

Hydrological monitoring and seasonal forecasting: Progress and perspectives

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Abstract: Hydrological monitoring and seasonal forecasting is an active research field because of its potential applications in hydrological risk assessment, preparedness and mitigation. In recent decades, developments in ground and satellite measurements have made the hydrometeorological information readily available, and advances in information technology have facilitated the data analysis in a real-time manner. New progress in climate research and modeling has enabled the prediction of seasonal climate with reasonable accuracy and increased resolution. These emerging techniques and advances have enabled more timely acquisition of accurate hydrological fluxes and status, and earlier warning of extreme hydrological events such as droughts and floods. This paper gives current state-of-the-art understanding of the uncertainties in hydrological monitoring and forecasting, reviews the efforts and progress in operational hydrological monitoring system assisted by observations from various sources and experimental seasonal hydrological forecasting, and briefly introduces the current monitoring and forecasting practices in China. The grand challenges and perspectives for the near future are also discussed, including acquiring and extracting reliable information for monitoring and forecasting, predicting realistic hydrological fluxes and states in the river basin being significantly altered by human activity, and filling the gap between numerical models and the end user. We highlight the importance of understanding the needs of the operational water management and the priority to transfer research knowledge to decision-makers.

Keywords: hydrological monitoring; hydrological forecasting; uncertainty; modeling; remote sensing; climate model

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1 Introduction

Hydrological extremes such as drought and flood events have frequently struck many parts of the world in the past few decades (Andreadis *et al.*, 2005; Zhai *et al.*, 2010; Wang *et al.*, 2011a) and are likely to become more frequent under a changing climate (Milly *et al.*, 2002; Leng *et al.*, 2015, 2016; Hirabayashi *et al.*, 2008, 2013). These hydrological extremes usually bring significant and far-reaching impacts to the economy, society and environment. The reported annual losses from droughts and floods reached tens of billions of U.S. dollars, with thousands of people killed (Hirabayashi *et al.*, 2013) and millions of people affected each year across the world (Wilhite, 2000; Below *et al.*, 2007). One possible reason for such huge losses is the lack of prompt risk response strategies due to the scarcity of accurate drought/flood early-warning information. A hydrological monitoring and seasonal forecasting system is able to provide a reasonable quantitative measurement of land surface hydrological conditions in a real-time manner and predict their variations up to several months ahead, which will greatly benefit risk assessment, preparedness and mitigation.

Presently, numerous studies have been devoted to hydrological monitoring and seasonal forecasting, with the monitoring techniques varying from the in-situ/satellite measurements to model simulations and the forecasting approaches varying from statistical methods to physical hydrological models. This study synthesizes the past achievements of hydrological monitoring and seasonal forecasting, highlights the current challenges, and paints the future picture. The rest of the paper is organized as follows. Section 2 focuses on the uncertainties of the hydrological monitoring and forecasting. Sections 3 and 4 give general overviews regarding to the hydrological monitoring and seasonal forecasting respectively, and Section 5 summaries the available practices in China. The present challenges and the future perspectives are highlighted in Section 6.

2 Uncertainties in hydrological monitoring and forecasting

Reliable and accurate hydrological monitoring and forecasting are two keys for better hydrological services and water resources management decision-making. However, both hydrological monitoring and forecasting are plagued by various sources of uncertainties, which often put their usefulness into questions. There are two kinds of uncertainties: (1) the epistemic uncertainty which arises due to lack of knowledge of a quantity of interest, sometimes also known as subjective uncertainty; (2) aleatoric uncertainty, which is an inherent variation associated with a quantity, also called as natural variability or stochastic uncertainty. The former uncertainties are to be reduced, while the latter ones are to be quantified. In the following, we discuss the uncertainties associated with hydrological monitoring and forecasting separately, and suggest the ways to quantify or reduce them.

