Hydrol. Earth Syst. Sci. Discuss., 10, 1987–2013, 2013
www.hydrol-earth-syst-sci-discuss.net/10/1987/2013/
doi:10.5194/hessd-10-1987-2013

Hydrology and Earth System Sciences
Discussions
Open Access

On the sources of global land surface hydrologic predictability

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Received: 26 January 2013 – Accepted: 28 January 2013 – Published: 12 February 2013

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

Abstract

Global seasonal hydrologic prediction is crucial to mitigating the impacts of droughts and floods, especially in the developing world. Hydrologic prediction skill at seasonal lead times (i.e. 1–6 months) comes from knowledge of initial hydrologic conditions (IHCs – primarily the state of initial soil moisture and snow) and seasonal climate forecast skill (FS). In this study we quantify the contributions of IHCs and FS to seasonal hydrologic prediction skill globally on a relative basis throughout the year. We do so by conducting two model-based experiments using the Variable Infiltration Capacity (VIC) macroscale hydrology model, one based on Ensemble Streamflow Prediction (ESP) and another based on Reverse-ESP (rESP), both for a 47 yr reforecast period (1961–2007). We compare cumulative runoff (CR), soil moisture (SM) and snow water equivalent (SWE) forecasts obtained from each experiment with a control simulation forced with observed atmospheric forcings over the reforecast period and estimate the ratio of Root Mean Square Error (RMSE) of both experiments for each forecast initialization date and lead time. We find that in general, the contributions of IHCs are greater than the contribution of FS over the Northern (Southern) Hemisphere during the forecast period starting in October and January (April and July). Over snow dominated regions in the Northern Hemisphere the IHCs dominate the CR forecast skill for up to 6 months lead time during the forecast period starting in April. Based on our findings we argue that despite the limited FS (mainly for precipitation) better estimates of the IHCs could lead to improvement in the current level of seasonal hydrologic forecast skill over many regions of the globe at least during some parts of the year.

1 Introduction

Drought and floods are among the most important natural disasters globally in terms of socio-economic losses (Dilley et al., 2005; Wilhite, 2000). Since 2010, a record number of extreme drought and flood events have impacted many regions across the globe

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(Blunden and Arndt, 2012; Blunden et al., 2011) and caused enormous losses. For example, according to the US National Climate Data Center, the number of deaths and total economic losses (adjusted to 2012 dollars) attributed to drought (including wild fires) and flooding, in 2010 and 2011 alone, was at least 209 and 33.6 billion US dollars, respectively (http://www.ncdc.noaa.gov/billions/).

Some recent studies have linked changes in the frequency and severity of natural hazards to climate Change (Lau and Kim, 2012; Peterson et al., 2012; Trenberth and Fasullo, 2012) and projected a higher likelihood of occurrence of these kinds of extreme events in the future in many regions of the globe (Burke et al., 2006; Dai, 2011; Hirabayashi et al., 2008; Kundzewicz et al., 2010; Sheffield and Wood, 2008). Global climate change and unprecedented population growth as well as industrial development has put global water resources in ever greater stress (Oelkers et al., 2011; Oki and Kanae, 2006; Vörösmarty et al., 2000). Therefore the stakes for the implementation of global hydrologic and drought prediction systems to provide outlooks for water resources conditions globally in real-time are rising. Development of a Global Drought Information System was a key recommendation of a World Climate Research Program workshop "*Drought Predictability and Prediction in a Changing Climate*" held in 2011 (Heim and Brewer, 2012; Pozzi et al., 2013). Thus far though, the implementation of a global seasonal hydrologic prediction system has largely been elusive notwithstanding major strides in the last two decades or so in the development of large scale hydrologic models (Liang et al., 1994; Mitchell, 2004; Wang et al., 2009) and improvement in seasonal climate forecast skill (Barnston et al., 2010; Goddard et al., 2001, 2003; Palmer et al., 2004; Saha et al., 2006; Yuan et al., 2011).

Hydrologic prediction skill at seasonal lead times (1 to 6 months) is derived from knowledge of initial hydrologic conditions (IHCs; including soil moisture and snow water storage) and seasonal climate forecast skill (FS). In the past numerous studies have investigated the contributions of the IHCs and/or FS in seasonal hydrologic predictability over different regions of the globe. For example, Maurer and Lettenmaier (2003) used multiple regression to identify the sources of hydrologic predictability in the Mississippi

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River basin and found that initial SM was the primary source of runoff predictability at 1 month lead in all seasons the summer months over the western mountainous region, where snow dominated the runoff predictability. In a similar study using Principal Component Analysis, Maurer et al. (2004) investigated the controlling factors to the runoff predictability over all of North America and concluded that the IHCs (SM and SWE) could provide useful levels of seasonal hydrologic predictability beyond what is available via climate anomalies only. Berg and Mulroy (2006) utilized a residual analysis approach and found that for a statistically significant number of stations in the Saskatchewan/Nelson River basin in Canada even macroscale estimates of initial SM could be used to improve streamflow predictability at 1 to 3 months lead time. Likewise Mahanama et al. (2008) showed that in the tropical island country of Sri Lanka, initial SM could contribute to the seasonal hydrologic predictability for up to 3 months lead time. They found the correlation of initial soil moisture and monthly runoff to be the highest at 1 month lead time mainly during April-May-June (AMJ) and July-August-September with the island-wide correlation significant at 5 % significance level for 3 months lead time during AMJ. Based on their results they concluded that improving the estimate of initial SM is far more achievable than the improvement in seasonal precipitation forecast skill. More recently, Koster et al. (2010) and Mahanama et al. (2011) used a suite of hydrologic models to evaluate the contributions of SM and snow to streamflow predictability across the conterminous United States.

