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# Hydroclimatic Variability and Predictability: A Survey of Recent Research

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**Abstract.** Recent research in large-scale hydroclimatic variability is surveyed, focusing on five topics: (i) variability in general, (ii) droughts, (iii) floods, (iv) land-atmosphere interactions, and (v) hydroclimatic prediction. Each surveyed topic is supplemented by illustrative examples of recent research, as presented at a 2016 symposium honoring the career of Professor Eric Wood. Taken together, the recent literature and the illustrative examples clearly show that research into hydroclimatic variability continues to be strong, vibrant, and multifaceted.

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## 1 Introduction

Drought has been linked to the collapse of several ancient societies, including Mesopotamia's Akkadian empire (Cullen et al. 2000), late Bronze-Age cultures in the Eastern Mediterranean (Kaniewski et al 2013), and the Mayan (Haug et al. 2003), Mochica, Tiwanaku and Anasazi civilizations (deMenocal 2001). Flooding may have contributed to the decline of the Cahokia settlement in the Mississippi River floodplain near modern-day St. Louis about a thousand years ago (Benson et al. 2007; Munoz et al. 2015). While these particular societal impacts of hydrological variability are rather extreme, more moderate and common impacts of the variability are still profound. Droughts continue to generate tremendous economic losses across the globe through their impacts on crop productivity and water supply. Flooding causes extensive damage worldwide; the flooding of the Mississippi River in 1993, for example, caused over 15 billion dollars of damage (NOAA, 1994). Even minor hydrological variations are becoming ever more relevant in the face of increasing populations across the globe and concomitant reductions in water quality.

Humans, attuned to such vulnerability, have been quantifying hydrological variability and its impacts on society for millennia. Dooge (1988) notes that thousands of years ago, specific and quantified stages of the Nile were tied to hunger (drought) at the low end and to disaster (flooding) at the high end. Leonardo da Vinci documented floods on the Arno River, driving him to formulate some of the first scientifically-based theories of hydrological variability (Pfister et al. 2005). Humans have long struggled, in fact, to control hydrological variations and thereby mitigate their negative impacts. Over the centuries, reservoirs have been built specifically to provide water to society during dry periods and to serve as a buffer against flooding during pluvial periods, and reservoir operation algorithms have evolved to optimize their effectiveness for both roles. More recently, techniques have been devised for quantified predictions of hydrological variations. Seasonal streamflow predictions, for example, are tied to snowpack, soil moisture, and climatic state (e.g., Maurer and Lettenmaier, 2003). Precipitation forecasts have become an essential product of operational seasonal forecasting systems (NRC, 2010). Such predictions, if accurate, can inform water management and can help society prepare for some of the more costly and dangerous manifestations of hydrological variation.

Analyses of large-scale hydrological variations and our ability to predict them underlie much of the science of hydroclimatology, the study of the hydrological cycle in the context of the global climate system. While much valuable work on hydrology and hydrological prediction still occurs at catchment and smaller scales (e.g., Abrahart et al. 2012, Wang et al. 2015), the need for a global-scale perspective – one not limited by either political or catchment boundaries – has long been recognized (e.g., Eagleson 1986, Dirmeyer et al. 2009), and this perspective continues to grow in importance. If meteorological drought (i.e., a rainfall deficit), for example, is ever to be predicted, it would be through consideration of the connections, through the atmospheric circulation, between the local rainfall and the large-scale spatial patterns of ocean and land conditions. Another topic requiring a global-scale perspective is anthropogenic climate change, which has the potential to produce significant changes in the large-scale hydrological cycle and thus in local hydrological variations. Such impacts raise serious, pressing questions about the sustainability of society's water resources and further underline the need to solidify our understanding of hydrological variations and what controls them (Jiménez Cisneros et al. 2014).