2.1 Uncertainties in hydrological monitoring

Two kinds of uncertainties occur in hydrological monitoring, one from the data generation stage and the other from data processing stage. The uncertainties from the data generation stage can be random noises during measurements or errors due to factors such as improper use of the equipment, and/or human errors in obtaining, processing and communicating the monitoring data. The uncertainties from the data processing stage may come from the in-

herent limitations of the monitoring methods or due to human errors. For example, when gauge-based in-situ monitoring data is used to represent a quantity over a spatial domain, sampling errors are bound to occur (e.g., estimating precipitation over a spatial domain based on rain gauge data). This kind of errors may be reduced by introducing more gauges in the analysis. On the other hand, remote sensing data is promising to provide a spatial estimate of a quantity by inferring it from the optical signals, but the accuracy of such techniques is highly dependent on the inversion algorithms used to convert the optical signals into the quantities of interest. Many of those inversion algorithms are built based on empirical, statistical relationships between the signals and the quantities of interest that are far from being precise. Further, the satellite signal sources are often contaminated by the obstacles between the sensors and the objects (e.g., clouds, water surfaces, among others).

In general, the errors in monitoring data are manifested in three forms: (1) systematic errors, (2) random errors, and (3) spurious errors. The systematic errors are usually resulted from data generation stage as described above, and appropriate steps must be taken to correct them according to their error sources. Random errors can be corrected readily using methods such as Kriging, artificial neural network (ANN), or other statistical methods. For these errors, statistical assumptions are often made about their properties (i.e., probability distributions). Gaussian distribution is the most often used probability distribution for many variables (e.g., surface air temperature, surface air pressure, geometric measurements). However, for certain variables, other distributions must be used, for example, Gamma type distributions for precipitation errors or streamflow discharge errors. The spurious errors may be readily detectable, but are not easy to correct. Those errors are usually associated with subjective, human errors in the data generation or processing stage (e.g., coding errors, misreading of the numbers, or improper use of equipment).

2.2 Uncertainties in hydrological forecasting

Hydrological forecasting is generally made with a hydrological model, which may be based on statistical input-output relationships (i.e., black-box model or system models), or observed or assumed empirical relationships among various hydrological variables (i.e., conceptual models), or physical laws of mass, energy and momentum conservations (i.e., physically based models). All hydrological models involve hydrological inputs (e.g., precipitation, surface air temperature, potential evapotranspiration) and outputs (e.g., streamflow, actual evapotranspiration, snowmelt). In conceptual or physically based models, there are also hydrological state variables (e.g., soil moisture content, areal snow coverage, snow depth, and lake water level). Uncertainties exist in all phases of hydrological modeling, including hydrological inputs, hydrological state variables, model structure and parameters, model outputs, and all related observational data.

Errors in hydrological inputs are generally of two types: the errors associated with the observations and the errors associated with the forecasts. The observational errors are the errors carried over from hydrological monitoring, as discussed in Section 2.1. When monitoring data such as precipitation or surface air temperature datasets are used as inputs to a hydrological model, one must first ensure that the uncertainties in those datasets are reduced or quantified. The forecasting errors usually refer to the errors in precipitation or temperature forecasts generated by a numerical weather or climate model (e.g., QPF – quantitative

precipitation forecast or QTF – quantitative temperature forecasts). All raw QPFs and QTFs contain biases, and they are usually incompatible with a given hydrological model because of the scale difference between them. Further the uncertainties in the forecasts are generally greater than that associated with the observations. Statistical post-processing methods have been widely used to deal with the errors in QPFs and QTFs (Glahn and Lowry, 1972; Krzysztofowicz and Sigrest, 1999; Schaake *et al.*, 2007). Data assimilation methods have been widely used to reduce the uncertainty associated with the initial conditions (ICs) used in the hydrological models. Popular data assimilation methods include ensemble Kalman Filter (EnKF) method, the 3-dimensional and 4-dimensional variational methods (3dVAR and 4dVAR) (Evensen, 1997; Wang *et al.*, 2008; Huang *et al.*, 2009). The effects of using data assimilation methods to merge observational data and model state variables have shown to be significant in improving hydrological forecasting (Clark *et al.*, 2008; Liu *et al.*, 2012).

