improvement in skill is less than 0.2 (and also restricted to a much smaller domain). This indicates that over certain regions some RCMs perform much better than other RCMs Best Model also shows appreciable improvement over parts of California and the Southeast, mainly at leads 3-4, which is of practical importance because this is a location where statistically downscaled CFS forecasts show large improvements relative to ESP. As shown in Fig. 5.5 the Best Model shows more spatially widespread statistically significant improvements in hydrologic forecast skill relative to statistically downscaled CFS at all leads than do any individual model or Multimodel. Those improvements are mainly apparent over the mountainous Western U.S. and north central/Great Plains regions.

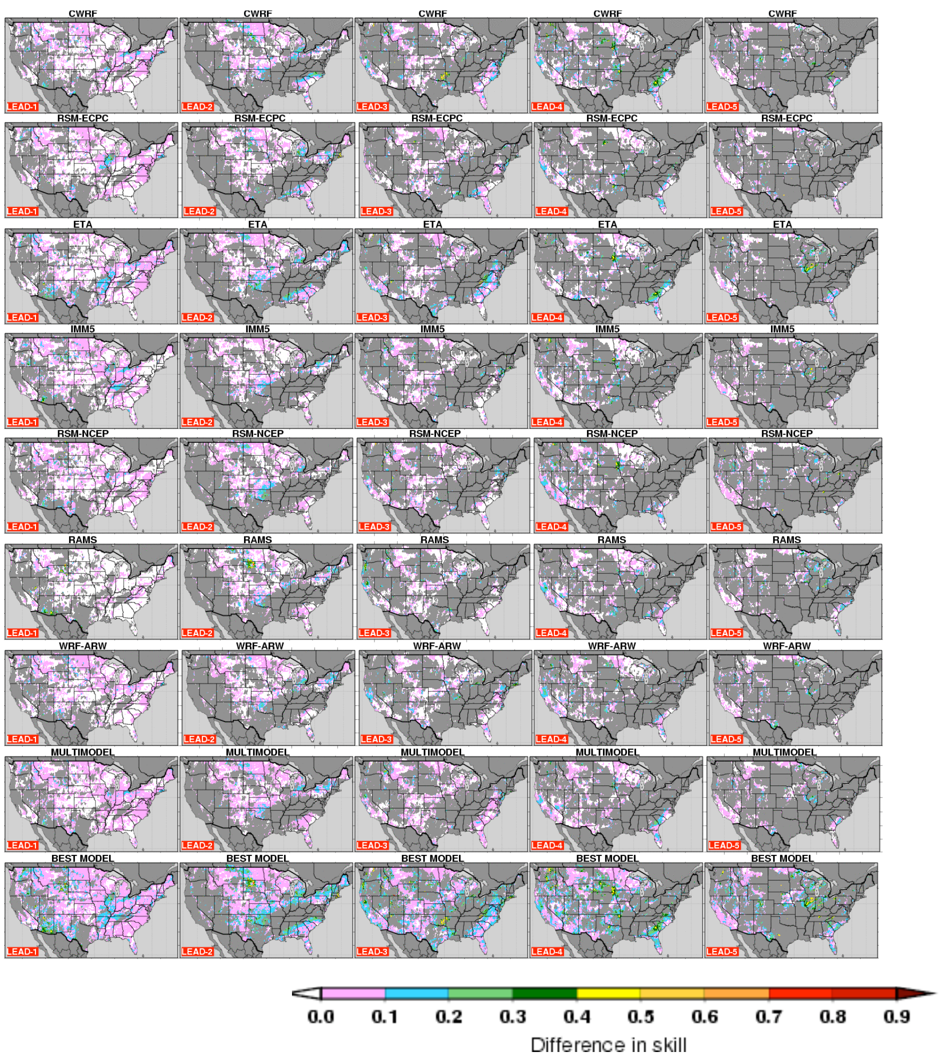


Figure 5.4: The difference in runoff forecast skill derived from dynamically and statistically downscaled CFS forecasts. Each of the first seven rows represent the runoff forecast skill (correlation between ensemble mean forecast and observations) obtained from the RCMs used in the MRED project, individually. The last two rows represent the skill of Multimodel average (Average of all RCMs and all ensembles) and of the RCM

(ensemble mean) with the highest runoff forecast skill for any given grid cell and lead-time. Only those regions are shaded where the skill is significant at 90% level.

3.2.2 Soil moisture forecasts

Fig. 5.6 shows improvements in SM forecast skill when dynamically downscaled CFS forecasts are used relative to simple statistically downscaled forecasts at 1- to 5-months lead. At 1-month lead, SM forecast skill improvements are significant across the CONUS (hence no grey regions), however the difference in forecast skill relative to statistically downscaled CFS forecasts is small (i.e. < 0.1) or less than 0 (degradation of skill) in most cases. This nominal difference could be due to the fact that the baseline skill (i.e. the skill derived from using statistically downscaled CFS forecasts) is high (due to high contributions from the IHCs toward SM forecast skill), leaving little room for improvement (e.g. correlation values can be as large as 1, so if the baseline skill is 0.9 the improvement in skill cannot be more than 0.1). Similar to runoff forecast skill, Best Model is almost always better than Multimodel, and shows at least some improvement across the country (less area in white in Fig. 5.6).

Fig. 5.7 shows the statistical significance of the improvement in SM forecast skill for dynamical relative to statistical downscaling of CFS forecasts. There are some regions, mainly scattered over the mountainous northwestern and north-central U.S. where the improvement in skill for dynamical downscaling is significant at 95% and 90% confidence levels. Once again, the areas of improvement in skill are more widespread for the Best Model than Multimodel.