Global-scale modeling systems are critical tools for large-scale hydroclimatic studies. Gridded models of land surface processes driven with meteorological forcing derived from decades of observational data allow the characterization of

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hydrological variability across extensive time and space scales. When such gridded land models are combined with numerical models of atmospheric and oceanic processes, simulations of the global climate system itself are possible. Such climate simulations can have tremendous value; they can reveal how the different facets of the global hydrological cycle connect to each other, and understanding such connections is essential to our hopes for predicting drought and other manifestations of large scale hydroclimatic variability. Critical limitations to such studies are deficiencies in the models' abilities to capture teleconnections existing in nature (the effect of variations in one part of the system on remote variations in another, such as the impact of the ENSO cycle on continental precipitation) and, as a result, the improvement of these models has long been a high priority research topic. As with hydroclimatic science itself, the complexity and richness of the large-scale models has been growing steadily with time.

A large cross-section of hydrologists and hydroclimatologists met in June 2016 at a symposium in Princeton, New Jersey, USA to honor the career of Professor Eric Wood, and the broad range of topics covered in the symposium touch on many of these aspects of large-scale hydrological variability. Given these contributions, and given the ever-evolving state of this important subject, the gathering was seen as an opportunity to survey recent, relevant state-of-the-art hydroclimatic research. We provide such a survey in the present paper, recognizing the fact that hydroclimatological research is but a subset of the much broader range of research underlying the science of hydrology. Here we specifically emphasize research of a large-scale nature; we do not pretend to cover the extensive work being performed, for example, at or below the catchment scale.

In this paper, for each of a number of subtopics relevant to large-scale hydrological variability (namely, general variability and trends, droughts, floods, land-atmosphere interaction, and hydrological prediction), we briefly summarize some findings in the recent literature, going back to about 2010. The survey, while not exhaustive, should serve to provide interested readers with multiple starting points for further study. For each subtopic, we also provide some state-of-the-science findings that were presented at the symposium. Each of these findings is presented in the form of a self-contained, stand-alone figure and caption; together, the figures illustrate the many facets of hydrological variability and the variety of approaches used to investigate it.

## 2 Recent Advances in Hydrological Variability and Predictability

### 2.1 General Studies on Variability and Trends

#### 2.1.1 Recent Literature

The last several years of research into the characterization of Earth's hydroclimatic variability reflect, to some extent, two key facets of the problem: (i) the continually growing availability of powerful computational tools for examining this variability, and (ii) the potential for changes in this variability with changes in the global climate. Amongst the most important modern computational tools, at least for continental- or global-scale hydroclimatic analyses, is atmospheric reanalysis: a mathematically optimal blending of modeling and observations that produces complete fields in space and time of important hydrological variables (e.g., Kanamitsu et al. 2002, Dee et al. 2011, Bosilovich et al 2015, Kobayashi et al. 2015; see also https://reanalyses.org/). Collow et al. (2016), for example, utilize a global reanalysis to characterize the dynamical evolution of meteorological variables during the lifecycle of extreme storms in the Northeast United States, and Maussion et al. (2014) use a regional reanalysis to examine precipitation variability over the Tibetan Plateau, linking it, for example, to certain features of the overlying atmospheric circulation. Of course, reanalyses are far from perfect; Trenberth et al. (2011) indicate disparities between the different reanalyses in their treatments of large-scale moisture transports and associated hydrological variables such as streamflow.

Another computational tool used heavily in the last decade for continental- or global-scale hydrological analysis is the "land data assimilation system", or LDAS, basically a gridded array of land model elements driven with observations-based meteorological forcing, some of which is derived from reanalyses. Explored early on by Dirmeyer et al. (2006), more recent applications of the LDAS approach have benefitted from improved global forcing datasets (e.g., Sheffield et al. 2006, Weedon et al. 2011) and accordingly provide improved descriptions of large-scale land surface hydrology and its variations (Reichle et al. 2011, Xia et al. 2012, Balsamo et al. 2015). Wood et al. (2011) emphasize the importance to society of developing hyper-resolution (≤1 km resolution) land surface modeling systems at continental to global scales.

