A review on climate-model-based seasonal hydrologic forecasting: physical understanding and system development
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Climate-model-based seasonal hydrologic forecasting (CM-SHF) is an emerging area in recent decade because of the development of coupled atmosphere-ocean-land general circulation models (CGCMs) and land surface hydrologic models, and increasing needs for transferring the advances in climate research into hydrologic applications within the framework of climate services. In order to forecast terrestrial hydrology from monthly to seasonal time scales, a CM-SHF system should take advantage of important information from initial land surface conditions (ICs) as well as skillful seasonal predictions of atmospheric boundary conditions that mostly rely on the predictability of large-scale climate precursors such as the El Niño Southern Oscillation (ENSO). The progresses in the understanding of seasonal hydrologic predictability in terms of ICs and climate precursors are reviewed, and future emphases are discussed. Both the achievements and challenges of the CM-SHF system development, including multimodel ensemble prediction, seamless hydrologic forecasting, dynamical downscaling, hydrologic post-processing, and seasonal forecasting of hydrologic extremes with the hyper-resolution modeling framework that is able to address both the climate change and water resources management impacts on terrestrial hydrology, are presented. Regardless of great strides in CM-SHF, a grand challenge is the effective dissemination of the information provided by the seasonal hydrologic forecasting system to the decision-makers, which cannot be resolved without cross-disciplinary dialog and collaboration. © 2015 The Authors. WIREs Water published by Wiley Periodicals, Inc.

INTRODUCTION

Global change is influencing the frequency and severity of hydrologic extremes, including floods and droughts,1 resulting in a number of issues with respect to food and water security. While decadal plans for infrastructure adaptation and capacity building are important for managing water resources under a changing climate, timely early (seasonal) warning, or so-called seasonal hydrologic forecasting (SHF), is essential for hydrologic hazard mitigation by increasing preparedness. Basically, the aim of SHF is to predict the land surface hydrologic variables (e.g., streamflow, soil moisture) at monthly to seasonal time scales. It is also named as long-term hydrologic forecasting in the hydrologic community because it is targeted for the forecasting of persistent land surface hydrologic conditions.
anomalies (e.g., drought), which is different from short-term flood forecasting. A successful SHF not only requires accurate initial land surface conditions (ICs) from upstream river flow, snow cover, and/or soil moisture, but also relies on skilful seasonal prediction of surface meteorological conditions (e.g., precipitation, temperature) that act as the forcings for the land surface hydrology.

Traditional SHF approaches (Figure 1) are primarily based on time series modeling, by relating remote large-scale climate indices such as sea surface temperature (SST) over tropical eastern Pacific Ocean and/or local antecedent land surface conditions with hydrologic predictands. As the conceptual and distributed hydrologic models emerged, predicting seasonal hydrology with physical models became popular. They resolve the surface and subsurface water movement and conserve the water balance vertically and horizontally. One example is the Ensemble Streamflow Prediction (ESP) system that has been applied by the National Weather Service since the 1970s. The ESP system initializes a physical hydrologic model with current land surface hydrology. The downscaling can be carried out using statistical methods or using regional climate models (RCMs) for dynamical downscaling.

As shown in the flowchart (Figure 2), the hydrologic model can produce SHF when fed with initial hydrologic conditions and downscaled atmospheric forcings; the system can also be augmented with multiple hydrologic models. Last but not the least is the hydrologic post-processing procedure that is similar to the atmospheric post-processing but is applied to the hydrologic model outputs (e.g., streamflow, soil moisture), which can correct streamflow forecast bias because of nonlinear relationship between rainfall and runoff and errors in hydrologic models that cannot be calibrated out.