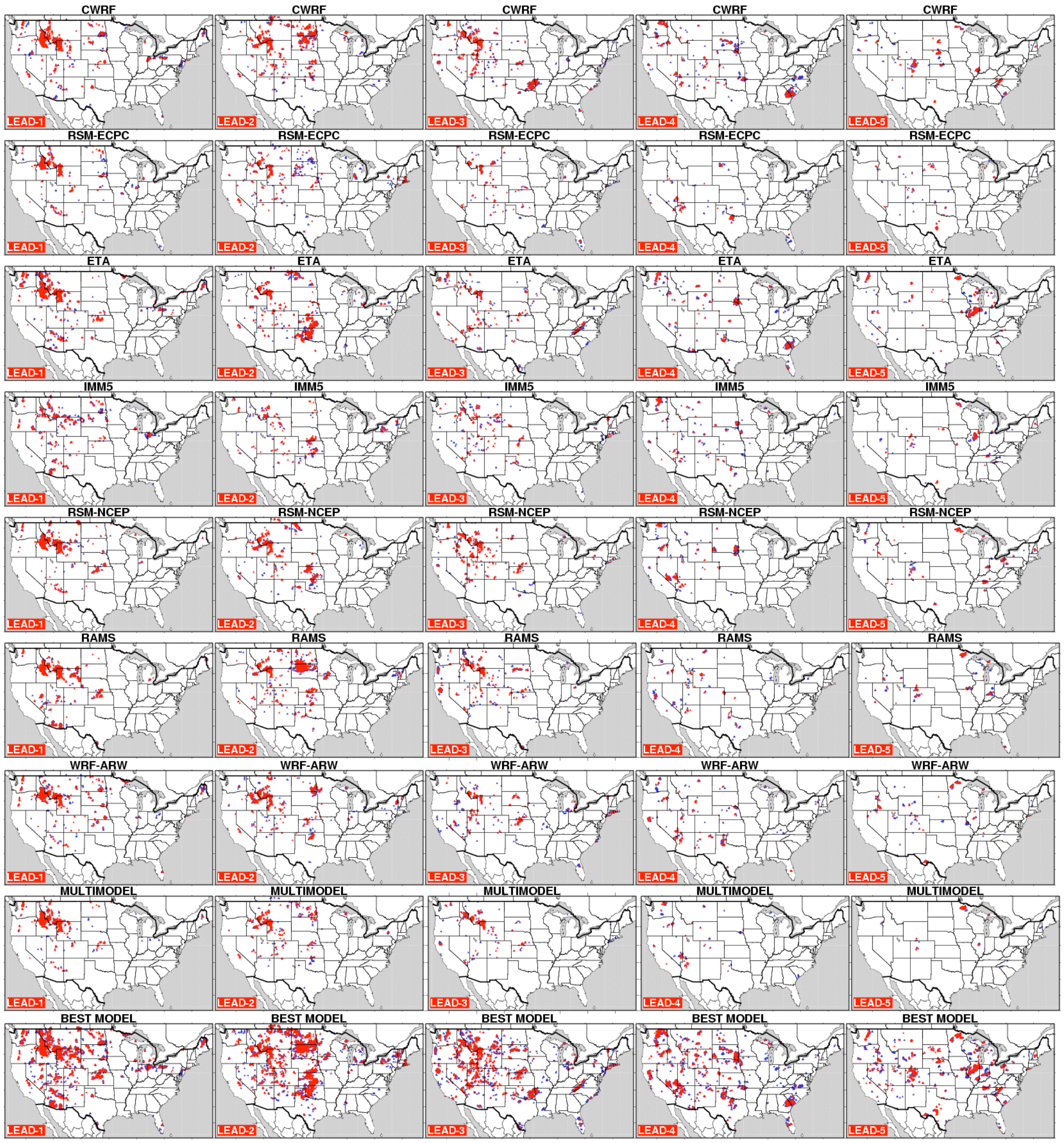


Figure 5.5: Significance level of the difference in runoff forecast skill (correlation of ensemble mean with observations) derived from dynamically and statistically downscaled CFS forecasts. Each of the first seven rows represent the skill obtained from individual RCMs used in the MRED project. The last two rows represent the skill of Multimodel average and of the RCM with the highest skill for any given grid cell and lead-time. Only those regions are considered where the hydrologic skill of the dynamically downscaled forecasts is significant at 90% level. (Red color shows 95% significance whereas blue color shows 90% significance)

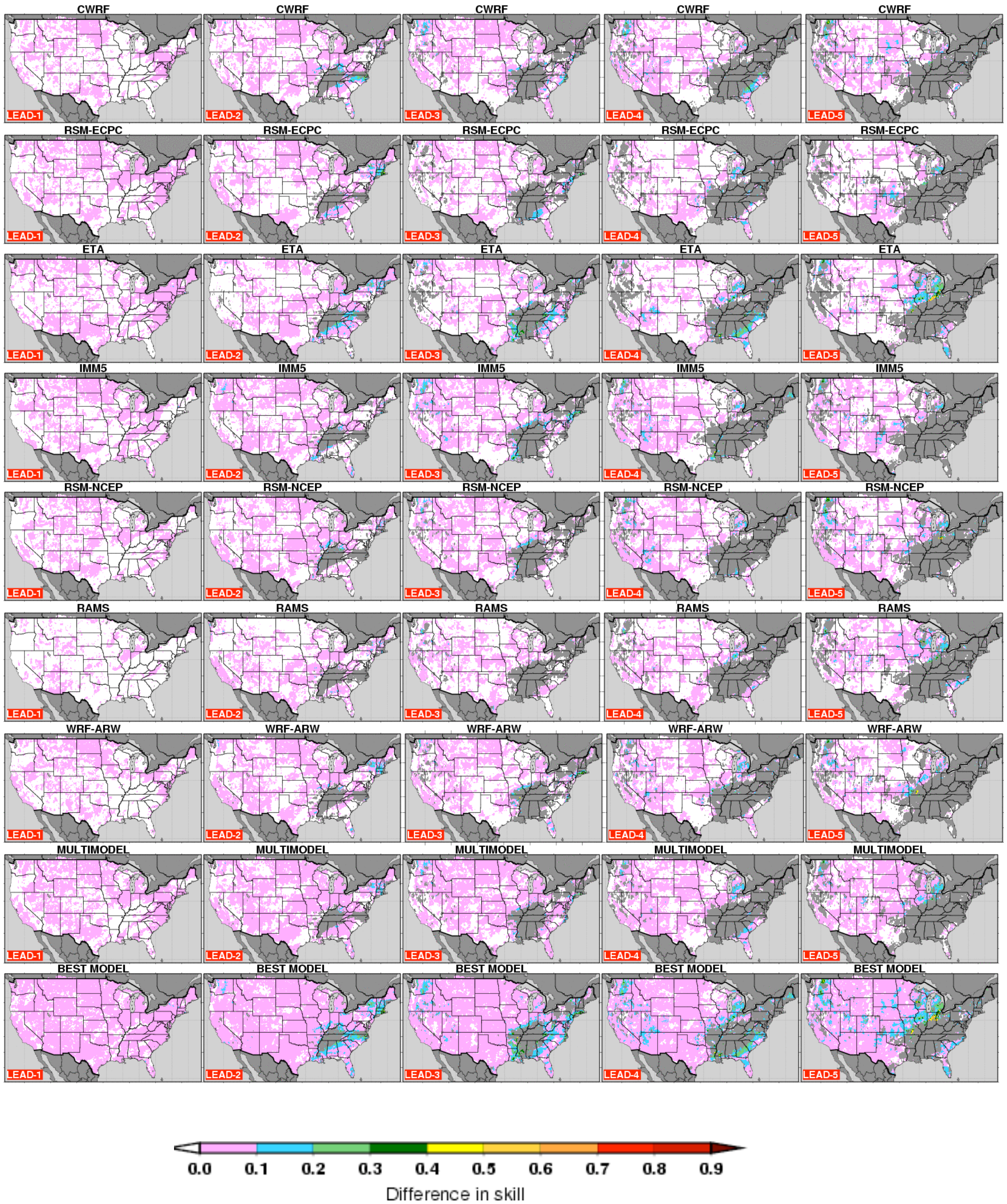


Figure 5.6: Same as Fig. 5.4 but for SM forecast skill

3.2.3 Snow Water Equivalent forecasts

Fig. 5.8 shows the difference in SWE forecast skill at leads 1 to 5 months obtained from dynamically and statistically downscaled CFS forecasts. We show those regions only where the SWE forecast skill is significant at 90% the level and the long term SWE mean is greater than 10 mm. Overall the improvement in SWE forecast skill obtained by dynamically relative to statistically downscaling CFS forecasts is negligible and is less than < 0.1 for most places, except in northern Wisconsin and the mountainous Upper Colorado River Basin, for certain RCMs. Multimodel shows positive skill differences for 1-month lead only. Best Model shows larger areas with positive differences, mainly over mountainous western U. S. regions at all lead times.

Fig. 5.9 highlights those regions where improvement in SWE forecast skill is significant at leads 1 to 5 months. The area of significant improvement in SWE forecast skill is relatively small and limited to the interior part of the mountainous western U.S.. Best Model consistently shows more regions of significant improvement in skill than does any individual model or Multimodel. Parts of the mountainous Upper Colorado River Basin show significant improvement in SWE forecast skill at lead-3 to -4 months for almost all the models. This improvement in SWE forecast skill could be valuable due to its contribution in summer runoff.