Model calibration is a process in which model parameters are tuned to best match model predictions with corresponding observations (Duan *et al.*, 2006). Many advances have been made in terms of using model calibration methods to reduce the uncertainties inherent in the specification of model parameters (Duan *et al.*, 1992; Beven and Binley, 1992; Wang *et al.*, 2014, 2016). As hydrological models are highly nonlinear, treating uncertainties in different phases of hydrological modeling independently may lead to biased model parameter estimates. Recently, integrated approaches to model calibration have been becoming an emerging area. For instance, Kavetski *et al.* (2002) proposed a Bayesian Total Error Analysis (BATEA) to address errors in model inputs and model parameters. Ajami *et al.* (2007) developed the Integrated Bayesian Uncertainty Estimation (IBUNE) method to consider errors in model inputs, model parameters and model structure.

Model structural errors are a fact of life as all models are just simplifications of the real world systems. To deal with the model differences, many multi-model ensemble approaches have emerged, including Bayesian Model Averaging (BMA) methods proposed by Raftery *et al.* (2005) and superensemble approach (Krishnamurti *et al.*, 1999), which strive to obtain consensus model predictions by weighing model predictions based on their consistency with observations. Ensemble forecasting approach has not only been used to develop multi-model predictions, it is also a popular approach in treating uncertainties from different sources, including model inputs, ICs, and model parameters. To date, human activities are posing significant influence to terrestrial water cycle (Gerten *et al.*, 2008) directly by water withdrawals, like crop irrigation (Tang *et al.*, 2008; Leng *et al.*, 2013), reservoir regulation (Döll *et al.*, 2009) and groundwater pumping (Leng *et al.*, 2014; Ferguson and Maxwell, 2012) and indirectly by altering the land cover (VanShaar *et al.*, 2002). How to effectively parameterize such human interventions into land surface hydrological models is of critical importance for an improved knowledge of terrestrial hydrological variations under a changing environment.

To better understand the uncertainty of seasonal hydrologic prediction, a few attempts have also been made to investigate the source of hydrological predictability, like exploring the potential linkage of ICs with the runoff variations using the statistical methods (e.g., Maurer *et al.*, 2004), or employing an ensemble streamflow prediction (ESP) or reverse-ESP theoretical framework (Wood and Lettenmaier, 2008) to isolate the role of ICs and climate forecasts (CFs) (i.e., the hydrological inputs) in seasonal hydrological prediction at regional

(e.g., Wood and Lettenmaier, 2008; Li *et al.*, 2009; Yang *et al.*, 2014; Shukla and Lettenmaier, 2011a; Staudinger and Seibert, 2014) and global scale (e.g., Shukla *et al.*, 2013). Depending on which one of those factors dominates the seasonal hydrological predictability, targeted efforts can be put forward to reduce the uncertainties associated with that dominant factor (ICs or CFs), and thus enhances the seasonal hydrological forecast skills.

3 Hydrological monitoring, observations and data assimilation

Hydrological monitoring is able to provide real-time quantitative information of hydrological fluxes and states. An accurate monitoring is not only of great value for real-time assessment of the hydrological extremes (e.g., drought/flood), but also is the key premise for hydrological prediction.

In-situ measurement is a routine way to provide the ground truth of land surface hydrological fields. In present, the real-time hydrological information networks have been established and made available in some countries, such as the National Water Information System (NWIS) in the U.S. (<http://waterdata.usgs.gov/nwis>), the Hydrological Information Inquiry System (HIIS) in China (<http://www.hydroinfo.gov.cn/>). Although with great potential to serve as the ground reference for model verifications, such direct measuring technique usually suffers from the inconsistency at spatial and temporal scales, which hampers its effective use at a large scale (Tang *et al.*, 2009b; Pan *et al.*, 2012; Li *et al.*, 2013). More importantly, several key variables, like the terrestrial water storage (TWS), are still hard to directly measure at the monitoring sites.