All the studies cited above and various others not mentioned here have addressed the question "*What are the sources of and their relative influence on seasonal hydrologic predictability*?" Various methods have been used, however to our knowledge there has been no attempt to answer this question for the entire globe with one consistent method. Understanding the relative contributions of the IHCs and FS to seasonal hydrologic prediction skill at different forecast initiation dates and lead times globally is important for identifying those regions of the globe where useful skill can be attained in any given season, given current global hydrologic monitoring capability (the basis for providing the IHCs) and seasonal FS. For example, depending on which one

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of those factors dominates the seasonal hydrologic prediction skill, efforts can be focused toward improving the estimation of the IHCs (e.g. by data assimilation, or model improvement that reduce prediction uncertainty in the land surface models used to estimate IHCs) or FS. This knowledge could also lead to better understanding of the uncertainty of seasonal hydrologic forecast skill for any region and season. Hence the primary objective of this study is to provide a consistent estimate of the relative contributions of the IHCs and FS in seasonal hydrologic predictability over the entire globe throughout the year. We use an Ensemble Streamflow Prediction (ESP) framework based on an experimental design structure proposed by Wood and Lettenmaier (2008) (described in Sect. 2.1) to conduct this analysis. ESP (Day, 1985; Shukla and Lettenmaier, 2011; Wood and Lettenmaier, 2008; Wood et al., 2002) is a method widely used for seasonal hydrologic prediction that runs a physically based hydrology model up to the time of forecast using observation-based atmospheric forcings, then resamples ensemble forcing members from sequences of past observations so as to form ensemble based hydrologic forecasts that are based solely on IHCs (no FS). An alternative hypothetical structure termed reverse ESP (rESP) by Wood and Lettenmaier (2008) runs the model up to the forecast date using ensembles of past observation-based atmospheric forcings sequences, and pairs each with observations based atmospheric forcings (perfect FS) during the forecast period. The combination of ESP and rESP includes the two end points of no FS and perfect FS. Variations of the ESP/rESP approach have since been used in recent studies such as (Li et al., 2009; Paiva et al., 2012; Shukla and Lettenmaier, 2011; Singla et al., 2012) to partition the influence of IHCs and FS on seasonal hydrologic predictability.

2 Data and methods

We implemented the ESP/rESP approach to quantify the relative contributions of the IHCs and FS in seasonal hydrologic predictability as in (Li et al., 2009; Shukla and Lettenmaier, 2011; Wood and Lettenmaier, 2008). We conducted ESP and rESP

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experiments (Sect. 2.1) using the Variable Infiltration Capacity (VIC) land surface model (Sect. 2.2). In each experiment we generated two distinct sets of reforecasts of cumulative runoff (CR) (accumulated over 1 to 6 months lead time), soil moisture (SM) and snow water equivalent (SWE) for the entire globe over 1961–2007, for 4–6 months long forecast periods starting on 1 January, 1 April, 1 July and 1 October. To calculate the skill of each set of reforecasts we used a long term consistent data set of CR, SM and SWE that was simulated by the VIC model by forcing the model with observational atmospheric forcings (Sect. 2.2). Then we used a simple Root Mean Square Error (RMSE) based score to quantify the skill of both experiments (Sect. 2.3). The ratio of the RMSE score of the two experiments was used to measure the relative contribution of the IHCs and FS to the seasonal hydrologic prediction skill.

2.1 Experiments

In the first (ESP) experiment, the VIC model was initialized with a "true" IHC (for any given initialization day) and was forced with the ensembles of atmospheric forcings (precipitation, maximum (T_{max}) and minimum (T_{min}) temperature, wind speed) randomly sampled from the period 1961–2007 (the total number of ensembles was 46, leaving out the target year). The IHC is "true" in the context of the VIC model simulation. In the second (rESP) experiment, the model was initialized with ensembles of the IHCs randomly sampled from the same climatological period as in the ESP experiment, again leaving out the IHC of the target year. Each ensemble sequence was forced from the forecast date onwards with observed (assumed true) atmospheric forcings for the target year (equivalent to perfect climate forecast skill). The ESP experiment derives its skill from the knowledge of the IHCs only whereas the rESP experiment derives its skill solely from the observed forcings (perfect FS).

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2.2 Observational analysis

We used a long-term simulated dataset of CR, SM, and SWE as the reference data set to verify the skill of the ESP and rESP experiments. The availability of long-term and spatially distributed observations of CR, SM and SWE globally is scarce at best. Therefore we used the VIC model-derived simulated values of those variables, generated by forcing the model with observed atmospheric forcings, as the assumed truth for CR, SM, and SWE.

2.2.1 Atmospheric forcings

We used gridded daily precipitation, temperature maximum, temperature minimum and wind speed data developed by Sheffield et al. (2006) to drive the VIC model. Originally this dataset spanned the period 1948–2008 at one degree latitude-longitude spatial resolution and 3-hourly temporal resolution. However for the purpose of this study we spatially interpolated the data to 0.5 degrees and temporally aggregated to a daily time step. The original Sheffield et al. (2006) data set was constructed by combining multiple ground and satellite based global observational datasets with the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis. Further details on the methodology involved in the generation of this dataset can be found in Sheffield et al. (2006).