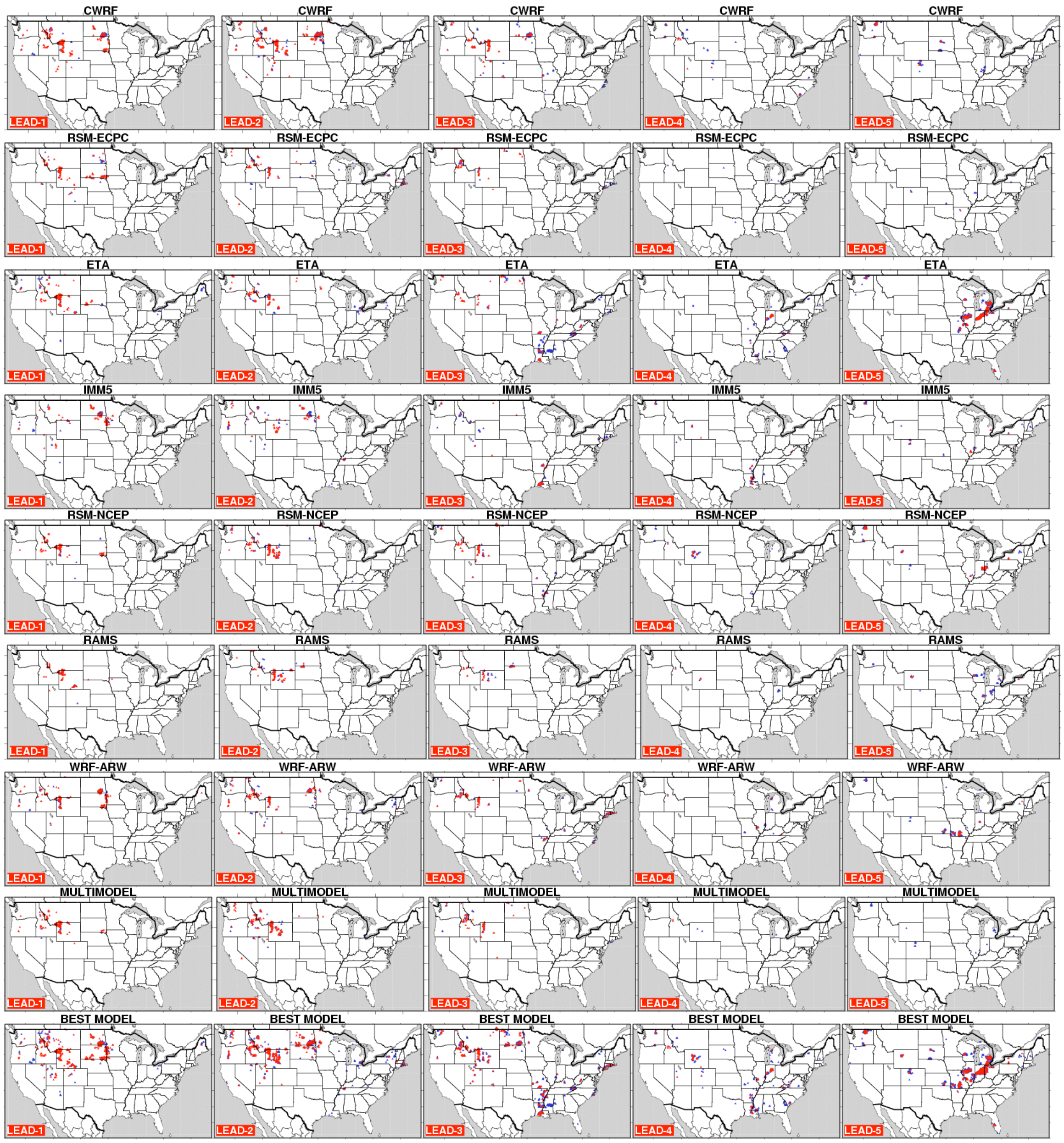


Figure 5.7: Same as Fig. 5.5 but for SM forecast skill.

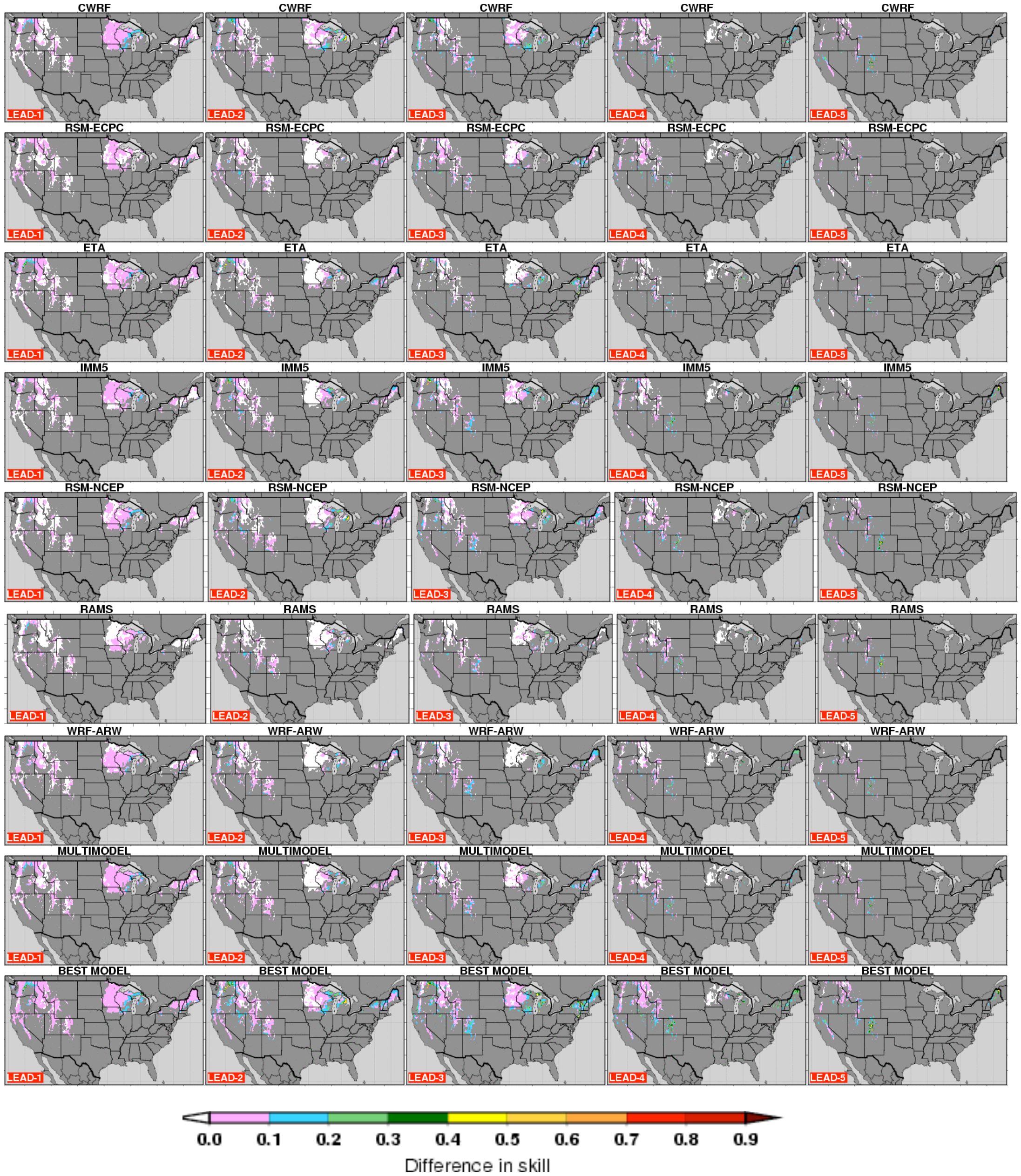


Figure 5.8: Same as Fig. 5.4 but for SWE forecast skill. Only those grid cells are considered where the long term mean SWE during the forecast period is greater than 10 mm.