A climate model in "free-running" mode (i.e., without the assimilation of observational data) is a computational tool with a special role in hydroclimatic analysis, being particularly suitable for sensitivity analyses and for analyses requiring extensive (e.g., multi-century) climate data. Using such a model, for example, Tierney et al. (2013) show a connection between Indian Ocean sea surface temperatures (SSTs) and East African rainfall on multi-decadal timescales through the impact of the former on the Walker circulation. Indeed, the second topic noted above (the idea that hydroclimatic variability is changing with time) is now largely being addressed through sensitivity studies using such climate models. With climate models, one can artificially modify the concentration of $CO_2$ in the atmosphere, among other climate elements, and quantify the model's long term responses. Dirmeyer et al. (2014a), for example, analyze projected water cycle changes in the Coupled Model Intercomparison Project Phase 5 (CMIP5; a climate evolution experiment involving multiple climate drivers performed by dozens of climate modeling groups), finding that a strongly warmed climate may lead to significant increases in drought and flood risk. Orlowsky and Seneviratne (2012) point to difficulties in extracting hydrological trends from the CMIP5 results but nevertheless find some robust signals, including $CO_2$-induced increases in drought frequency in regions such as the Mediterranean, South Africa, and Central America.

One of the expectations of a warming climate, supported by such modeling studies (e.g., Held and Soden, 2006; Chou and Lan 2012, Kumar et al. 2013), is that currently dry areas will get drier and wet areas will get wetter. One manifestation of such a trend is the narrowing of the Intertropical Convergence Zones (ITCZ) and the expansion of the drier subtropical area (e.g., Su et al. 2014; Lau and Kim 2015); such a change appears to broadly resemble the observed change in the past several decades (e.g., Wilcox et al. 2012, Fu 2015), which contributed to the shortening of both North and South American monsoon seasons (Arias et al. 2015). Greve et al. (2014), however, upon examining multiple long-term observational datasets, conclude that the "dry gets drier, wet gets wetter" paradigm is not consistently supported by the historical data, at least over land.

Coumou and Rahmstorf (2012) cite numerous studies documenting recent rainfall and storm extremes that, taken together, suggest that greenhouse warming has affected their frequency. An observations-based analysis of global evapotranspiration fields indicates a positive trend between 1982 and 1997 that has declined thereafter (Jung et al. 2010). A similar evapotranspiration trend change in regions of North America was attributed to variability of precipitation amount (Parr et al., 2016), while Miralles et al. (2013) point to the El Niño cycle as a major control over global-scale evapotranspiration variability. Milly and Dunne (2016) warn that some estimates in the literature of increased potential evapotranspiration (PET) in a warming climate may be overestimated, even those that rely on the well-considered Penman-Monteith equation for estimating PET (Monteith 1965).

Trends in streamflow are of critical relevance to water management and have been evaluated recently (largely with historical data) in many areas (see Lorenzo-Lacruz et al. [2012] and references therein). Milly et al. (2008) argue that the historical strategy of assuming stationarity in hydrological statistics for developing water management infrastructure is no longer tenable in the face of such climatic trends. Serinaldi and Kilsby (2015), however, illustrate difficulties in using nonstationary models for the associated hydrological frequency analysis. Future climate predictions suggest that the range of hydrologic variability over many locations may move completely outside the historical ranges (Dirmeyer et al. 2016a).