This article reviews and discusses the achievements and challenges for the CM-SHF in terms of the understanding of the sources of seasonal hydrologic predictability including ICs and large-scale climate precursors; the forecast techniques such as multi-model ensemble prediction, statistical and dynamical downscaling, and hydrologic post-processing; and the forecast practices such as seasonal forecasting of predicting temperature and precipitation at seasonal scales: the understanding of ocean–atmosphere teleconnections such as El Niño Southern Oscillation (ENSO) and land–atmosphere coupling that forms the physical basis of seasonal climate prediction, the observational data assimilation and computing resources that facilitate high-resolution numerical simulations with improved initial atmospheric and oceanic conditions, and the development of coupled atmosphere-ocean-land general circulation models (CGCMs) for seasonal climate predictions. Consequently, combining the ESP approach with CGCMs for a climate-model-based seasonal hydrologic forecasting (CM-SHF; Figure 1) is receiving more attention over the last 10 years.

A typical CM-SHF system consists of CGCMs, initialization procedures, dynamical and/or statistical downscaling procedures, hydrologic models, and hydrologic post-processing procedures (Figure 2). While the system may share similar initialization packages (e.g., land data assimilation) as the ESP, its major difference from ESP is the incorporation of seasonal climate prediction from the CGCMs. It uses ensemble forecasts of precipitation and surface air temperature from a single CGCM or multiple climate forecast models. Therefore, how to select or combine climate forecast models for a skillful and reliable ensemble forecast is essential for the system. Another key procedure is the downscaling. This is because CGCM predictions inevitably have biases and their spatial resolutions are usually too coarse for hydrologic applications. The downscaling can be carried out using statistical methods or using regional climate models (RCMs) for dynamical downscaling.

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hydrologic extremes. This review article introduces the basic concepts and practices for those who are new to CM-SHF and discusses the challenges and opportunities for both research and operational development.

**SOURCES OF SEASONAL HYDROLOGIC PREDICTABILITY**

**Initial Land Surface Conditions**

Similar to ESP, the CM-SHF also heavily relies on the ICs, i.e., the anomalies from initial soil moisture and snow etc. Unlike quantifying the contribution of ICs to seasonal climate predictability using land–atmosphere-coupled modeling approaches,\(^29,30\) the contribution of ICs to seasonal hydrologic predictability is often investigated using hydrologic models in a standalone mode.\(^4,6,13,14,31\)–\(^36\) One of the theoretical frameworks to separate the contributions of ICs and atmospheric boundary forcings is called reverse ESP (revESP).\(^31\) In traditional ESP, a hydrologic model with assumed perfect ICs is forced by ensemble meteorological forcings resampled from history;\(^12\) while in the revESP, the hydrologic model is driven by observed meteorological forcings (a perfect meteorological forecast), with ICs resampled from history.\(^31\) Forecast skill is assessed both for ESP and revESP to identify the dominance of the source of hydrologic predictability—from the ICs or meteorological forcings. The revESP framework was first applied over two river basins over the western USA\(^31\) with a semi-distributed, grid-based hydrologic model, the variable infiltration capacity (VIC)\(^37\) model. It was found that ICs yield streamflow prediction skill for up to 5 months over northern California during the transition between the wet and dry seasons, but have less impact over southern Colorado basin because of a weaker annual cycle of precipitation.\(^31\) The revESP framework was also used for assessing the role of ICs for the entire USA\(^33\) and the globe.\(^14\)

As an important land surface storage term, snow has long been recognized as a major source of seasonal hydrologic predictability, particularly over high altitude\(^35,38\) and high latitude\(^4,14\) regions, where its impact can last for 3–6 months especially during cold seasons.\(^14\) Because of the strong control from...
snow, the climate forecasts of temperature could be as important as precipitation for streamflow forecast in high-latitude snow-fed river basins through the temperature–snow melt relationship. Even in monsoonal basins where the variability of monsoon dominates the forecasting skill, the ICs of snow can still contribute to streamflow predictability where snow-melt streamflow exists. As compared with snow, soil water has less memory, but it contributes to hydrologic predictability even outside of snow-covered regimes. For example, the ICs of soil moisture have the strongest influence on the prediction of cumulative runoff in the first month over mid-latitude regions, and realistic soil moisture initialization can contribute to skill out to 6 months for certain basins and seasons.40