2.2.2 The Variable Infiltration Capacity (VIC) model

The VIC model is a semi-distributed macroscale hydrology model that parameterizes major surface, subsurface, and land-atmosphere hydrometeorological processes (Cherkauer et al., 2003; Liang et al., 1994, 1996). The VIC model has been widely used at global scale in many previous studies and has been demonstrated to capture the hydrology of different regimes well (Adam et al., 2007; Maurer et al., 2002; Nijssen et al., 1997, 2001). It represents the role of sub-grid spatial heterogeneity in soil moisture, elevation bands, and vegetation on runoff generation. The subsurface in the VIC model 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 (Liang et al., 1996). Baseflow is a non-linear function of the moisture content of the third soil-layer (Todini, 1996). For this study we ran the VIC model in water balance mode. In the water balance mode the model runs at daily time step (except the snow module that was run at 3 hourly time step) and the surface energy balance is not calculated, instead assuming that the soil surface temperature is equal to the surface air temperature. The global soil, vegetation and snow band parameters used to run the VIC model were the same as used by Su et al. (2005) and Voisin et al. (2008).

2.3 Forecast score

In order to quantify the relative contributions of the IHCs and FS on seasonal hydrologic prediction skill we calculated the RMSE of both experiments and then used the RMSE ratio to partition the influence of the IHCs and FS as in Li et al. (2009) and Shukla and Lettenmaier (2011). We considered that when the RMSE ratio is less than 1.0 then IHCs dominate the seasonal hydrologic prediction skill and vice versa.

3 Results

In this section we present and discuss the seasonal, spatial and temporal (with lead time) variability of the relative contributions of the IHCs and FS in seasonal hydrologic predictability globally. We first discuss the variation of the kappa (κ) parameter defined by Mahanama et al. (2011) and used by Shukla and Lettenmaier (2011) and then illustrate the predictability of CR, SM and SWE respectively in Sects. 3.2, 3.3 and 3.4.

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3.1 Variability of Kappa (κ) parameter

Kappa (κ) was defined by Mahanama et al. (2011) as the ratio of the standard deviation of total moisture (soil moisture and snow) at the time of forecast initialization to total precipitation during the forecast period. κ greater than 1 implies that variability of initial total moisture may dominate the hydrological forecasts and the reverse is implied by κ less than 1. Figure 1 shows the variation of κ globally at lead times of 1 to 6 months for forecasts starting on (a) 1 January, (b) 1 April, (c) 1 June and (d) 1 December. Red (blue) colors indicate greater (less) than 1 values of κ, with dark red (blue) colors indicating the lowest (highest) values. In general there is clear contrast in the spatial pattern of κ between the northern and Southern Hemisphere and the forecast period starting in 1 January and 1 July. Total moisture variability is higher than the precipitation variability (resulting in κ greater than 1) in most parts of the Northern Hemisphere for at least 3 month lead times during the forecast periods starting on 1 January (Fig. 1a) and in many parts of the Southern Hemisphere (with some exceptions) for forecast periods starting on 1 July (Fig. 1c). This contrast between hemispheres and forecast periods can be attributed to the fact that January to March are the highest precipitation months for most parts of the Southern Hemisphere and the forecast period starting in July is the high precipitation period for many regions in the Northern Hemisphere. There are some regions in the Northern Hemisphere that are noteworthy exceptions, for example the US Pacific Coast where January–March is the high precipitation period and July–September is usually the driest period of the year. This is why κ values are less than 1 for most of that region during the first three months of the forecast period starting on 1 January and greater than 1 for about 3 months during the forecast period starting on 1 July (Fig. 1c). In the snow-dominated regions of the world (mainly in Northern Hemisphere) κ values are less than 1 during at least the first three months of the forecast period starting on 1 January (Fig. 1a) and on 1 April (Fig. 1c). Snowmelt contributes to runoff and soil moisture during the otherwise dry summer months (June to September) in those regions. Again during the forecast period starting on 1 October

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(Fig. 1d) κ values are below 1 for the regions that are dry during October to March. Regions such as northern India, China, and Mongolia particularly stand out because $\kappa > 1$ for up to 6 months lead time in those regions. On the contrary for regions such as western US, and tropical regions (~ between 23° S to 23° N), $\kappa < 1$ starting at 1 month lead time.

3.2 Predictability of Cumulative Runoff (CR)

Figure 2 shows the RMSE ratios for CR forecasts globally at 1 to 6 months lead time during the forecast period starting on 1 January (Fig. 2a), 1 April (Fig. 2b), 1 July (Fig. 2c) and 1 October (Fig. 2d). CR at any lead time N is the sum of runoff during lead 1 to N months. Since κ at any lead time N (1, 3 and 6 months for this study as shown in Fig. 1) was also calculated using the total precipitation during lead 1 to N months (and the initial total moisture at the beginning of the forecast period) we expected the spatial and temporal pattern of RMSE ratio to be in agreement with κ. Shukla and Lettenmaier (2011) also showed a first order relationship between κ and the RMSE ratio.

The RMSE ratio is the ratio of RMSE_{ESP} and $\text{RMSE}_{\text{rESP}}$ so if its value is less than (greater than) 1 then it indicates that the relative contributions of the IHCs is larger (smaller) than the contributions of the FS in the CR forecasts. On the contrary, if the value of kappa is greater than (less than) 1 then it indicates that the variability of initial moisture is higher (lower) than the variability of the precipitation during the forecast period, which would in turn indicate greater (smaller) role of the IHCs in the CR forecasts.