Satellite remote sensing, featured with high temporal frequency and spatial continuity, provides an alternative opportunity for large-scale observations of land surface hydrological variables. Through combining multi-sensor microwave and infrared data with different algorithms, a few satellite-based global precipitation products, like TRMM Multi-satellite Precipitation Analysis (TMPA) (Huffman *et al.*, 2007) and the latest Global Precipitation Measurement (GPM) mission (Hou *et al.*, 2014), have been generated and investigated with great potentials for flood/drought monitoring (Hong *et al.*, 2007; Zeng *et al.*, 2012; Zhao *et al.*, 2015). The satellite-based evapotranspiration (ET) can be successfully estimated in real-time as given the real-time inputs from Moderate Resolution Imaging Spectroradiometer (MODIS) and surface radiation products derived from geostationary satellites (Tang *et al.*, 2009c). The near-surface (i.e. the top few millimeters to centimeters) soil moisture content can be operationally estimated with passive microwave remote sensing products like the Advanced Microwave Scanning Radiometer 2 (AMSR2) (Fujii *et al.*, 2009; Kim *et al.*, 2015), or the combination of active and passive frequencies like the Soil Moisture Active Passive (SMAP) mission (Entekhabi *et al.*, 2010). Some passive and active merged products, such as the European Space Agency Climate Change Initiative (ESA CCI) soil moisture retrievals, are being used to monitor short-term droughts (Yuan *et al.*, 2015a). With the aid of the passive microwave data from the Special Sensor Microwave Imager/Sounder (SSMIS), the National Snow and Ice Data Center (NSIDC) can update global sea ice concentrations and snow extent in near real-time (<https://nsidc.org/data/nise1>). The advent of Gravity Recovery and Climate Experiment (GRACE) made it feasible to monitor the variations of TWS at a spatial scale of several hundred kilometers (Tapley *et al.*, 2004). In addition, a few satellite-aided

ellite-aided drought monitoring were carried out through detecting the changes in surface temperature or land cover (e.g., Li *et al.*, 2010). Although the satellite remote sensing is promising, the non-closure of terrestrial water budgets is still an open issue (Tang *et al.*, 2009b; Sheffield *et al.*, 2009; Gao *et al.*, 2010).

After decades of development, land surface hydrological modeling has gained great progress, which enables the large-scale consistent estimates of different components of terrestrial water cycle. So far, land surface hydrological models have been successfully implemented at both regional (e.g., Maurer *et al.*, 2002; Yang *et al.*, 2004; Tang *et al.*, 2007, 2008; Hu *et al.*, 2012; Zhang *et al.*, 2014) and global scales (e.g., Sheffield and Wood, 2007, 2008; Haddeland *et al.*, 2011; Pan *et al.*, 2012). With the aid of real-time meteorological forcings, many model-based hydrological monitoring practices have been conducted to support a real-time flood/drought diagnosis. For example, an operational Global Flood Monitoring System (GFMS), based on the global real-time rainfall estimates from Tropical Rainfall Measuring Mission (TRMM) satellite and a distributed hydrological model, has been explored to provide the past 24-hour global streamflow information (Hong *et al.*, 2007; Yilmaz *et al.*, 2010; Wu *et al.*, 2014). Unlike the flood risk, drought is inherently defined in the context of a long-term climatology (Andreadis and Lettenmaier, 2006; Shukla *et al.*, 2011b), and thus requires the real-time hydrological estimates (e.g., runoff, soil moisture) to be consistent with the long-term retrospective simulations. Actually, the gauge-based meteorological data used for retrospective simulations are barely reported in real-time manner due to the time latency for quality controlling. Thus, a main challenge for an operational drought monitoring is the inconsistency of real-time meteorological forcings and gauge-based observations (Tang *et al.*, 2009a; Tobin and Bennett, 2010; Sheffield *et al.*, 2014; Nijssen *et al.*, 2014; Zhang and Tang, 2015). To resolve this issue, Tang *et al.* (2009a) proposed an index station percentile method (ISPM) to estimate the real-time precipitation of all index stations based on the limited number of real-time stations. Alternatively, when the satellite data is used as real-time source of model drivers, an equal quantile mapping method was usually employed to remove its systematic bias relative to ground observations (Tobin and Bennett, 2010; Zhang and Tang, 2015). By doing so, the real-time hydrological estimates can be directly compared with the multi-decadal retrospective simulations and thus greatly benefits the real-time drought diagnosis and detection (Sheffield *et al.*, 2014). Following this way, a few experimental drought monitoring systems have been correspondingly established at continental (Wood and Lettenmaier, 2006) and global scale (Nijssen *et al.*, 2014).