In addition to snow and soil moisture, groundwater is an under-explored source of hydrologic predictability. Groundwater acts as the lower boundary of soil water and is expected to have longer memory. Although limited observation and model parameterization hinder the understanding of the contribution of groundwater in SHF, a few studies begin to show that ICs of groundwater are important during low-flow period and region with strong rainfall seasonality. Finally, the ICs of surface water are important for streamflow prediction in rivers with low slope and large floodplains because of longer catchment concentration times.40

Besides theoretically assessing the contribution of ICs to hydrologic predictability through the revESP framework, the ESP results were also directly compared with CM-SHF in a ‘real-forecast’ mode. The ICs were found to be more important in a CM-SHF system than in the ESP system. This is because the ESP will quickly erase the memory from ICs by forcing the hydrologic model with climatological atmospheric boundary (forcing) conditions; while the climate forecast models can have skill in predicting the anomalies of atmospheric boundary conditions that can enhance or offset the anomaly from ICs in a more realistic way, especially for ENSO-influenced regimes.40 As for the CM-SHF, the ICs in ENSO years usually have less impact than in neutral years. Therefore, the role of ICs may have interannual variations, or even seasonal variations. For example, the ICs could be a major source of hydrologic predictability after the onset of hydrologic extremes such as droughts or wet spells, but only have a secondary impact at predicting their onset.42

In fact, investigating the role of ICs during extreme events is more important because of the devastating impacts of hydrologic extremes on the human and natural systems. However, limited attention has been received in this regard because of the deficiency in the framework of ESP that only considers the climatological forcings. With the development of CM-SHF (Figure 2), the contribution of ICs to the predictability of hydrologic extremes could be investigated more realistically. Another limitation is that except for a few studies, most predictability analyses are based on a single hydrologic model. Actually, because of the deficiencies and uncertainties in the parameterizations of the hydrological processes, hydrologic models can produce substantially different results even when forced with identical atmospheric boundary (forcing) conditions and especially for extremes. Therefore, the uncertainties in the hydrologic models should be considered in the predictability analysis, and two possible solutions for quantifying the uncertainty are the parameter perturbation based on a single hydrologic model and the multiple hydrologic model ensemble. Lastly, most ICs are generated by forcing calibrated hydrologic models with observed antecedent atmospheric boundary conditions. How to assimilate in-situ observations and/or remote satellite retrievals for improving the understanding of ICs within the CM-SHF framework needs more investigation. Some experiences in data assimilation could be transferred from short-term flood ensemble prediction.

Large-Scale Climate Precursors

Besides local memory from ICs, other important sources of hydrologic predictability come from remote large-scale climate precursors, such as ENSO. ENSO is an atmosphere–ocean coupled mode of climate variability in the tropical Pacific because the SSTs and winds change synergistically: as the easterly trade winds weaken, SSTs in the eastern tropical Pacific increase, and the easterly winds will be further reduced because the warming of SSTs will change the atmospheric zonal circulation and convection zone. The large spatial shift in tropical Pacific rainfall associated with ENSO alters the global circulation and rainfall, and therefore, ENSO has been considered as a major source of seasonal climate predictability. In addition to the tropical Pacific, the SST anomalies over the tropical Atlantic Ocean and Indian Ocean also offer predictability for regional climate. In addition, a combination of SST anomalies in Pacific and Indian Oceans may lead to widespread and persistent droughts over mid-latitude regions.