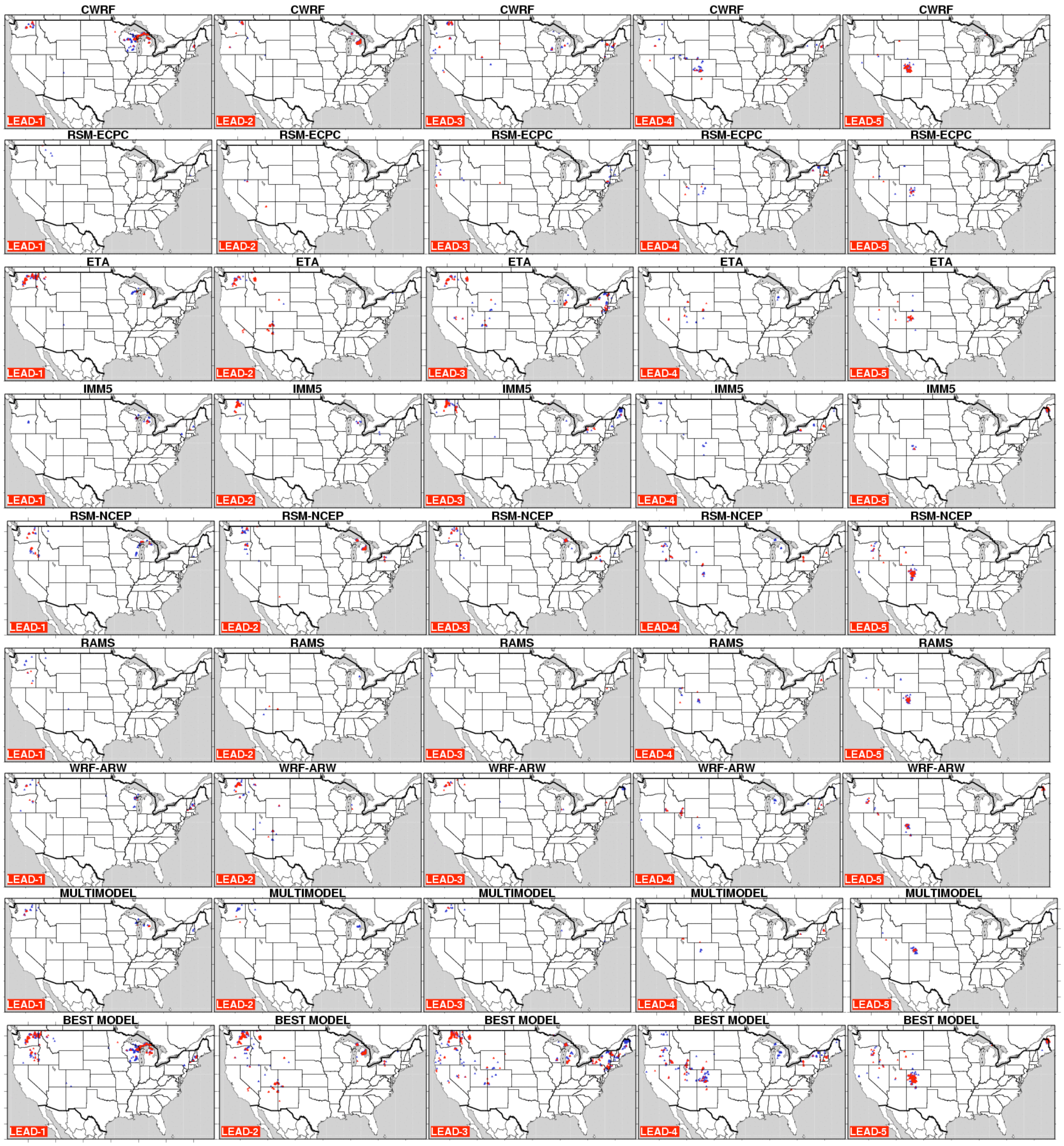


Figure 5.9: Same as Fig. 5.5 but for SWE forecast skill. Only those grid cells are considered where the long term mean SWE during the forecast period is greater than 10 mm.

3.3 Comparison of hydrologic skill of Best Model, Multimodel and statistically downscaled CFS over 13 major river basins/regions

In this section we show results of the comparison of the hydrologic skill derived from the Best model, Multimodel and statistically downscaled CFS over each of the 13 major CONUS river basins and regions as defined in *Maurer et al.*, [2002]. We performed this analysis to investigate the variability of the difference between the skill of each of the RCMs spatially across the CONUS and with lead-time. Figs. 5.10-5.12 show the distribution of the hydrologic skill for RO, SM and SWE respectively, as derived from the Best Model (green), Multimodel (blue) and CFS (red) for all the grid cells in each of the 13 regions/basins, using Box-whisker diagrams. If the median value of the hydrologic skill for the Best Model is higher than Multimodel, then over the given basin, some RCMs (or at least one) have higher skill than the other RCMs. Larger differences in median skill of multimodel and best model imply higher variability among RCMs.

As shown in Fig. 5.10, in terms of runoff forecast skill, Best Model has higher median skill (correlation) than Multimodel and CFS over almost all basins and lead times. In general, this difference is higher for higher lead times, which is understandable because at short lead times the hydrologic skill in each case (Best Model, Multimodel and CFS) is influenced by the IHCs. Some basins such as Lower Mississippi, Arkansas-Red, Ohio and South Central Gulf stand out because for those basins at higher lead time (lead-3 and -4 months) the median of Multimodel is lower than CFS; however, the Best Model median is much higher than Multimodel. This indicates that, over those regions, there is a large range of individual RCM skill, and careful selection of the RCMs for hydrological forecast applications is critical.

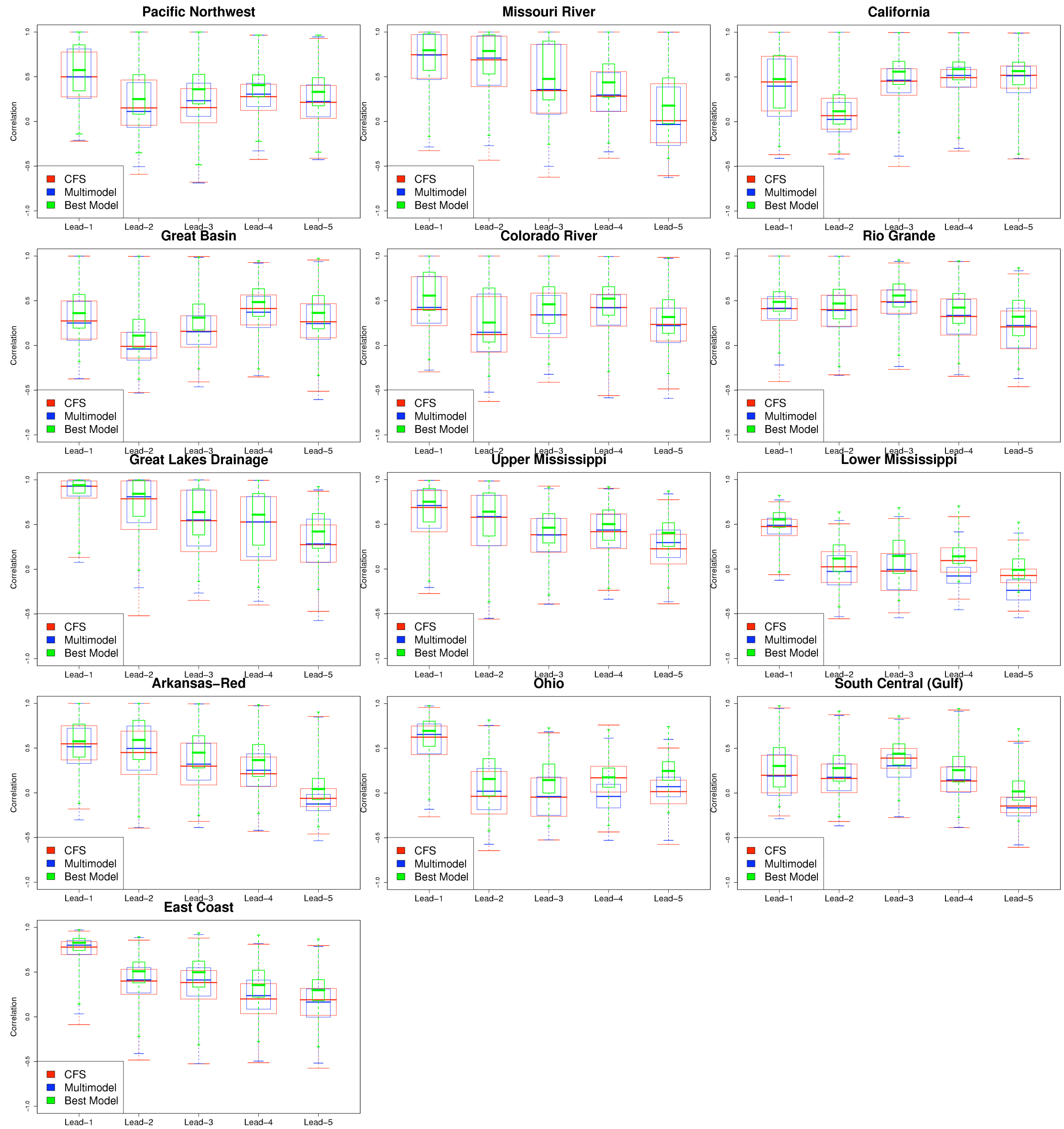


Figure 5.10: Spatial distribution of the runoff forecast skill for each of the 13 major basins/regions in (Maurer et al. 2002)), derived from statistically downscaled CFS forecasts (Red), Multimodel average of dynamically downscaled CFS forecasts (Green) and Best Model (Blue). (The width of the box and whisker for all three forecast skills has been kept different to avoid the overlap of one box over another).