### 2.1.2 Examples from the Symposium

Real-world variability, including climatic trends, was addressed by several presentations at the symposium. Rivers in northern Canada are seen to exhibit strong interannual and interdecadal variability (see Figure 1), though no trend in total discharge for 1964-2013 (Déry et al. 2016). In another study, variability of rainfall over Australia is found to be potentially controlled more by nearby sea surface temperatures (SSTs) than by distant climate phenomena such as El Niño (Figure 2). Estimating trends in discharge over the coming decades is made possible with climate projection data applied to a land model with improved (reduced bias) treatments of evapotranspiration and dynamic vegetation; a default model and a bias-corrected model produce contrasting trends in streamflow associated with future drought (Figure 3). Properly accounting for vegetation response to meteorological and hydrological variables and feedbacks with these variables has important implications for the overall characterization of hydrological variability in a changing climate (Figure 4).

Increased computational power provides new opportunities for examining hydrological variability. Improved atmospheric simulation of the jet stream, for example, is made possible with higher resolution models, opening the door to improved simulation of atmospheric rivers and associated heavy cold season precipitation (Figure 5). Globally distributed estimates of runoff generation may improve with a new computational approach keyed to certain dominant landscape processes (Figure 6).

## 2.2 Drought

### 2.2.1 Recent Literature

Given its societal relevance, drought has been tracked extensively in recent years. In the United States, the U.S. Drought Monitor (http://droughtmonitor.unl.edu/Home.aspx) provides a current weekly map of drought conditions, and the U.S. Seasonal Drought Outlook (http://www.cpc.ncep.noaa.gov/products/expert_assessment/sdo_summary.php) gives an indication of where drought is likely to develop or break over the coming months. The Australian Bureau of Meteorology similarly issues detailed drought statements (http://www.bom.gov.au/climate/drought/). Drought research in recent years has intensified as well, with substantial input from new measurement approaches, particularly satellite-based remote sensing. Damberg and AghaKouchak (2014), for example, utilize remotely sensed precipitation datasets to characterize recent droughts in the Northern and Southern Hemispheres. Remotely-sensed estimates of land water storage, made possible by measurements from the Gravity Recovery and Climate Experiment (GRACE) satellite, provide indications of water storage deficits that can aid in the characterization of drought (Thomas et al. 2014). Research addressing more traditional observational sources and indices has been published as well; Sheffield et al. (2012), for example, illustrate that the traditional Palmer Drought Severity Index, based on Thornthwaite potential evaporation, may lead to overestimates of drought severity and trends.

Along with new measurement approaches come improved statistical and modeling treatments of drought, as reviewed by Mishra and Singh (2011). A Bayesian approach was recently applied by Kam et al. (2014) to connect drought probability to phases of the Atlantic Multi-decadal Oscillation (AMO), Pacific Decadal Oscillation (PDO) and El Niño / Southern Oscillation (ENSO) cycles. Pan et al. (2013) use a Copula (joint probability distribution) approach focusing on a soil moisture-based drought index and precipitation forecasts to characterize uncertainties in drought recovery. Land surface modeling in combination with observations of meteorological forcing provides a unique means for monitoring drought on the global scale (e.g., Nijssen et al., 2014). Numerical climate models have evolved substantially in the last decades, and their application to drought studies is growing; Hoerling et al. (2014), for example, use such models to analyze the 2012 United States Great Plains drought, and Coats et al. (2015) evaluate their ability to reproduce the character of paleoclimatic megadroughts in southwest North America.

The specter of climate change largely manifests itself in concerns that drought frequency will increase. Numerical model simulations of changing climate provide much of the needed data for focused study; Seager and Vecchi (2010) use these models to examine the character of future drought in southwestern North America, concluding that drought there can be expected to increase in the coming century due to reduced precipitation from large-scale atmospheric circulation changes during winter months. Cook et al. (2014) examine climate model simulations to quantify the relative impacts on agricultural drought of changes in precipitation and temperature (through evapotranspiration) and demonstrate that the temperature impact is substantial. Dai (2013) evaluates the historical record and climate change simulations in the context of aridity changes and concludes that the models are generally consistent with the historical record up to 2010. Regarding California drought, Mao et al. (2015) studied the historical record (rather than climate simulations) and conclude that the 2013-2014 drought was induced by reduced precipitation rather than by the observed temperatures trend, while Diffenbaugh et al. (2015) find that reduced precipitation in California is more likely during anomalously warm years. Mo and Lettenmaier (2015) find that flash drought, based on a definition of concurrent heat extreme, soil moisture deficit and evapotranspiration (ET) enhancement, has been in decline over the US during the last 100 years (though with a rebound after 2011), while recent work by Wang et al. (2016) indicates that the occurrence of flash drought in China has doubled during the past 30 years; a severe flash drought in the summer of 2013, for example, ravaged 13 provinces in southern China. Trenberth et al. (2015) highlight some of the difficulties associated with characterizing changes in drought behavior over time, pointing to deficiencies in the precipitation datasets being used and to the need to account properly for sources of natural variability, such as ENSO.