Those climate precursors are not only found to affect seasonal climate predictability at large scale but also are used to understand seasonal hydrologic predictability over river basins. For example, as compared with ICs, ENSO and the Arctic Oscillation play a crucial role in hydrologic predictability in high-latitude snow-fed river basins. This is because the warming of SSTs will change the atmosphere–ocean coupled mode of climate variability in the tropical Pacific, which leads to widespread and persistent droughts over mid-latitude regions.
are important indicators for runoff prediction over the eastern part of the Mississippi river basin at lead times of one season or greater.\textsuperscript{62} Over 66 river basins in Europe, the North Atlantic Oscillation (NAO)\textsuperscript{63} predicted in the winter time contributes significantly to the streamflow predictability in the subsequent summer.\textsuperscript{64} Over a catchment in northeastern Australia, the Southern Oscillation index (SOI)\textsuperscript{65} has been applied to resample the atmospheric boundary forcings in the ESP system and successfully enhanced the monthly to seasonal streamflow forecast skill.\textsuperscript{66} Recently, a comprehensive experiment has been carried out to investigate the seasonal streamflow predictability over 6192 small catchments worldwide\textsuperscript{13} and to discuss the predictability contribution from 21 large-scale climate precursors including ENSO (Nino3.4),\textsuperscript{67} SOI,\textsuperscript{65} Indian Ocean Dipole,\textsuperscript{59} NAO,\textsuperscript{63} North Pacific index,\textsuperscript{68} Pacific Decadal Oscillation index,\textsuperscript{69} Southern Hemisphere Annual Mode index,\textsuperscript{70} and Mean Southern Hemisphere Subtropical Ridge Intensity and Location\textsuperscript{71} as examples. Different climate indices have different contributions for different regions, and the incorporation of ENSO into the ESP system consistently increases the streamflow forecast skill in equatorial South America and Southeast Asia.\textsuperscript{13}

Although large-scale climate precursors have been extensively investigated for their contributions to seasonal hydrologic predictability based on historical observations, they are seldom considered in the CM-SHF framework, where CGCMs are skillful in predicting large-scale precursors such as ENSO SST at long leads.\textsuperscript{15,19} In fact, most studies used the so-called post-ESP framework by resampling historical atmospheric forcings conditional on the antecedent climate indices, while they ignored examining the role of concurrent climate indices that can be predicted by CGCMs. Such examination could either be performed within CGCM or CM-SHF frameworks (Figure 2), although the former could be a little difficult because of the deficiency in the CGCMs’ land surface models, usually without calibration. One promising research area is to investigate how to use the Model Output Statistics (MOS)\textsuperscript{72,73} procedure that links the predictands (e.g., precipitation, surface air temperature) to those large-scale climate precursors and then explore the hydrologic predictability within the CM-SHF framework.

**SHF SYSTEM DEVELOPMENT**

Based on the understanding of the sources of seasonal hydrologic predictability, the CM-SHF systems (Figure 2) that make use of ICs and large-scale climate precursors have been developed. They have been extensively evaluated through a number of case studies\textsuperscript{22,21,74,75} and interannual to decadal hydrologic hindcast experiments.\textsuperscript{6,23,22,42,76–80} One of the first hindcast experiments to test the CM-SHF system was carried out over the eastern USA for a dry summer and an El Niño winter.\textsuperscript{21} The monthly precipitation and surface air temperature predictions from National Centers for Environmental Prediction (NCEP) Global Spectral Model (GSM)\textsuperscript{81} at T42 (∼2.8125°) horizontal resolution were bias corrected and downscaled to one-eighth degree, and the downscaled monthly atmospheric forcings were used to scale randomly selected daily series. Then the scaled daily series were used as input to drive the VIC model to provide hydrologic forecasts out to 6 months. Such CM-SHF system was able to translate climate forecast signals to hydrologic variables, qualitatively.\textsuperscript{21} However, an evaluation of 21-year hydrologic hindcasts with GSM/VIC over the western USA showed that the CM-SHF system had negligible skill improvement over the ESP.\textsuperscript{76} The NCEP GSM was later replaced by its successor, the Climate Forecast System (CFS),\textsuperscript{82} with a T62 (∼1.875°) resolution. Also the corresponding CFS/VIC system, which was created through a Bayesian merging downscaling method\textsuperscript{83} and was developed at Princeton University,\textsuperscript{22} showed marginal to moderate advantage against ESP/VIC based on 19-summer hydrologic hindcasts over the Ohio basin in the eastern USA.\textsuperscript{22} Recently, with the release of NCEP’s latest operational seasonal forecast system, the Climate Forecast System version 2 (CFSv2)\textsuperscript{84} at T126 (∼0.938°) resolution, the Princeton’s seasonal hydrologic forecasting system was upgraded.\textsuperscript{6} A set of 27-year seasonal hydrologic hindcasts was conducted and evaluated over 1734 river basins in conterminous USA, and gradual improvements from ESP to CFS and to CFSv2 were observed.\textsuperscript{6} From the evolution of the CM-SHF systems, it is found that the CM-SHF has been pushed forward by the advances in seasonal climate prediction. And it is expected that the CM-SHF will be further improved with the development of climate forecast models that will have better observation networks and the corresponding data assimilation systems, higher model resolution supported by high-performance computing resources, and more realistic representations of physical processes.