Fig. 5.11 is similar to Fig. 5.10, but for SM forecasts. For SM forecasts, the difference between the median skill derived from Best Model, Multimodel and CFS at lead-1 is nominal at best. This is again due to the strong influence of the IHCs on SM forecasts at short lead times, which is why the skill of precipitation and temperature has little impact on the SM forecast skill. The difference between the SM forecast skill of Best Model (green), Multimodel (blue) and CFS (red) does increase with lead time; however, that difference is not as discernable as in the case of runoff forecasts. The difference is higher over eastern U.S. basins such as the Ohio, Lower Mississippi, Arkansas-Red and the East Coast than for the rest of the country. This could be attributed to the difference in the skill of RCMs, as well as smaller influence of IHCs in those regions relative to the rest of the country.

Fig. 5.12 shows the distribution of SWE forecast skill for basins/regions that receive snow (we considered only those basins where there at least 100 grid cells have greater than 10mm SWE for any given month) for Best Model (green), Multimodel (blue) and CFS (red). Best model almost always had greater skill than Multimodel and CFS. The difference in skills was lowest at lead-1 month, due to the influence of initial snow conditions. The basins/regions where the difference between Best Model, Multimodel and CFS skill was highest are the Colorado and Rio Grande Basins, and Great Lakes and East Coast regions.

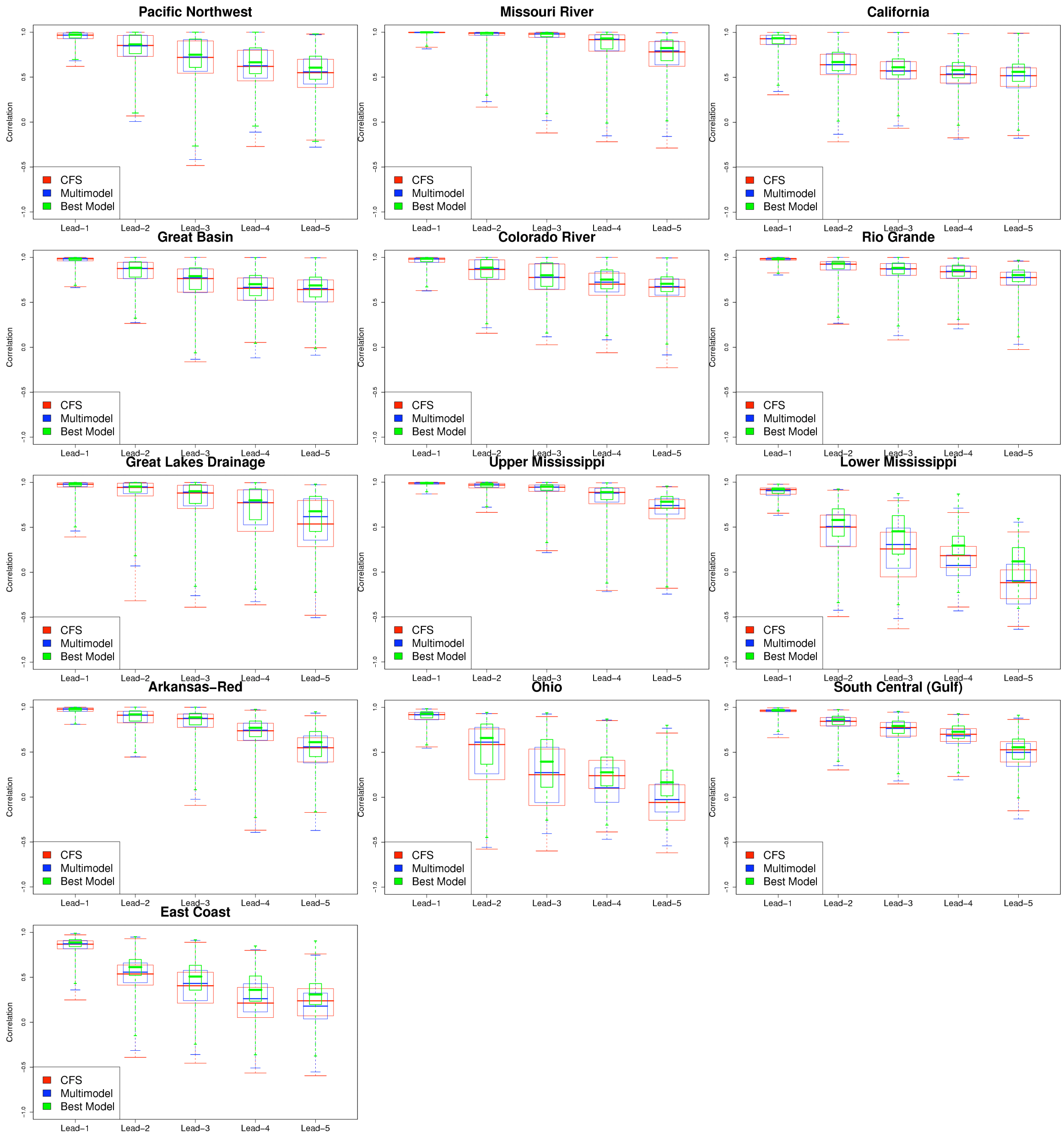


Figure 5.11: Same as Fig. 5.10 but for SM forecast skill.

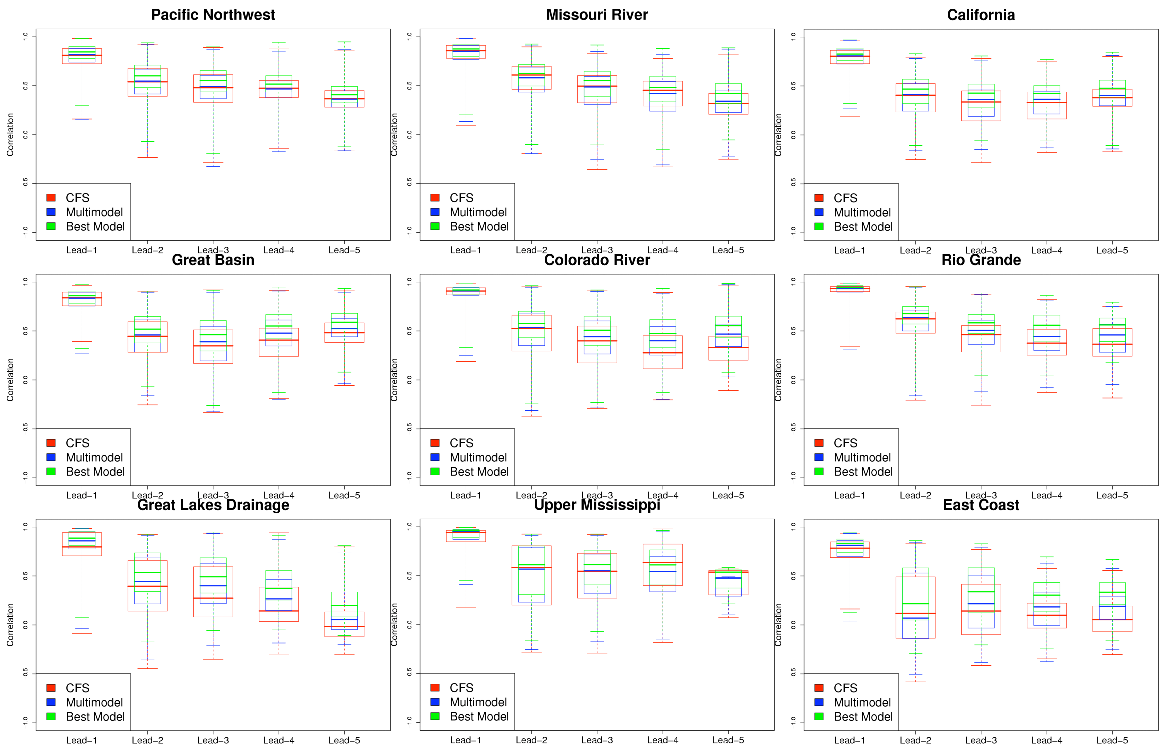


Figure 5.12: Same as Fig. 5.10 but for SWE forecast skill. Only those basins/regions are considered where there were at least 100 grid cells with > 10 mm long term mean SWE.