Given its importance, drought has been the subject of several recent overview and review papers; the interested reader is directed to these papers for further information. Mishra and Singh (2010) describe drought definitions and drought indices and identify important gaps in drought research. Wood et al. (2015) provide a synthesis of research (largely focused on North American drought) performed by the National Oceanographic and Atmospheric Administration's Drought Task Force, and Schubert et al. (2016) review the latest understanding of meteorological drought as it manifests itself around the world. Kiem at al. (2016) reviews the current understanding and history of drought in the Australian context, including implications for future droughts given climate change. Peterson et al. (2013), in their overview of droughts in the United States, provide additional useful references.

**2.2.2 Examples from the Symposium**

Drought was the subject of many symposium papers, two of which are represented here. One focused on the predictability of seasonal meteorological drought in northern China and on global warming-induced changes in flash drought over southern China (Figure 7). Observed connections between soil moisture, clouds, convection, and subsidence may underlie a mechanism by which soil moisture influences not only local rainfall, but also the large-scale atmospheric circulation in such a way as to sustain dry anomalies from spring to summer, potentially contributing to drought forecast skill (Figure 8).

### 2.3 Floods

#### 2.3.1 Recent Literature

Much recent research has addressed flash floods in Europe. Gaume et al. (2009), for example, describe their compilation of nearly 600 flash flood events in Europe, and Marchi et al. (2010) characterize European flash floods in the context of basin morphology, rainfall characteristics, antecedent soil moisture, and other factors. An extensive field experiment aimed at quantifying facets of flash floods in the northwestern Mediterranean was conducted in the fall of 2012 (Ducrocq et al., 2014). The nature of floods has been studied in other areas as well; Gochis et al. (2015) analyze the meteorological and hydrological conditions underlying the September 2013 Colorado flood event in great detail, addressing forecast capabilities and also pointing to new observations that may help prepare for future events. Berguijs et al. (2016) examine the mechanisms underlying flood generation in the continental US and find that precipitation in isolation is not a good predictor of maximum annual flow; precipitation needs to be considered in conjunction with soil moisture and snow amounts. Tuefel et al. (2016) perform a meteorological analysis of the June 2013 Alberta floods. Huang et al. (2014) used a combination of ground-based and satellite data to map flood inundation in the Murray-Darling Basin of Australia.

Many recent studies have addressed potential changes in flood character associated with changes in climate. Mallakpour and Villarini (2015) examined the observational record in the central United States and found an increase in the frequency of flood events there, though not an increase in the largest flood peaks. Regarding future changes, Hirabayashi et al. (2013) combined climate change projections from a number of climate models with a global river routing model to determine that regions such as Southeast Asia and eastern Africa may be subject to greater flood frequency by the end of the century. Similarly, Arnell and Gosling (2016) ingest the results of climate projections from multiple climate models into a global hydrological model and, considering impacts on future distributions of human population, find indications of increased flood risk, though the magnitudes of the impacts are uncertain given the variability in the projections. Hallegatte et al. (2013) address the costs of flooding in coastal cities, which are especially prone to the effects of subsidence and sea level rise.