Apart from feeding the CM-SHF system with the state-of-the-art CGCMs, additional techniques such as multimodel ensemble prediction,\textsuperscript{22,84} dynamical downscaling,\textsuperscript{25,86} and hydrologic post-processing\textsuperscript{27,87} are also found to increase the forecast skill and reduce the uncertainty. Recently, more attention has been paid to the seasonal forecasting of hydrologic extremes (e.g., droughts)\textsuperscript{2,42} since the extreme events
are projected to be more frequent and severe in a warming climate.\textsuperscript{1,88} If the CM-SHF system (Figure 2) is linked with impact models such as crop model and reservoir model, skillful and reliable early warning of hydrologic extremes can be used to reduce the damages from droughts or wet spells for a number of sectors such as agricultural and water resources management, and thus reduce the risks of food and water insecurity in a changing climate. This section will review techniques that include multimodel ensemble prediction, downscaling and hydrologic post-processing, and forecast practices such as seasonal forecasting of hydrologic extremes.

**Multimodel Ensemble Prediction**

Ensemble prediction is necessary because of the chaotic nature of the climate system. For example, the ENSO SST is a major source of predictability for seasonal climate, but it is sometimes difficult to predict by the CGCMs because of stochastic forcing from the atmosphere (e.g., the initiation of El Niño in 2003).\textsuperscript{89} Therefore, operational weather forecast centers are generating ensembles from realizations with different initial conditions, either by perturbing wind stress and SST\textsuperscript{19} or running the model with different start dates (i.e., time-lagged ensemble).\textsuperscript{82} Over the last decade, multimodel ensemble is receiving more attention\textsuperscript{90,91} because it is expected to be more reliable and skillful.\textsuperscript{84,92} The multimodel ensemble has also been considered as a useful approach to cascade uncertainties in hydrologic forecasting at other time scales (e.g., medium range).\textsuperscript{48,50} However, even a multimodel ensemble could lead to over-confidence because many models are sharing similar atmospheric or oceanic components. For example, clustering analysis found that several climate forecast models developed in USA produce similar precipitation or temperature forecasts and thus degrade the performance of multimodel ensemble.\textsuperscript{93} However, when combining them with the models developed in Europe through the clustering method, the results have been significantly improved.\textsuperscript{93} This indicates that the magic of multimodel ensemble is to increase the independence among the models. Of course, the models should also have comparable skill and complimentary features,\textsuperscript{84} i.e., one can hardly expect added values of multimodel ensemble if combining a good model with a ‘totally bad’ model. Although the multimodel ensemble mean or median is not necessarily better than the ensemble mean of the best single model, the multimodel ensemble is found to be consistently superior to the ensemble of a single model in term of probabilistic forecast skill and reliability,\textsuperscript{19,20,84} and the reliability is quite important for the probabilistic forecasting of extremes given limited skill.\textsuperscript{94}

Over recent decades, the products from various multimodel ensemble projects such as the Development of a European Multimodel Ensemble System for Seasonal-to-Interannual Prediction project\textsuperscript{91} and the North American Multimodel Ensemble (NMME) project\textsuperscript{20} are successfully being used for improving SHF from river basin to continental and global scales.\textsuperscript{22,23,42} However, the potential of multi-CGCM ensemble in hydrologic prediction should be further explored through analyzing the covariance structure of CGCMs to avoid over- or under-confident ensemble.

The multimodel ensemble prediction for a CM-SHF system can be built using ensembles not only from multiple CGCMs\textsuperscript{22,23,42} but also from multiple hydrologic models. Although the uncertainty of hydrologic models could be reduced through calibration\textsuperscript{26} or climatological scaling,\textsuperscript{95} the existing discrepancy could raise challenges for the analysis of extremes.\textsuperscript{47} Therefore, the uncertainty from hydrologic models in a CM-SHF system is not necessarily secondary, especially for the forecasting of hydrologic extremes. In fact, there are many regional to global simulation or monitoring systems using multiple hydrologic models,\textsuperscript{24,26,40,43–47,96,97} it is now the time to consider how to effectively incorporate them into a CM-SHF system to enhance the forecast skill and increase diversity.