In Fig. 2 we only show the RMSE ratio for those grid cells where $\text{RMSE}_{\text{rESP}}$ or both RMSE_{ESP} and $\text{RMSE}_{\text{rESP}}$ are greater than zero (RMSE_{ESP} and $\text{RMSE}_{\text{rESP}}$ both could be zero for desert areas, e.g. in Africa, Central Asia and Australia). Figure 2 shows that at 1 month lead over most regions in the Northern Hemisphere the RMSE ratio is less than 1 (the main exceptions are parts of the western US and northern South America). In the Southern Hemisphere the RMSE ratio is greater than 1 at 1 month lead time, except over dry regions. As the lead time increases, the influence of the

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IHCs decreases and over most regions of the globe the value of the RMSE ratio at 6 months lead time becomes greater than 1, reflecting the greater influence of FS on CR forecasts. The influence of FS is particularly apparent in the Southern Hemisphere where almost the entire region is shown in dark blue colors, indicating RMSE ratio > 1.

The spatial pattern of the RMSE ratio over the forecast period starting on 1 April (Fig. 2b) is different from the forecast period starting on 1 January (Fig. 2b). There are some higher latitude regions in the Northern Hemisphere and almost all of the tropical regions where the RMSE ratio is greater than 1 even at 1 month lead time and the influence of the IHCs in the Southern Hemisphere is much stronger (and for some regions persists up to 6 months lead time) than in the case of forecast period starting on 1 January. In the snow-dominated regions of the Northern Hemisphere the RMSE ratio is lower than 1 even at 6 months lead time, showing the strong influence of the IHCs in those regions during the forecast period starting on 1 April (Fig. 2b). This strong influence of the IHCs as indicated in many previous studies (mainly focusing on North America) is due to snow that acts as a reservoir and generates runoff during spring/summer months.

Figure 2c shows the variability of the RMSE ratio globally during the forecast period starting on 1 July. In general, except over some snow dominated regions in the Northern Hemisphere and desert areas, the RMSE ratio is greater than 1 starting at 1 month lead time. On the other hand, over most of the Southern Hemisphere the RMSE ratio is below 1 for at least 3 months lead-time indicating the dominant role of the IHCs in the CR forecasts. The influence of FS on CR forecasts is particularly evident over tropical regions during this forecast period. That comes as no surprise because these months are usually when that part of the globe receives most of its precipitation.

Figure 2d shows the RMSE ratio globally for the forecast period starting on 1 October. The influence of the IHCs in many regions of the Northern Hemisphere is much stronger and persists until 6 months lead time. However the Pacific Northwest and California in the US, eastern and central Europe, and the tropical regions are exceptions to this general pattern in the Northern Hemisphere. In these regions the RMSE ratio

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is greater than 1 at 1 month lead and beyond, indicating the importance of FS in the seasonal CR forecasts at this time of the year. Overall the RMSE ratio for the CR forecasts over the Southern Hemisphere regions is around or greater than 1 (except over deserts) for the entire forecast period indicating the importance of the FS.

3.3 Predictability of Soil Moisture (SM)

Figure 3 shows the variability of the RMSE ratio in SM forecasts globally. The major pattern that stands out is the strong influence of the IHCs almost globally (with exceptions mentioned below) at 1 month lead time, indicated by the low values of RMSE ratio. Shukla and Lettenmaier (2011) and Mo et al. (2012) also found a predominant effect of SM persistence (hence dominance of IHCs) at short leads.

Figure 3a shows the RMSE ratio for SM forecasts at 1, 3 and 6 months lead time during the forecast period starting on 1 January. At 1 month lead over almost the entire Northern Hemisphere the RMSE ratio ranges from 0 to 0.5, indicating the strong influence of IHCs on the SM forecast. Over northern and northeastern South America and the Southeast Asian countries in the Asia-Pacific region such as Malaysia, Indonesia, Singapore the influence of the IHCs is weaker even at 1 month lead time. The IHCs also dominate the SM forecasts in many parts of the Southern Hemisphere (except northern Australia). As the lead time increases to 3 months, over the coastal US, much of eastern Europe, and the tropical regions in the Northern Hemisphere, the contribution of the IHCs diminishes and the contribution of FS becomes stronger (Fig. 2a). In the Southern Hemisphere FS dominates the SM forecast almost everywhere at 3 month lead time. At 3 months lead time the overall spatial contrast between the regions where the IHCs dominate vs the regions where FS dominates the SM forecasts is much more similar to the CR forecasts (Fig. 2b) than it is at 1 month lead time. At 6 months lead time, except over the desert regions in central Asia and Africa, the IHC contribution diminishes to either being close to the FS (over the regions where RMSE ratio is around 1) or negligible. This means that improvement in FS globally would be required to obtain

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any improvement in SM forecast skill at 6 months lead time if the forecast is initialized in January.

The influence of the IHCs is strong at 1 month lead time during the forecast period starting 1 April, except over the tropical regions and some high latitude regions of North America, Europe and Asia (Fig. 3b). The contribution of IHCs is also stronger over all of the Southern Hemisphere at 1 month lead time during this forecast period than it is for the forecast period starting on 1 January. At 3 month lead time, the IHC contribution to SM forecasts over much of the Northern Hemisphere diminishes, except over the interior mountainous western US, parts of central Eurasia and desert regions. The highest values of the RMSE ratio, indicating the strong influence of FS on SM forecasts, are over the eastern half of US, and tropical regions such as central and southern Mexico, north and northeastern South America, Southeast and East Asia. Over the Southern Hemisphere, however, the influence of FS is not as strong at 3 months lead time; the RMSE ratio is around or slightly above or in some cases much below 1 (southern Africa). By 6 month lead time the RMSE ratio is greater than 1 over almost the entire globe, except arid regions.