It has been demonstrated that a single data source (e.g., in-situ/satellite measurement, land surface modeling) is insufficient to comprehensively understand the land surface hydrologic states and fluxes as well as their spatial and temporal variations across different scales (Pan *et al.*, 2008). It is essential to produce a set of optimal hydrological estimates, which can comprehensively harness the advantage from different data sources (Pan *et al.*, 2012). To this end, the data assimilation scheme, which can blend the sparse land observations with the background fields from land surface hydrological modeling, was introduced to improve the model-derived hydrological estimates. Presently, several studies have made considerable attempts to assimilate the satellite- and ground-based SWE observations (Andreadis and Lettenmaier, 2006; De Lannoy *et al.*, 2010, 2012) and/or soil moisture (Han *et al.*, 2014) into the modeling. Moreover, for a comprehensive identification of drought, a GRACE Data

Assimilation System, based on the incorporation of the GRACE-based TWS into the Catchment Land Surface Model (CLSM) (Zaitchik *et al.*, 2008), has been successfully applied into the North American Drought Monitor (NADM) system to fill up the ignored subsurface water storage information (Houborg *et al.*, 2012). Coincidentally, there are also a large number of operational data assimilation systems that have been made publicly available at large scale to provide the multi-source-based optimal fields, such as the Global Land Data Assimilation System (GLDAS) (Rodell *et al.*, 2004), North American Land Data Assimilation System (NLDAS) (now upgraded to Phase 2 (NLDAS-2)) (Mitchell *et al.*, 2004), European Land Data Assimilation System (ELDAS), and West China Land Data Assimilation System (WCLDAS) (Li *et al.*, 2004). Therefore, the data assimilation approach is being a promising area to yield the ‘best’ hydrological monitoring.

4 Seasonal hydrological forecasting

Real-time monitoring is the base to predict the near future. With the advances in the monitoring techniques, and the improved understanding of global water cycle, predicting land surface hydrological conditions at seasonal time scales are being augmented from using statistical approaches to dynamical forecasting with physical hydrologic models and seasonal climate forecast models (see Figure 1 in Yuan *et al.*, 2015c for a recent review).

The statistical-based hydrological forecast is mostly based on the long-term time series and limited to the single-variable outcome (e.g., streamflow). One common way is to regress seasonal streamflow volume on the corresponding hydro-climatic predictors (e.g., precipitation, temperature, and SWE) (Garen, 1992; Kwon *et al.*, 2009; Pagano *et al.*, 2009). Some other statistical methods, such as the independent component analysis (Westra *et al.*, 2008), the nonparametric statistical analysis (Robertson and Wang, 2012; Di *et al.*, 2014; Singh and Cui, 2015), were also largely employed for seasonal streamflow forecast. However, the statistical-based forecast model are usually trained with multi-decadal time series, leaving it hard to capture the transient relationship between the climatic predictors and predictand (e.g., streamflow), particularly in the context of a changing climate and non-stationary hydrology. Furthermore, volume of streamflow was simply recognized as the function of indicative predictors (e.g., precipitation, temperature, and streamflow) in this forecast approach, without describing the physical processes of the terrestrial water cycle.

Along with the advance in land surface hydrological models, the physical model-based seasonal forecast has been becoming popular. One example is the so-called ESP approach, wherein the climate forcings during the forecast period are taken from an ensemble of previous years for the same period (Day, 1985). Accordingly, the forecast skill of ESP is solely dependent on the knowledge of ICs such as initial snow and soil moisture. As a primary land surface moisture storage term, snowpack affects seasonal hydrological forecast skill over the snow-fed river basins (Maurer *et al.*, 2004), particularly over those high-latitude (Yossef *et al.*, 2013; Shukla *et al.*, 2013) and mountainous regions (Staudinger and Seibert, 2014). For those regions with little snow impact, ESP forecast skill is mostly controlled by the antecedent soil moisture (Koster *et al.*, 2010). Particularly, for the regions characterized with dry climate regime, the dominance of soil moisture condition can last for 3-month (Yuan *et al.*, 2013a; Yang *et al.*, 2014). This may be because the precipitation amount and variation are