**Statistical and Dynamical Downscaling**

Given the climate predictions from a single CGCM or multimodel ensemble, downscaling techniques are indispensable because the spatial resolution of CGCM is usually coarser than the hydrologic model, and the predictions from CGCM inevitably have biases. In terms of CM-SHF, downscaling can be carried out using statistical correction methods\textsuperscript{21} or RCMs.\textsuperscript{25} In general, statistical downscaling methods for the CM-SHF system can be divided into two types,\textsuperscript{98} (1) the unconditional methods such as bias removing or quantile-mapping,\textsuperscript{21} where they match the forecast climatological distribution with observational climatological distribution by up to the first or higher orders of moments (e.g., mean, variation) and (2) the conditional methods like the conditional distribution of normal distribution method\textsuperscript{99} or Bayesian method,\textsuperscript{83} where they consider the model performance, i.e., if the model is very skillful, the posterior forecast will be very close to the observation, otherwise the posterior will be very close to the climatology. For most CM-SHF applications, the predictand and predictor
in the downscaling method are the same variable. For example, if the downscaling is applied to the precipitation, then only the observed and predicted precipitation data are used. The shortcoming is that such downscaling sometimes could not help more given the limited skill in predicting precipitation at long leads. Actually, many remote climate precursors (e.g., ENSO) are found to affect local rainfall and can be incorporated into the downscaling system through a Bayesian joint probability modeling approach. In the future, the MOS method that is relatively mature for bias correction and downscaling in the field of weather forecast should be considered in statistically downscaling of CGCM-seasonal predictions for the CM-SHF system.

Another under-explored area is dynamical downscaling. Although dynamical downscaling is not a new topic, using RCM to downscale CGCM seasonal-climate prediction emerged just a decade ago. In 2008, the Climate Prediction Program for the Americas (CPPA) sponsored by National Oceanic and Atmospheric Administration (NOAA) initiated the Multi-RCM Ensemble Downscaling (MRED) project, where multiple RCMs were nested with NCEP CFS for the multi-decadal downscaling experiments during the cold seasons. The rationale for dynamical downscaling of seasonal prediction is that the CGCMs are able to correctly capture the large-scale forcing signals (e.g., ENSO), and the RCMs can accurately represent the regional-local climate responses. The dynamical downscaling, when applied with advanced RCMs, can effectively reduce the CGCM forecast errors at daily-to-seasonal scales because of better representations of orographic effects (e.g., shallow convection) or land surface processes (e.g., frozen soil, snow).

However, in terms of temporal variability, the dynamical downscaling could be very challenging in both summer (winter for Southern Hemisphere), when the CGCM climate predictability is low, and winter (summer for Southern Hemisphere), when the RCM regional advantage diminishes because of the large-scale forcing dominance. In other words, once the CGCM made a bad large-scale circulation prediction, RCM would transfer the wrong signal to local processes (e.g., precipitation) and scales through the lateral and lower boundary control and can hardly predict the anomaly correctly. Besides further improving the corresponding physics in both CGCM and RCM, one possible solution is to develop coupled ocean–atmosphere RCM and let the RCM predict the SST by itself, rather than by direct interpolation from CGCM predictions. Other techniques for improving the dynamical downscaling include multi-RCM ensemble or ensemble downscaling using different parameterizations within a single RCM. For example, using different combination of microphysics, cumulus, land surface, and radiation schemes in a RCM, which is driven by one realization of CFS seasonal prediction, is found to outperform the CFS ensemble precipitation prediction with realizations from different initial conditions.