4. Summary and Conclusions:

We have investigated whether seasonal hydrologic forecasts forced with dynamically downscaled CFS winter seasonal forecasts (December - April) can be more skillful than the similar hydrologic forecast forced with statistically downscaled CFS forecasts. We conclude that:

(1) The winter seasonal CFS forecasts as used in this study do provide useful skill for hydrologic forecast application when evaluated relative to the ESP method. The greatest improvements in runoff and SM forecast skill, relative to ESP, were observed over the

southwestern and southeastern U.S. at lead-3 to -5 months. Significant improvements in SWE forecast skill were also found over parts of the mountainous Western regions at lead 3-5.

(2) Dynamically downscaled forecasts do increase the runoff forecast skill beyond what is achievable by statistically downscaled CFS forecasts, however the significant improvements in skill were mainly limited to parts of the mountainous western and north central U. S. In almost all cases and at all lead times across the CONUS the RCMs with the highest skill (Best Model) showed higher improvement in runoff forecast skill than the Multimodel average.

(3) In the case of SM forecasts the improvements in hydrologic forecast skill relative to the skill derived from statistically downscaled CFS forecasts were not as discernible as in the runoff forecasts. The differences between both sets of forecast skills were particularly low at 1-month lead. Significant improvements in skill were found in parts of the interior mountainous West and some parts of the north central U.S. Again, Best Model showed much more widespread improvement in skill than did Multimodel.

(4) Finally, the improvements in SWE forecast skill were sparse. Statistically significant improvements were mostly limited to the Great Lakes region, Colorado and interior northwestern mountainous regions.

As to the question of whether dynamical downscaling provides hydrologically useful information relative to what is achievable by performing a simple statistical downscaling of the global model, we find that the answer is mostly no. In general, the overall skill of dynamically downscaled climate forecasts is mostly limited by the skill of the global model in simulating large-scale climate phenomena (mainly in winter months). Some modest additional skill can be derived, however, through use of multiple RCMs, and choosing the RCM with the highest hindcast forecast skill. In the operational setting the "Best Model" for any given basin would be decided based on the RCMs' hindcast skill over a given basin or region. Use of a weighted multimodel average (where the weights could be proportionate, for instance, to the hindcast skill of each RCM for the given basin) rather than using a single RCM could be a better strategy.

It is important to emphasize that we have focused on hydrologic forecast skill at monthly/seasonal lead times. We have not investigated the ability of RCMs to forecast sub-daily or daily hydrologic extremes, and application that may better exploit the inherent capabilities of RCMs.

VI. CONCLUSIONS AND RECOMMENDATIONS

Although significant progress has been made towards developing and implementing new drought monitoring and prediction tools in recent decades, challenges still remain. This dissertation has sought to investigate how land surface models in conjunction with weather and climate forecasts can be used to address some of those challenges.

In Chapter I, I posed four questions that motivated the research reported in Chapters II-V. The first question was "*How well do drought management decisions based on an LSM-based Drought Monitoring System (DMS) compare with decisions made in practice during historical drought events*?" In Chapter II, I showed that a Drought Monitoring System (DMS) based on LSM indicators would have been able to detect drought onset and recovery up to 4 months in advance of official drought declarations in the case of four droughts in Washington State over the last 35 years.

The second question I posed in Chapter I is "*What are the relative contributions of the primary hydrologic moisture storage variables (i.e. snowpack, soil moisture) and the atmospheric forcings (i.e. precipitation and temperature) to seasonal drought prediction and how do they vary spatially and seasonally across the United States*?". In Chapter III, I showed that the initial hydrologic conditions (IHCs) (i.e. snowpack and soil moisture state) generally have the strongest influence on seasonal hydrologic/drought prediction at one-month lead, beyond which their influence decays at rates that depend on location, lead time, and forecast initialization date. The strongest contribution of IHCs was observed over the Western U.S. during spring and summer months.

The third question posed in Chapter I is *"Can seasonal drought prediction be improved by merging weather forecasts with seasonal climate forecasts, and to what extent?".* In Chapter IV, I showed that there is potential to improve monthly runoff and SM forecast skill beyond the IHC effect at lead-one (and up to three months in a few cases) by exploiting medium range weather forecast skill. In general the Great Plains, Midwest, parts of the Southwestern U.S. and the Eastern U.S. would benefit most during forecast periods starting in April through November. On the other hand, the mountainous Western U.S. would benefit most during forecast periods starting in November through the winter months (DJF).

Finally the fourth question posed in Chapter I was "*What is the value added in improvement of seasonal drought prediction through dynamical as contrasted with statistical downscaling of climate forecasts?*". In Chapter V, I showed that dynamically downscaled forecasts do somewhat increase hydrologic forecast skill (mainly runoff) during the winter season, beyond what is achievable by statistically downscaled CFS forecasts. However, improvements in skill were mostly limited to parts of the Western and the north central U.S.

This dissertation showed that land surface models are viable tools for drought monitoring and prediction, and despite the limited seasonal climate forecast skill, useful seasonal drought prediction skill can be achieved by exploiting the skill from the initial hydrologic conditions, and from medium range weather forecasts – neither of which is done in practice at present. During the course of this dissertation it became clear that additional work is warranted to address questions in several areas, which essentially would constitute extensions of the work reported here. These include:

1. How does the role of IHCs in seasonal drought prediction skill change during drought events when the IHCs are drier than normal?

2. Can dynamical downscaling of climate forecasts improve seasonal hydrologic forecasts during the summer season (when local scale features generally have greater influence over precipitation than in the winter season) relative to statistical downscaling?

I believe that the methods outlined in this dissertation are appropriate to address these questions. There are compelling motivations for doing so, both on scientific and practical bases, given the pervasive and costly – both in economic and human terms – implications of drought.

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Voisin, N., A. F. Hamlet, L. P. Graham, D. W. Pierce, T. P. Barnett, and D. P. Lettenmaier, 2006: The role of climate forecasts in western US power planning. J. Appl. Meteor., 45, 653–673.

Voisin, N., F. Pappenberger, D. P. Lettenmaier, R. Buizza, and J. C. Schaake, 2011: Application of a Medium-Range Global Hydrologic Probabilistic Forecast Scheme to the Ohio River Basin. Weather and Forecasting, 26, 425–446.

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Wilhite, D. A., and M. Buchanan-Smith, 2005: Drought as hazard: Understanding the natural and social context. D.A. Wihite (ed.) Drought and Water Crises: Science, Technology, and Management Issues, Taylor and Francis.

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Wood, A. W., A. Kumar, and D. P. Lettenmaier, 2005: A retrospective assessment of National Centers for Environmental Prediction climate model–based ensemble hydrologic forecasting in the western United States. J. Geophys. Res., 110, D04105.

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Wood, A. W., and D. P. Lettenmaier, 2008: An ensemble approach for attribution of hydrologic prediction uncertainty. Geophysical Research Letters, 35, L14401.

Wood, A. W., E. P. Maurer, A. Kumar, and D. P. Lettenmaier, 2002: Long-range experimental hydrologic forecasting for the eastern United States. J. Geophys. Res, 107, 4429.

Wood, A. W., L. R. Leung, V. Sridhar, and D. P. Lettenmaier, 2004: Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Climatic Change, 62, 189–216.

Xia, Y., K. E. Mitchell, M. B. Ek, B. Cosgrove, J. Sheffield, L. Luo, C. J. Alonge, H. Wei, J. Meng, B. Livneh, Q. Duan, and D. Lohmann, 2011a: Continental-Scale Water and Energy Flux Analysis and Validation for North-American Land Data Assimilation System Project Phase 2, Part 2: Validation of Model-Simulated Streamflow. J. Geophys. Res. J. Geophys. Res., 117, D03110, doi:10.1029/2011JD016051.

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Xue, Y., R. Vasic, Z. Janjic, F. Mesinger, and K. E. Mitchell, 2007: Assessment of dynamic downscaling of the continental US regional climate using the Eta/SSiB Regional Climate Model. J. Climate, 20, 4172–4193.