During the forecast period starting on 1 July (Fig. 3c) the RMSE ratio is below 1 for the entire Southern Hemisphere and most of the Northern Hemisphere, except parts of Canada, Alaska, parts of the US Southwest, tropical regions, and most of Southeast and East Asia. At 3 month lead the contribution of the IHCs is stronger than FS in SM forecasts mainly over the Southern Hemisphere and desert regions in the Northern Hemisphere. The strong influence of the IHCs over the Southern Hemisphere indicates that improvement in methods of IHC estimation, such as improvement in land data assimilation, hydrologic modeling, and/or parameter estimation could improve SM forecast skill at 3 month lead in that region during the forecast period starting on 1 January. In contrast, improved FS would be required for improvement in SM forecast skill over much of the Northern Hemisphere during this forecast period beyond 1 month lead time. Again, at 6 month lead the signal from the IHCs on 1 July is negligible at over most of the globe (excepting desert regions).

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Later in the year when the forecast is initialized on 1 October (Fig. 3d), the influence of the IHCs is still apparent at 1 month lead time, however it is more (less) widespread and stronger (weaker) over the Northern (Southern) Hemisphere during this forecast period than it was during the forecast period starting on 1 July. At 3 month lead time, except over high latitude regions such as northern Canada, Alaska, and Russia, parts of central and east Asia, and deserts, the contribution of the FS is higher than of the IHCs. Most of those regions in the Northern Hemisphere where the IHCs influence is stronger than FS are snow covered during this time of the year. The IHC signal in the high latitude regions of the Northern Hemisphere persist up to 6 months lead time, and for most of the rest of the globe FS that dominates SM forecast skill at 6 months lead.

3.4 Predictability of Snow Water Equivalent (SWE)

Snow plays a major role in the annual water supply for nearly half of the Northern Hemisphere (Barnett et al., 2005). In those regions snows accumulates through the winter and melts in the spring and/or summer months to replenish runoff and soil moisture. Figure 4 shows the ratio of κ calculated using initial SM variability (κ_{SM}) and initial SWE variability (κ_{SWE}). We focus on those grid cells only where κ values (calculated using both SM and SWE variability) are greater than 1 (i.e. the regions where initial total moisture variability is higher than then total precipitation variability) and where κ_{SWE} is greater than 0.1 (grid cells where there is an apparent contribution of snow to hydrologic predictability). This figure shows that during forecast periods starting in January and April the relative contribution of snow is higher than the contribution of SM (i.e. those grid cells where $\kappa_{\text{SM}}/\kappa_{\text{SWE}}$ is less than 1) over large parts of the high latitude regions of the Northern Hemisphere. This in turn implies that in those regions knowledge of the contributions of the IHCs and FS to the predictability of SWE is crucial to predict water supply.

Figure 5 shows the spatial and temporal variability of the RMSE ratios for SWE forecasts during the forecast period starting on 1 January (Fig. 5a), 1 April (Fig. 5b), 1 July (Fig. 5c) and 1 October (Fig. 5d). In this figure we show those grid cells only for

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months for which the long term mean SWE (calculated over 1961–2007) is higher than 50 mm. This screening based on the long term mean values of SWE allows us to focus on those regions of the globe that receive substantial amounts of snow. Figure 4 shows that at short leads the IHCs dominate the SWE forecast, which is expected because SWE is a state variable.

During the forecast period starting on 1 January which consists of the months with highest values of SWE during most years, over the high latitude regions of Asia and North America the IHC influence on the SWE predictability persists through at least 3 months lead time.

4 Discussion

We have evaluated the relative contributions of the IHCs and FS on the seasonal hydrologic predictability globally. While we believe that our study is unique in the extent of its domain as well as the length of the period of analysis, there are some caveats that need to be highlighted.

Components of initial hydrologic conditions taken into account in this study were soil moisture and snow only. However, for some regions of the globe and over major river basins, knowledge of the initial level of surface water (e.g. lakes and wetlands) and/or ground water could also provide useful skill in the forecast of streamflow or water availability. For example in a recent study, Paiva et al. (2012) investigated the role of surface water state variables, such as river discharge and water levels, surface runoff and floodplain storage, as well as soil moisture, ground water and the meteorological forcings, on river flow forecasts in the Amazon basin. They concluded that the uncertainties in the knowledge of surface water state variables and ground water storage at the time of forecast initialization is the major source of uncertainties in the hydrological forecast for up to 3 months lead time. In contrast, in Sects. 3.2 and 3.3, we argue that, in general, it is the FS that mainly accounts for the uncertainties in the forecast of CR and SM in that region. Our conclusions do agree with the findings of Paiva et al. (2012) when they

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considered only SM as the state variable and showed that in that case, the lead time T until which the spread of the ESP ensemble becomes larger than the reverse-ESP is less than 10 days. They concluded that *Soil moisture is not as important as other state variables as a source of hydrological prediction uncertainty* in the Amazon basin and our findings are in agreement with that conclusion.

Furthermore, in this study we have not accounted for the effects of glaciers. Although many previous studies have indicated that glacier melt can be an important source of water supply to many major basins (Barnett et al., 2005; Huss, 2011; Kaser et al., 2010) a recent study by Schaner et al. (2012) showed that over much of the global domain which Barnett et al. (2005) showed as snow dominated, the contribution from glacier melt to runoff is a small fraction of that derived from seasonal snow melt (which we accounted for). Moreover in this study we focus on runoff accumulated over up to 6 months, therefore we believe that the impact of not prescribing glaciers on our findings is minimal in a global context (notwithstanding that in some locations it can be important).