### Hydrologic Post-processing

As shown in Figure 2, the CM-SHF system can make a seasonal hydrologic forecast with a CGCM, a hydrologic model, downscaling and initialization procedures. However, because of the uncertainty in the hydrologic model and the uncorrected errors in downscaled atmospheric boundary forcings that may grow nonlinearly through the rainfall-runoff and surface-subsurface hydrologic processes, a post-processing procedure is also essential for a skillful and reliable hydrologic forecast. In fact, the post-processing could be as important as hydrologic model calibration for seasonal streamflow forecasting, and post-processing can correct the errors in hydrologic models that cannot be eliminated through calibration.

Similar to the atmospheric post-processing (i.e., bias correction and downscaling), the hydrologic post-processing can be carried out based on the joint distribution of observed and CM-SHF system predicted hydrologic variables (e.g., streamflow). A set of interesting experiments were carried out using the CFSv2/VIC system over 50 rivers within Ohio basin for streamflow forecasting, and the results showed that: (1) the hydrologic post-processing could be as important as the downscaling of atmospheric boundary forcings and (2) the forecast skill and reliability were increased after post-processing the streamflow from the CFSv2/VIC system. The reason is that although the downscaling procedure generates reliable atmospheric boundary forcings, the streamflow forecast ensemble from the CFSv2/VIC system is not necessarily reliable (e.g., it is over-confident in that case); therefore, the post-processing that matches forecast distribution with observation distribution is not a trivial step. The over-confidence from the original CFSv2/VIC system does not necessarily come from ICs because it disappears when the predicted streamflow are validated against VIC offline-simulated streamflow. In other words, feeding the system with the same ICs for different ensemble members is not responsible for the over-confidence, while the uncertainty from hydrologic model is.
In the future, the post-processing could be used to: (1) directly post-process global runoff or streamflow predictions from CGCMs for local hydrologic applications, which needs less computation efforts using CGCM forecasts that are publically available (e.g., CFSv2 real-time forecasts); (2) merge hydrologic predictions from different hydrologic models within the CM-SHF framework; and (3) downscale soil moisture and streamflow from CM-SHF for applications that need hyper-resolution forecasts, such as reservoir modeling. However, the non-stationary hydrology, under a changing environment (e.g., climate change, catchment modification) makes the hydrologic post-processing more challenging, and perhaps an integrated modeling framework is necessary.

Seasonal Forecasting of Hydrologic Extremes

After post-processing, the forecast results can be used for hydrologic applications. One of them is the seasonal forecasting of hydrologic extremes. The occurrences of hydrologic extremes are primarily the results of natural climate change and variability as the response to meteorological anomalies, but such response can be altered by the land surface characteristics such as the topography, vegetation, and hydrogeological conditions. In addition, the duration and severity of hydrologic extremes could be affected by land use changes, including reservoir regulation, crop irrigation, and groundwater pumping. Therefore, it is necessary not only to understand the relationship between meteorological extremes and hydrologic extremes at different spatiotemporal scales but also to investigate the effects of land use changes on hydrologic extremes.

While there is a long history for predicting hydrologic extremes statistically, seasonal forecasting of hydrologic extremes with the CM-SHF system just becomes popular in recent years. Hydrologic extremes like droughts are difficult to predict by seasonal climate forecast models at local scales, especially over those areas with insignificant ENSO impact, but they can be predicted well several months ahead (against ESP or a climatological forecast) at river basin scales in terms of drought area, especially over dry basins or during dry seasons. A Sub-Saharan African Drought Monitoring and Forecasting system developed by integrating remote sensing data, weather and seasonal climate forecast models, and large-scale land surface hydrologic model, is a successful example contributing to building capacity through technology and knowledge transfer.

Nevertheless, most studies on seasonal forecasting of hydrologic extremes are based on large-scale land surface hydrologic modeling. Those hydrologic models are useful to transfer large-scale climate anomaly to regional, continental, and global hydrologic variations, but they need to be improved for considering small-scale human-induced catchment change processes including reservoir regulation, crop irrigation, and groundwater pumping etc. Therefore, developing hyper-resolution land surface hydrologic models within the CM-SHF framework is necessary to account for both the climate change and human influences, and to make prediction useful for the adaptation to hydroclimate extremes under a changing environment.