Yoon, J.-H., K. Mo, and E. F. Wood, 2011: Dynamic Model Based Seasonal Prediction of Meteorological Drought over the Contiguous United States. J. Hydrometeor,. http://dx.doi.org/10.1175/JHM-D-11-038.1.

Yoon, J.-H., L. R. Leung, and J. Correia Jr., 2012: Comparison of downscaled seasonal climate forecasts during cold season for the U.S. using dynamic and statistical methods. J. Geophys. Res,.(*In review*)

Zar, J. H., 1972: Significance testing of the Spearman rank correlation coefficient. Journal of the American Statistical Association, 578–580.

Zorita, E., and H. Von Storch, 2010: The analog method as a simple statistical downscaling technique: comparison with more complicated methods. J. Climate, vol. 12 (8), 2474-2489

CURRICULUM VITAE

EDUCATION

- **University of Washington**, Seattle, WA
  PhD in Civil and Environmental Engineering, 09/27/2006 – 06/09/2012
- **Indian Institute of Technology**, Kharagpur, India
  Masters in Water Resources Development and Management, 07/2003 – 06/2005
- **Chandra Shekhar Azad University of Agricultural and Tech.**, Kanpur, India
  Bachelors in Technology in Agricultural Engineering, 07/1999 – 06/2003

RESEARCH EXPERIENCE

University of Washington, Seattle, WA, 09/2006 –06/2012

Department of Civil and Environmental Engineering, ***Graduate Research Assistant***

Projects:

- "Using NOAA Climate Forecasts with Hydrologic Assessment to Reduce Drought Vulnerability and Improve Water Management in Washington State" Funded by NOAA-Sectoral Applications Research Program (SARP).
  - Participated in the development of a web-based drought monitoring system (DMS) for Washington State.
  - Transitioned the system to state-level water managers in Washington and to reservoir managers in the Yakima River basin.
  - Evaluated the performance of the DMS for reconstructing historical drought events in the state.
  - Developed a runoff -based drought indicator (Standardized Runoff Index) for monitoring hydrological drought.
  - Maintain the DMS on a daily basis.
- "Real-time Soil Moisture, Snow, and Runoff Products for Drought Assessment and Prediction in the Continental U.S." Funded by NOAA- Transition of Research Applications to Climate Services (TRACS).
  - Participated in the implementation of new drought assessment and prediction products to the University of Washington (UW)- Surface Water Monitor (SWM); an experimental national hydrologic monitor.
  - Examined the sources of differences between the UW-SWM and the National Centers for Environmental Prediction (NCEP)-Environmental Modeling Center (EMC)'s drought monitoring system.
  - Maintain the UW-SWM on a daily basis.
- "Seasonal Hydrologic and Drought Predictability Using the University of Washington Westwide Seasonal Hydrologic Forecast System" Funded by NOAA-

Climate Prediction Program for Americas (CPPA).

- Examined the relative contributions of the initial hydrologic conditions and the climate forecast skill in seasonal hydrologic and drought prediction skill in Conterminous United States (CONUS).
- Evaluated the value of medium range weather forecast skill to the seasonal hydrologic and drought prediction in the CONUS.
- Currently working on examining the relative value of dynamical vs. statistical downscaling of climate forecasts in terms of improvement in seasonal hydrologic and drought prediction skill.

École Polytechnique Fédérale De Lausanne, Lausanne, Switzerland, 10/2005-06/2006

School of Architecture, Civil and Environmental Engineering, ***Research Assistant***

Project:

- "COMMON Sense (Community-Oriented Management and Monitoring of Natural Resources through sensor network)".
  - Goal: To design and develop an integrated solution for agricultural management in the rural semi-arid areas of developing countries.
  - Participated in designing and conducting field and lab experiments to test the sensor network system to measure soil moisture.

Indian Institute of Technology, Kharagpur, l, 07/2003-06/2005

Department of Agricultural and Food Engineering, ***Graduate Research Fellow***

Project:

- "Modeling Sediment Transportation in Furrow Irrigation".
  - Designed a furrow irrigation system and conducted field experiments to monitor sediment transportation.
  - Developed a sediment transportation model based on the field experiments.

Central Institute of Agricultural Engineering, India

Summer Trainee

Project:

- "Watershed Management and Artificial Groundwater Recharge".
  - Determined reservoir capacity using topographic data.

PEER-REVIEWED PUBLICATIONS

- Mo, K. C., L. Chen, **S. Shukla**, T. Bohn, and D. P. Lettenmaier. 2012. Uncertainties in North American Land Data Assimilation Systems over the Contiguous United States. *J. Hydrometeor. (accepted).*
- **Shukla, S.**, and D. P. Lettenmaier. 2011. Seasonal hydrologic prediction in the United States: Understanding the role of initial hydrologic conditions and seasonal climate forecast skill. *Hydrol. Earth Syst. Sci.* 15, 3529-3538, doi:10.5194/hess-15-3529-2011.
- Muñoz Arriola, F., S. Rabadán, J. Humberto, M. Rocchiccioli, Heléne, **S. Shukla**, G. D. Reyes, A. L. Sánchez, and René. 2011. Surface hydrology in Grijalva river basin: Calibration of the Variable Infiltration Capacity model (VIC). *Aqua-LAC*. 3(1): 68 - 80.
- **Shukla, S.**, A. C. Steinemann, and D. P. Lettenmaier. 2011. Drought monitoring for Washington state: Indicators and Applications. *J. Hydrometeor.* 12: 66–83, 10.1175/2010JHM1307.1.
- Mishra, V., K. Cherkauer, and **S. Shukla**. 2009. Assessment of drought due to historic climate variability and projected future climate change in the Midwestern United States. *J. Hydrometeor.* 11: 46-68, 10.1175/2009JHM1156.1.
- **Shukla, S.** and A.W. Wood. 2008. Use of a standardized runoff index for characterizing hydrologic drought. *Geophys. Res. Letters*. 35: L02405, doi:10.1029/2007GL032487.

PUBLICATIONS (IN REVIEW/IN PREPARATION)

- **Shukla, S.**, N. Voision, and D. P. Lettenmaier. 2012. Value of medium range weather forecasts skill in seasonal hydrologic prediction. *Hydrol. Earth Syst. Sci.* 9, 1827-1857, doi:10.5194/hessd-9-1827-2012 (*in review*).
- Mo, K. C., L. Chen, **S. Shukla** and D. P. Lettenmaier. 2012. Agricultural Drought Prediction based on the Climate Forecast System version 2. (*to be submitted*).
- **Shukla, S.**, and D. P. Lettenmaier. 2012. The relative value of dynamically vs. statistically downscaled CFS seasonal forecasts for seasonal hydrological forecasting (*to be submitted*).
- **Shukla, S.**, J. Sheffield, E. F. Wood, and D. P. Lettenmaier. 2012. Relative contributions of initial hydrologic conditions and seasonal climate forecast skill to seasonal hydrologic prediction globally (*in preparation*).
- **Shukla, S.**, F. Muñoz Arriola, D. P. Lettenmaier and coauthors. 2012. Agricultural droughts in Mexico (*in preparation*).
- Safeeq, M., **S. Shukla**, V. Mishra, and G.E. Grant. 2012. Characteristics of drought under varying geology and snow dynamics. *Geophys. Res. Letters* (*in preparation*).

OTHER PUBLICATIONS/CONFERENCE PROCEEDINGS

- Munoz-Arriola, F., **S. Shukla**, T. Bohn, C. Zhu, B. Livneh, D.P. Lettenmaier, R. Lobato-Sanchez and A. Wagner-Gomez. 2009: Forecasting Surface Hydrology in North America, *Border Climate Summary*, July 13th: 1-5.
- **Shukla, S.**, M. Damodhara Rao, N.S. Raghuwanshi, and R. Singh. 2006. A simple mathematical model for simulating water flow in furrow irrigation. International Conference in University of Agriculture, Faisalabad, Pakistan.
- Mishra, V., N.S. Raghuwanshi, **S. Shukla**, J. Cullmann, and G.H. Schmitz. 2006. Understanding runoff generation process through scaling of flood peaks. International Conference in University of Agriculture, Faisalabad, Pakistan.
- **Shukla, S.**, M. Damodhara Rao, R. Singh, N.S. Raghuwanshi, G.H. Schmitz, and F. Lennartz, 2005. Modeling temporal variation of soil erosion in furrow irrigation. Proceedings of International Symposium on Recent Advances in Water Resources Development and Management, IIT-Roorkee, India, 2005.
- Mishra, V., N. S. Raghuwanshi, **S. Shukla**, and G. H. Schmitz. 2005. Regional flood frequency analysis of Freiberger Mulde catchment by L-moments. Proceedings of International Symposium on Recent Advances in Water Resources Development and Management. IIT-Roorkee, India, 2005.