Finally, the ESP and rESP experiments we conducted assume unconditional distributions (i.e. climatological spread) of the uncertainty related to climate forecast skill and the IHCs respectively. In reality however, the uncertainty in climate forecast skill and the estimate of IHCs in operational hydrologic prediction systems, is generally lower than the climatological spread. We used the climatology of atmospheric forcings (ESP) and the IHCs (rev-ESP) to assure that the only source of the skill in both experiments is the knowledge of the IHCs and climate forecast skill respectively, so we can easily differentiate between the contributions of both factors.

5 Conclusions

Our primary findings are:

1. IHCs play a crucial role in determining seasonal hydrologic skill globally. In general (with some exceptions) the contributions of IHCs are greater than the contribution

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of FS over the Northern (Southern) Hemisphere during the forecast periods starting in October and January (April and July) mainly at shorter lead times (i.e. 1 to 3 months). Over snow dominated regions in the Northern Hemisphere IHCs dominate CR forecast skill for up to 6 months lead time during the forecast period starting in April.

2. Overall the contribution of FS is higher than IHCs over the tropics (except desert areas) throughout most of the year.
3. The contribution of IHCs especially at lead-1 is generally stronger for SM forecasts than for CR.
4. The contributions of IHCs to SWE forecast skill is strongest for the forecast period starting in January, particularly over high the latitude regions of the Northern Hemisphere.

Our findings should have important implications for implementation of global hydrologic prediction systems for the forecast of floods and droughts at seasonal scale, several of which are now under development. Despite improvements in the understanding of climate variability (mainly ENSO) in the last few decades, precipitation forecast skill is generally limited to short lead times (one month or so) especially during non-ENSO years. Our work sheds light on regions of the globe where improvements in seasonal hydrologic forecast skill can be attained through better estimates of IHCs in at least some parts of the year, regardless of FS.

Acknowledgements. This work was facilitated through the use of advanced computational, storage, and networking infrastructure provided by the Hyak supercomputer system, supported in part by the University of Washington eScience Institute.

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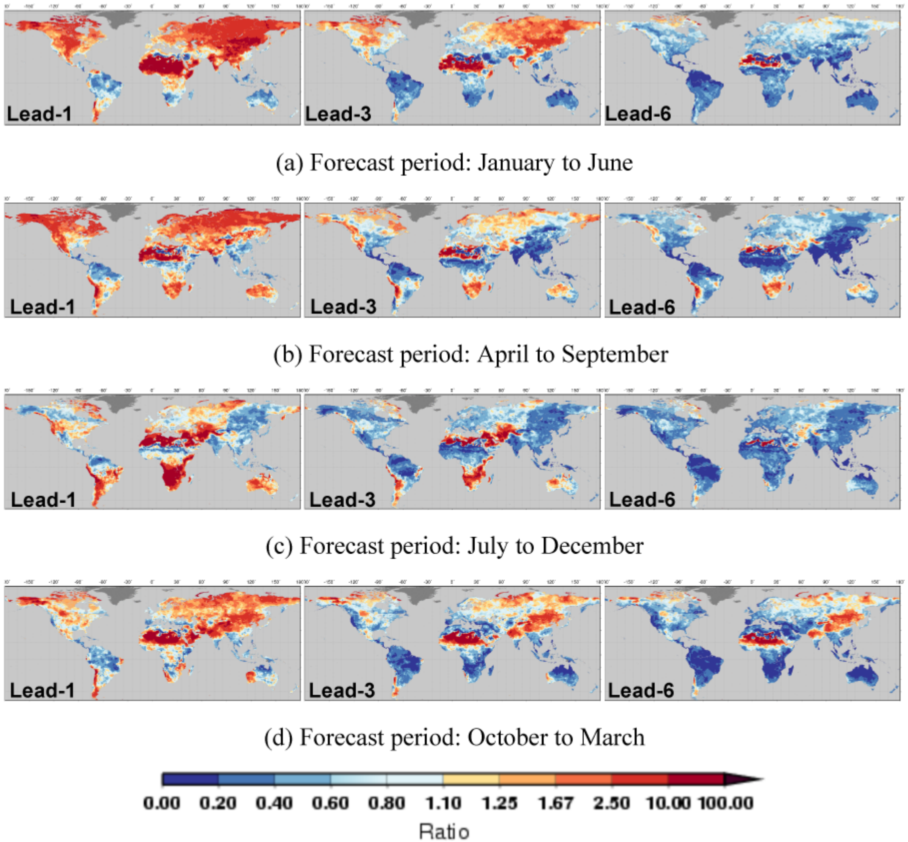

Fig. 1. Spatial variability of κ (ratio of the standard deviation of initial total moisture to total precipitation during the forecast period) at lead-1, -3 and -6 months for forecast initialization on **(a)** 1 January **(b)** 1 April **(c)** 1 July **(d)** 1 October.