CONCLUSION

The recent advances in climate forecast models with better representation of ocean–atmosphere teleconnections and effective (oceanic) data assimilations, the improvement in land surface hydrologic modeling that realistically resolves the terrestrial hydrology variations and variability across scales, and the application-oriented (e.g., climate services) efforts of the research community provide promising opportunities for the research and development of the CM-SHF. Seasonal hydrologic predictability originates both from remote large-scale climate precursors (e.g., ENSO) that affect subsequently hydroclimate through ocean–atmosphere teleconnections and local ICs that can persist for several months. While great strides have been made to understand the sources of hydrologic predictability and to quantify relative dominance from different sources over different regimes, future efforts could be spent as follows: (1) the contribution of ICs to predictability of hydrologic extremes (e.g., droughts) has to be fully understood through the CM-SHF framework besides using the revESP method; (2) the uncertainty of hydrologic models should be considered in investigating the role of ICs, and multiple hydrologic model ensemble that intends to reduce and/or quantify uncertainty and land data assimilation that incorporates in-situ station observation or remote satellite retrieval data into predictability analysis could provide more insights; (3) the MOS that is able to link predictands (e.g., precipitation) with large-scale climate precursors should be highlighted for the understanding of hydrologic predictability within the CM-SHF framework; and (4) instead of hydrologic simulation (e.g., revESP) or statistical regression (that links precipitation with climate precursors), hydrologic predictability should be carefully investigated by examining detailed physical processes that are responsible for specific hydrologic.
phenomena, which is more fundamental in terms of extending predictability.128

For system development, the CM-SHF has been extended from a single climate forecast model (but with multiple realizations) with a single hydrologic model21 to multiple climate and hydrologic models,42 dynamical downscaling has emerged as a critical component of CM-SHF for correcting errors in CGCM predicted meteorological forcings more physically, and the post-processing has been recognized as a useful procedure for a reliable seasonal hydrologic forecasting. However, several questions need to be highlighted in the future: (1) how to combine physical and statistical methods for creating a multimodel ensemble that has the largest model diversity without over-confidence? (2) how to integrate weather and climate forecast models for a seamless hydrologic forecasting129 system that could integrate the achievement in short-term flooding forecast (e.g., Hydrological Ensemble Prediction Experiment) and seasonal drought prediction? (3) how to improve the prediction of the interannual variability in downscaling, especially for the variables that are very relevant to hydrologic applications (e.g., precipitation)? and (4) how to develop hyper-resolution land surface hydrologic models that consider both the natural rainfall-runoff and surface-subsurface hydrologic processes as well as human interventions such as reservoir regulation, crop irrigation, and groundwater pumping, and how to effectively incorporate them into the CM-SHP system for predicting terrestrial hydrologic variations under a changing environment and providing adaptation guidelines? In fact, human intervention could be a key issue in hydrologic forecasting. For instance, a steady decrease in the hydrologic forecast skill over the Slovak reach of River Danube since the 1970s is attributed to the increased flow alteration by hydropower projects and land use changes.130 The land use changes affect the evapotranspiration and soil moisture dynamics significantly,131 and they could be important sources of uncertainty in seasonal hydrologic forecasting.

Lastly, a challenge similar to short-term hydrologic forecasting132 is how to transfer seasonal hydrologic forecasts into effective warnings and actions. In fact, a perfect forecast or timely early warning is useless unless decision-makers correctly understand the warning and take actions according to the prediction.133 The development of technology facilitates the dissemination of seasonal hydrologic forecast information to the end users, but scientists may have to consider how to communicate with decision-makers by interpreting the forecast results more effectively. For instance, probabilistic flood forecasts were seen as unwelcome,134 but they are being understood better after improved communications between scientists and decision-makers.135 Scientists and forecasters are now considering how to provide uncertainty and verification information in a form and context that is easily understandable and useful to customers136 and are carrying out innovative training and education activities to teach people from local agencies and authorities on how to use the probabilistic forecast system.123 Such activities will in turn raise new science questions and push seasonal hydrologic forecasting forward.

ACKNOWLEDGMENT

This work was supported by the Thousand Youth Talents Program.

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