SELECTED PRESENTATIONS/POSTERS

- **American Geophysical Union (AGU) Fall Meeting**
  - **Shukla, S.**, J. Sheffield, E. Wood and D. P. Lettenmaier. 2011. Relative contributions of initial hydrologic state and climate forecast skill to seasonal hydrologic prediction globally. AGU Fall Meeting, San Francisco, CA, Dec-2011.
  - **Shukla, S.** and D. P. Lettenmaier. 2010. Relative contributions of initial hydrologic state and climate forecast skill to seasonal drought prediction. AGU Fall Meeting, San Francisco, CA, Dec-2010.
  - **Shukla, S.**, A. C. Steinemann, and D. P. Lettenmaier. 2009. A drought prediction and monitoring system to reduce drought vulnerability and improve water management in Washington State. AGU Fall Meeting, San Francisco, CA, Dec-2009.
  - **Shukla, S.** and A. W. Wood. 2007. Application of LDAS-era land surface models for drought characterization and prediction in Washington State. AGU Fall Meeting, San Francisco, CA, Dec-2007.
  - Wood, A., **S. Shukla**, J. Vano and A. C. Steinemann. 2007. Connecting climate, hydrologic, and drought predictions to water resources management in Washington State. AGU Fall Meeting, San Francisco, CA, Dec-2007.
  - Wood, A., A. C. Steinemann, D. Alexander and **S. Shukla**. 2006. Applications of Medium Range To Seasonal/Interannual Climate Forecasts For Water Resources Management In the Yakima River Basin of Washington State. AGU Fall Meeting, San Francisco, CA, Dec-2006.

- **American Meteorological Society (AMS) Annual Meeting**
  - Mo, K. C., L. Chen, **S. Shukla** and D. P. Lettenmaier. 2012. Uncertainties in North American Land Data Assimilation Systems over the Contiguous United States. 92nd AMS Annual Meeting, New Orleans, LA, Jan. 2012.
  - **Shukla** S., and D. P. Lettenmaier. 2012. The Relative Value of dynamically vs. statistically downscaled CFS seasonal forecasts for seasonal hydrological forecasting. 92nd AMS Annual Meeting, New Orleans, LA, Jan. 2012.
  - **Shukla, S.** and D. P. Lettenmaier. 2011. Evaluating the role of weather forecast skill in seasonal drought prediction. 91st AMS Annual Meeting, Seattle, WA, Jan. 2011.
  - **Shukla, S.**, A. C. Steinemann and D. P. Lettenmaier. 2011. Drought characterization: Indicators and Decision-Making. 91st AMS Annual Meeting, Seattle, WA, Jan 2011.
  - Munoz-Arriola, F., **S. Shukla**, L. Luo, A. Munoz-Orozco, and D.P. Lettenmaier. 2009. Drought predictability in Mexico. 89th AMS Annual Meeting, Phoenix, AZ, Jan. 2009.
  - Wood, A., N. Voision, and **S. Shukla.** 2008. Medium-range ensemble hydrologic forecasting for western Washington State. 88th AMS Annual Meeting, New Orleans, LA, Jan. 2008.

- **NOAA's Climate Diagnostics and Prediction Workshop (CDPW)**
  - **Shukla, S.**, N. Voision, and D. P. Lettenmaier. 2011. Worth of medium range weather forecast skill in seasonal hydrologic and drought prediction. 36th Annual CDPW, Fort Worth, TX, Oct. 2011.
  - **Shukla, S.**, F. Munoz-Arriola, T. Bohn, A. C. Steinemann, and D. P. Lettenmaier. Assessment of ESP-based drought prediction skill. 33rd Annual CDPW, Lincoln, NE, Oct. 2008.

- **World Climate Research Programme (WCRP) Open Science Conference**
  - **Shukla, S.**, and D. P. Lettenmaier. 2011. Drought characterization using the University of Washington Surface Water Monitor. WCRP Open Science Conference. Denver, CO, Oct. 2011.
  - **Shukla, S.**, K. C. Mo and D. P. Lettenmaier. 2011. Uncertainties in the North American Land Data Assimilation Systems. WCRP Open Science Conference. Denver, CO, Oct. 2011.

- **Invited Presentation**
  - **Shukla, S.** and A. W. Wood. 2008. Application of a land surface model for drought monitoring and prediction in Washington State. The Water Center Annual Review of Research, Seattle, WA, Feb. 2008.

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- **Miscellaneous Conferences/Meetings**
    - **Shukla, S.**, A.C. Steinemann and D. P. Lettenmaier. 2010. Evaluation of a NOAA climate forecasts based drought prediction system for Washington State. Hydrology in the 21st Century: Links to the past and a vision for the future, Seattle, WA, March 2010.
    - Munoz-Arriola, F., **S. Shukla**, A. Hamlet, and D. P. Lettenmaier. 2009. Idaho climate and water forecast for 2010. CIG Annual Fall Forecast Meeting, Boise, ID, Oct. 2009.
    - Munoz-Arriola, F., **S. Shukla**, and D. P. Lettenmaier. 2009. Global climate and hydrological predictability. Foro de Expectativas del Sector Agroalimentario y Pesquero, Mexico City, Mexico, March 2009.
    - **Shukla, S.**, D. Alexander, A. C. Steinemann, and A. W. Wood. 2007. Applications of medium range to seasonal/interannual climate forecasts for water resources management in the Yakima River basin of Washington State. NOAA- Climate Prediction Applications Science Workshop (CPASW), Seattle, WA, March 2007.

AWARDS AND ACHIEVEMENTS

- Recipient of Earth System Science Interdisciplinary Center (ESSIC) travel award to attend NOAA's 36th Climate Diagnostics and Prediction Workshop (CDPW) at Fort Worth, TX. 2011
- Invited (with full financial support) by The Abdus Salam International Centre for Theoretical Physics (ICTP) to attend International Summer School on Hydrological Drought & Global Change in Trieste, Italy. 2008
- Recipient of "Best Student Oral Presentation" award at the Water Center Annual Review of Research, Seattle, WA. 2008
- Recipient of a NOAA student travel grant to attend Climate Diagnostics and Prediction Workshop in 2008.
- Recipient of departmental student travel grants to attend and present my research at American Geophysical Union fall meeting in 2007 and 2010.
- Recipient of Federal Commission Scholarship by the Swiss Government for the pursuit of a nine-month research project in EPFL at Lausanne, Switzerland. (The scholarship is awarded to students from selected countries. 2 students were chosen from India). 2005-2006
- Achieved 98.31 percentile in the Graduate Aptitude Test for Engineering (GATE)-2003 common entrance test conducted by all seven Indian Institute of Technology for post-graduation/masters studies.
- Recipient of Ministry of Human Resources and Development Scholarship for the pursuit of a master's degree at the Indian Institute of Technology. 2003-2005

ACADEMIC SERVICE

- Reviewer for journals such as *Hydrologic and Earth System Sciences*, *Journal of Hydrometeorology*, and *Water*.
- Facilitated the implementation of a mentorship program for the students at my

department, as the secretary of the Chi Epsilon Honor Society. 2009-2011
- Volunteered at Engineering Open House, CEE career fair, and graduate student orientation.
- Participated in the organization of and attended first “Hydrologic modeling and Forecast” workshop at Instituto Mexicano De Tecnología Del Agua (IMTA), México. 2008

CLUBS AND AFFILIATIONS

- Student member, American Water Resources Association, UW Chapter.
- Member, Chi Epsilon Honor Society, UW Chapter.
- Secretary/Treasurer, Chi Epsilon Honor Society, UW Chapter.
- Student member, American Geophysical Union.
- Student member, American Meteorological Society.