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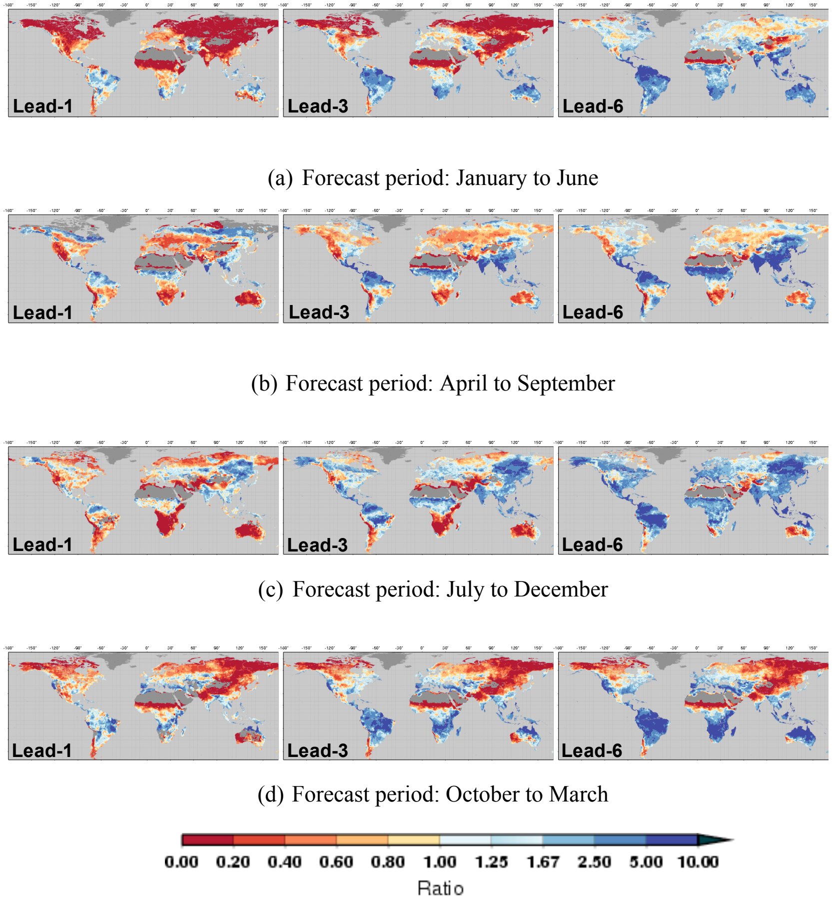

Fig. 2. RMSE ratio for cumulative runoff (CR) forecasts at lead-1, -3 and -6 months since the forecast initialization on **(a)** 1 January **(b)** 1 April **(c)** 1 July **(d)** 1 October.

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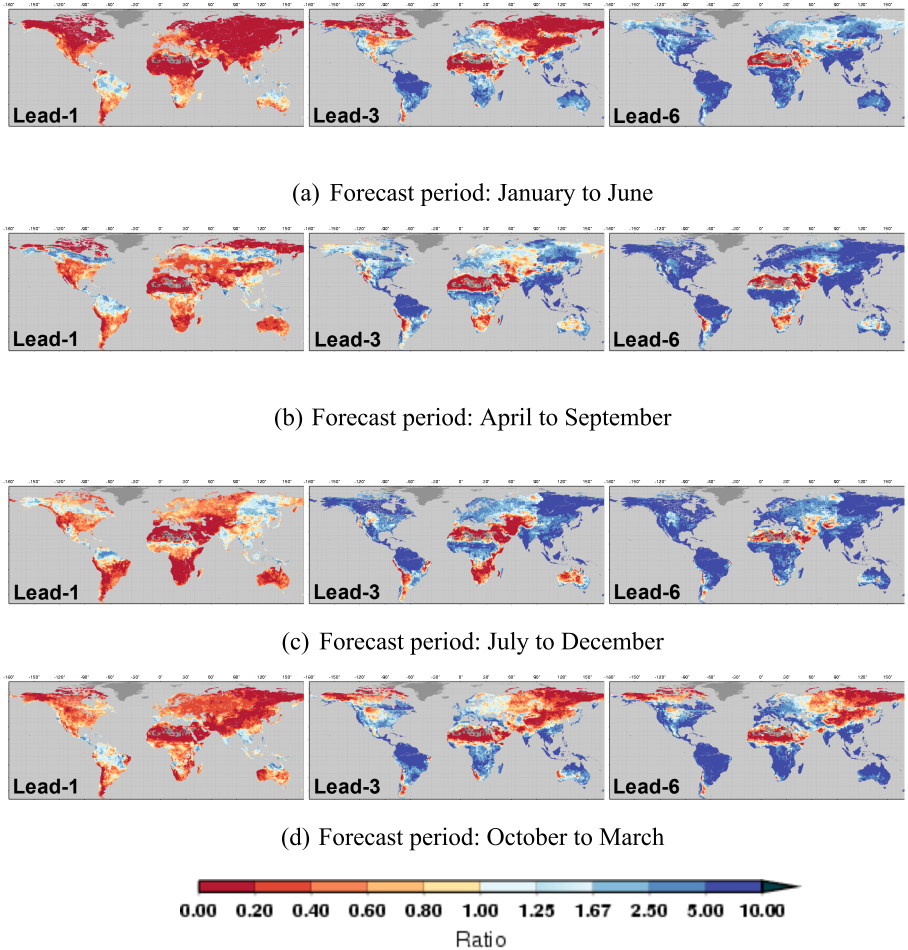

(a) Forecast period: January to June

(b) Forecast period: April to September

(c) Forecast period: July to December

(d) Forecast period: October to March

Fig. 3. RMSE ratio for soil moisture (SM) forecasts at lead-1, -3 and -6 months for forecast initialization on **(a)** 1 January **(b)** 1 April **(c)** 1 July **(d)** 1 October.