both low in the dry regions, leading to the weak influence of precipitation to the hydrological estimates (e.g., runoff and soil moisture) (Mo and Lettenmaier, 2014). In addition, the influence of ICs to seasonal hydrological predictability has an obvious interannual variability, e.g., with more important role in neutral years than in El Niño-Southern Oscillation (ENSO)-dominant years (Yuan *et al.*, 2013b; Sinha and Sankarasubramanian, 2013). Through an assessment during the hydrological extremes, the role of ICs differs on the phase of hydrological extremes. Specifically, the knowledge of ICs during the drought development phase generally outweighs that during predicting the onset of drought (Thober *et al.*, 2015).

The ESP approach was firstly implemented operationally by the National Weather Services (NWS) River Forecast Centers (Day, 1985), and was then augmented by relating the seasonal streamflow forecasts with large-scale remote climate indices (Hamlet and Lettenmaier, 1999; Werner *et al.*, 2004, 2005; Wang *et al.*, 2011b; van Dijk *et al.*, 2013). Subsequently, a test bed for seasonal hydrological forecasting approach was proposed to predict soil moisture and runoff up to several months over the U.S., wherein the historical simulation (used to form a long-term climatology), the real-time monitoring (used to provide the real-time accurate forecast ICs), and the seasonal forecast (used to predict the hydrological outputs out to several months) were integrated within an operational system (Wood and Lettenmaier, 2006).

In addition to ICs, the strong ocean-atmosphere teleconnection, such as ENSO associated with the change in SST anomalies and winds in the tropical Pacific, is another primary source of seasonal hydrological predictability (Smith *et al.*, 2012). The linkage of climate indices with seasonal hydrological predictability has been quantified over multiple river basins (Lan *et al.*, 2003; Maurer *et al.*, 2004; Bierkens *et al.*, 2009; Liu *et al.*, 2012; van Dijk *et al.*, 2013). With the improved representation of such large-scale climate phenomena (e.g., ENSO) in coupled atmosphere-ocean general circulation models (CGCMs) (Barnston *et al.*, 2012), predicting seasonal hydrology based on CGCMs has received considerable attentions over the recent years (Luo and Wood, 2008; Yuan *et al.*, 2015a). Practically, one challenge for such CGCM-based forecast approach is that the spatial resolution of seasonal CFs is too coarse to be directly used as hydrological model inputs. This inspired many researchers to explore the downscaling methodologies, such as the unconditional Bias Correction and Spatial Downscaling (BCSD) method (Wood *et al.*, 2002) and the conditional the Bayesian downscaling method (Luo *et al.*, 2007). Aside from the statistical downscaling scheme, the dynamical downscaling method, which employs the advantage of regional climate models (RCMs) (i.e., with satisfactory representation of local climate response) to effectively reduce the CGCM forecast errors at daily-to-seasonal scales (Yuan and Liang, 2011), is being under explored as well. For example, the Multi-RCM Ensemble Downscaling (MRED) project was initiated by Climate Prediction Program for the Americas (CPPA) to conduct the multi-decadal ensemble downscaling experiments during the cold seasons, in which multiple RCMs were merged with National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS) (Yuan and Liang, 2011; De Sales and Xue, 2013; Shukla and Lettenmaier, 2013). The CGCM climate outputs, after appropriate downscaling procedures, can be directly used to force the hydrological model for seasonal prediction of hydrological fields. Previous studies have assessed the CGCM-based seasonal forecast skill for a

multi-decadal hindcast period (e.g., Wood *et al.*, 2005; Luo and Wood, 2008; Mo *et al.*, 2012; Yuan *et al.*, 2013b; Bastola *et al.*, 2013; Mo and Lettenmaier, 2014), and broadly indicate that CGCM-based hydrological forecast skill has marginal improvement relative to ESP beyond 1 month. This suggests much more efforts are needed to improve the CGCMs' predictive skill, especially for those variables relevant to hydrology.

A CGCM-based drought monitoring and seasonal forecasting system, based on the seasonal climate forecasts from a newly developed CGCM (CFSv2; Saha *et al.*, 2014), the Bayesian downscaling scheme and historic observations from the Phase 2 of the North American Land Data Assimilation system (NLDAS-2; Xia *et al.*, 2012), were developed to carry out a Drought Forecast Analysis in support of the U.S. Seasonal Drought Outlook (Luo and Wood, 2007). In addition to the USA, similar experimental forecasting systems were developed over other continents like Europe (European Drought Observatory) (Vogt *et al.*, 2011) and Africa (Yuan *et al.*, 2013a; Sheffield *et al.*, 2014), as well as to the global scale (Yuan *et al.*, 2015b).

5 Hydrological monitoring and forecasting practices in China

Over the past few decades, China has experienced frequent hydrological extremes (e.g., drought and flood). In this context, numerous hydrological monitoring and seasonal forecast practices have been put in place for risk coping and reduction. Primarily, the Bureau of Hydrology (BoH) established a comprehensive station-based monitoring network over China, which includes over 90,000 hydrometric stations (wherein there are over 3200 hydrological stations), to provide the real-time measurement of river flow regime. Subsequently, the corresponding operational systems, such as Hydrological Information Inquiry System (HIIS) and Information Service System (ISS), were extensively implemented to provide official information services for water resource managers and decision-makers (<http://www.hydroinfo.gov.cn/>). In addition to the BoH, the National Climate Center (NCC) at CMA initiated a drought monitoring platform to provide insight into the real-time meteorological drought diagnosis over China (<http://cmdp.ncc.cma.gov.cn/en/>). Recently, a China Drought Meteorology Scientific Research Project has been launched since 2015, aiming at improving the monitoring and understanding of droughts from meteorological perspective to those for agricultural and hydrological applications. The project is also targeted at developing a refined drought early warning system in northern China based on multiple global climate forecast models (Ma *et al.*, 2015) and physical hydrologic models (Yuan *et al.*, 2015b).

The short-term flood forecast, based on the numerical weather prediction (NWP) and hydrological models, is also an active area with significant attentions in China (Lu *et al.*, 2008; Bao *et al.*, 2012). The BoH has implemented a universal flood forecasting system software platform, China National Flood Forecasting System (CNFFS), towards an effective flood control (Liu and Zhang, 2005; Zhang and Liu, 2006). As for seasonal hydrological forecast, the ESP scheme has been in wide use in China (Li *et al.*, 2008; He *et al.*, 2013; Yang *et al.*, 2014), while little attention has been paid in terms of CGCM-based forecast, except for a recent work focusing on the global major river basins (Yuan *et al.*, 2015b). To this end, a hydrological model-based experimental hydrological monitoring and seasonal forecast

framework for China was proposed (Figure 1). The framework seamlessly integrates the gauge-based historical simulation (Zhang *et al.*, 2014), satellite-aided real-time monitoring (Zhang and Tang, 2015), CFSv2-based seasonal forecast into an operational system. In addition, an experimental seasonal hydrological forecasting system is being developed over Yellow River Basin based on a well-calibrated hydrologic model and multiple CGCMs.