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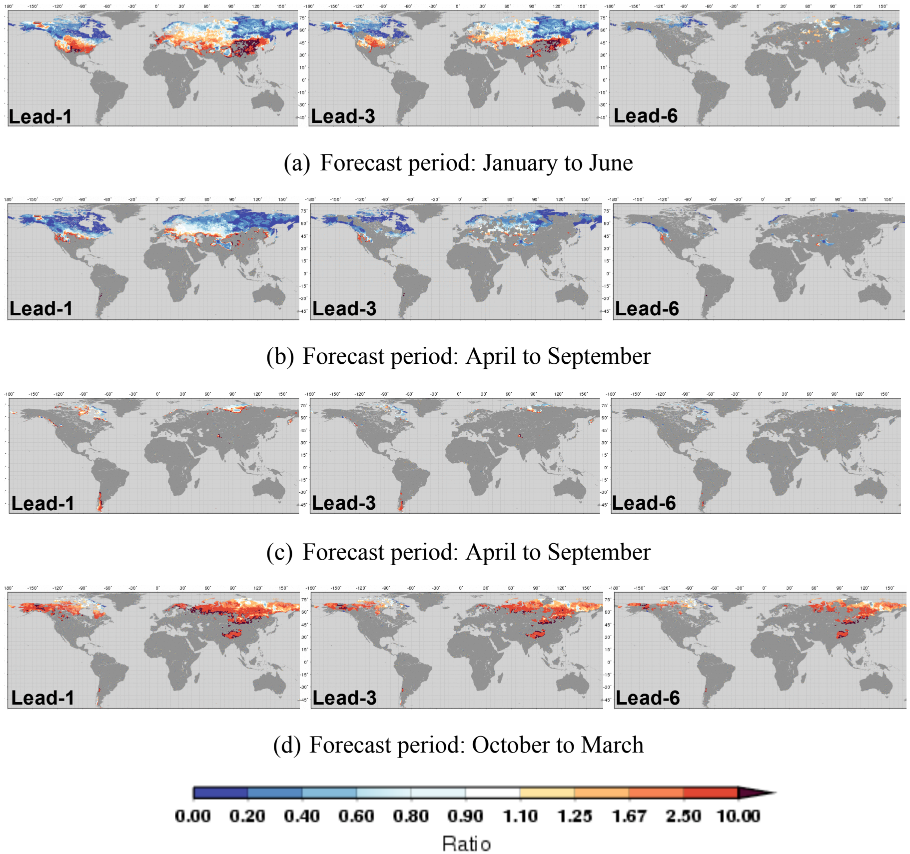

(a) Forecast period: January to June

(b) Forecast period: April to September

(c) Forecast period: April to September

(d) Forecast period: October to March

Fig. 4. Ratio of κ_{SM} to κ_{SWE} (depicting the contribution of SM relative to SWE in seasonal hydrologic predictability) at lead-1, -3 and -6 months since the forecast initialization on **(a)** 1 January **(b)** 1 April **(c)** 1 July **(d)** 1 October. (The regions shaded in grey are grid cells for which $\kappa < 1$ and $\kappa_{SWE} < 0.1$, or the regions that do not receive snow).

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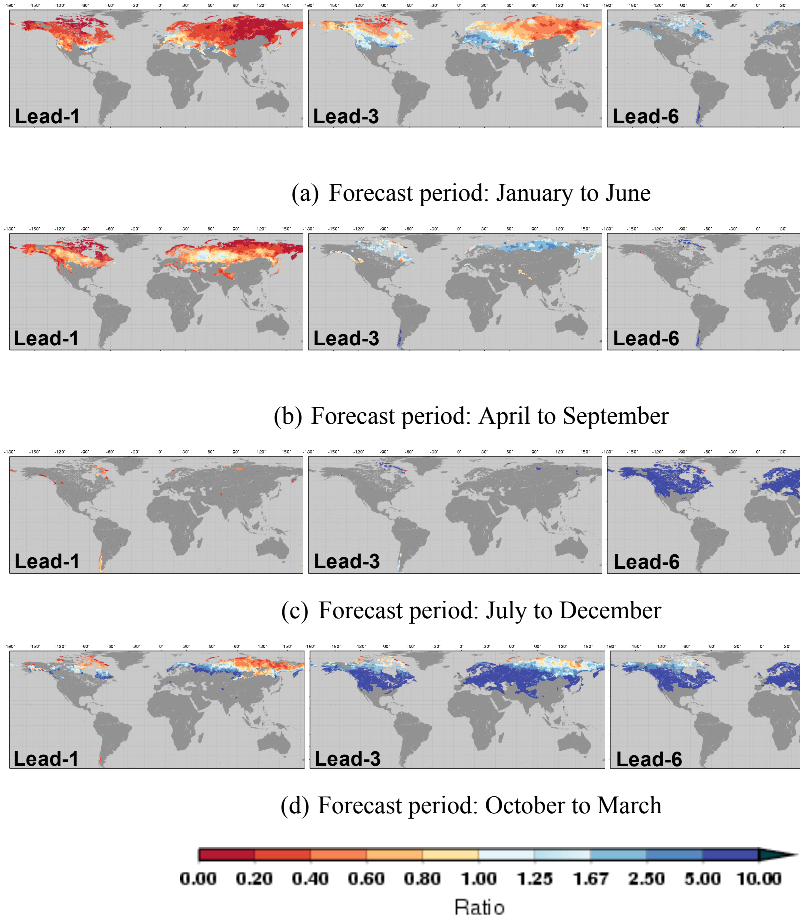

(a) Forecast period: January to June

(b) Forecast period: April to September

(c) Forecast period: July to December

(d) Forecast period: October to March

Fig. 5. RMSE ratio for Snow Water Equivalent (SWE) forecasts at lead-1, -3 and -6 months since the forecast initialization on **(a)** 1 January **(b)** 1 April **(c)** 1 July **(d)** 1 October. (The regions shaded in grey include grid cells for which long term mean SWE is less than 50 mm).

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