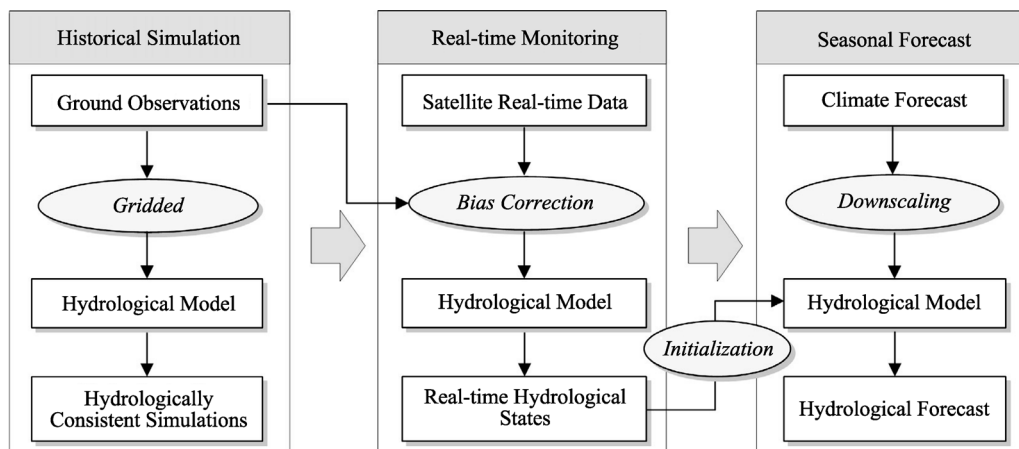


Figure 1 The configuration of hydrological monitoring and seasonal forecast framework for China

6 Summary and future perspectives

Over the past few decades, the hydrological monitoring technique has been largely improved along with the advances in remote sensing and numerical models. On one hand, many hydrological variables become acquirable in a real-time manner via automatic ground-based stations or satellite remote sensing. On the other hand, the calibrated hydrological model, being assisted by station and satellite data, has been demonstrated to provide reliable hydrological fluxes and states in real-time manner. A few satellite-assisted hydrological monitoring systems have been implemented across different scales and used for flood/drought diagnosis. Notably, there are considerable uncertainties residing in data generation and processing, which promotes the development of various mathematical methods to reduce or quantify such errors. While great progress has been achieved for hydrological monitoring, continued efforts are still in urgent need to improve the accuracy of measurement, such as by expanding the in-situ networks, and by improving the in-situ measurement techniques and satellite retrieve algorithms. In addition, it is of intense desire to incorporate the human-induced impacts (e.g., land cover, irrigation, and groundwater pumping) into land surface hydrological models by improving model parameterization scheme, with intent to simulate more realistic hydrological conditions.

The physical model-based hydrological forecast is becoming popular and implemented in two typical ways: (1) ESP-based framework that employs the ensemble of historical observations as the inputs of hydrological model and (2) climate model-based framework that drives the hydrological model with the downscaled outputs of climate forecast model. To date, considerable efforts have been devoted to assessing the reliability of seasonal hydrological prediction, such as by quantifying the contribution of initial conditions (ICs) and

climate forecasts (CFs) to seasonal hydrological predictability. Concurrently, a few operational hydrological seasonal forecast systems, with the aid of real-time monitoring of ICs, the climate model outputs, and the appropriate statistical or dynamical downscaling methods, were explored using either single (climate and hydrological) model or multiple models. To better constrain the ICs, data assimilation technique is essential to improve the mode-derived prediction through blending the in-situ/satellite observations into hydrological monitoring.

In China, the BoH has made a large amount of hydrological monitoring and forecasting practices, for example, establishing the river regime monitoring network and short-term flood warning system across China. In contrast, the area of seasonal hydrological forecasts, especially that based on the climate model outputs, is still in infancy. In following, it should put more focus on the CGCM-based seasonal hydrological forecasts over China, in terms of quantifying the source of hydrological predictability within a consistent diagnosis framework, developing an operational seasonal forecast system in support of China Seasonal Drought Outlook, and assimilating the in-situ measurement of ICs into the operation system to reduce the uncertainties associated with the ICs.

Although many practices have been made for seasonal hydrological forecasts, many challenges still exist and need to be further addressed in near future. Firstly, it is essential to combine the statistical-based and the physical-based models, with intent to create a multi-model ensemble that is characterized with the largest model diversity. Secondly, further efforts are needed to develop a hydrological forecast system that seamlessly integrates the weather forecast and climate forecast (Yuan *et al.*, 2014). This will greatly benefit integrating the achievement in short-term flood forecast and seasonal drought prediction. Furthermore, substantial attentions should be paid on investigating how to effectively incorporate human interventions into the operational monitoring and forecast system in the purpose of yielding more realistic hydrological conditions. Lastly, the final purpose for hydrological monitoring and seasonal forecasting is to provide useful guidance for the end users. Thus, to explore the solutions, which can effectively convert the probabilistic forecast consequences into the understandable and valuable information for the decision-makers (Demargne *et al.*, 2014), is perhaps of equal to or greater importance than the development of such operational systems.

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