Hall et al. (2014), citing many recent studies, provide a thorough review of flood regime changes inferred in Europe based on observations and model experiments. Johnson et al. (2016) provide a review of historical trends and variability of floods in Australia, along with an assessment of future flood hazards given climate change. Kundzewics et al. (2014) offer a global look at flood potential in the context of climate change and indicate a low level of confidence in current projections of the character (magnitude and frequency) of floods.

#### 2.3.2 Examples from the Symposium

Several flood presentations at the symposium described highly developed monitoring and forecasting systems, important sources of information for mitigating the societal impacts of floods. One such system is the Aqueduct Global Flood Analyzer, which estimates flood risks across the globe, considering aspects like flood hazard, exposure, and vulnerability (Figure 9). One symposium presentation emphasized that floods and droughts need to be considered together in reservoir design and operation – their joint impacts vary spatially, leading to global variations in the relative difficulty of managing hydrological variability (Figure 10).

### 2.4 Land-Atmosphere Coupling

#### 2.4.1 Recent Literature

An important facet of climate science is the idea that the land surface is an active, dynamic component of the climate system rather than simply a passive respondent – the idea that soil moisture variations, for example, can imprint themselves on the overlying meteorology and on associated hydrological variability. Seneviratne et al. (2010) provide an extensive overview of research into the nature of this land-atmosphere coupling, and Dirmeyer et al. (2016b) provide an updated review, with a focus on climate modeling studies. The continuing research is shedding new light on the ability of soil moisture to influence, for example, rain variability and heat waves.

The soil moisture-air temperature connection is intuitive; drier soils evaporate less and thus experience less evaporative cooling, leading to higher temperatures for the local system. This connection has been examined, for example, in the context of the 2003 European heat wave (Fischer et al. 2007). More difficult to pin down is the soil moisture-precipitation connection. Indeed, the literature indicates complexities regarding the directions of the feedback, i.e. in whether increased soil moisture leads to increased or decreased rainfall. For example, Findell et al. (2011) find that over the eastern United States, increased soil moisture leads to a greater probability of afternoon rainfall, supporting the idea of positive feedback, whereas Taylor et al. (2012) provide observational evidence that rainfall tends to fall over the drier patches in a landscape. Guillod et al. (2015) address the apparent contradiction by showing that while large-scale wet conditions are in general favorable to increased precipitation (a positive temporal correlation at the large scale), rainfall can favor the drier patches within the broadly wet conditions (a negative spatial correlation). Theory suggests that some atmospheric conditions promote a positive soil moisture-rainfall feedback whereas others promote a negative one; Ferguson and Wood (2011), through an analysis of satellite-based data, separate the globe into the associated different coupling regimes, and Roundy et al. (2013) extend the methodology to show how the coupling regime in a given location can change with time.

Naturally, land-atmosphere coupling has been studied extensively within climate models. One recent study (Saini et al., 2016) examines past drought events using a regional climate model with different soil moisture initializations; soil moisture feedback is found to be much more important for the development of the 2012 drought in the central U.S. than for the development of the 1988 drought there, due to the lack in 2012 of a clear large scale forcing favoring drought. Using a different model, Koster et al. (2016) show that soil moisture deficits in the interior of North America can help generate atmospheric circulation patterns that in turn can contribute to the persistence and areal expansion of the dryness. Regarding the impact of climate change on land-atmosphere coupling, Dirmeyer et al. (2013a,b, 2014b) analyze the water cycle in CMIP5 models in several ways, noting evidence for enhanced land-atmosphere feedbacks in a changing climate arising in concert with increasing extremes. Worth noting, though, is that models with parameterized convection may have difficulty in properly representing land-atmosphere coupling. Recent advances in convection-permitting modeling may lead to better simulations of convection and land-atmosphere interactions (e.g., Hohenegger et al. 2009; Leung and Gao 2016).

Some recent work has advocated a more holistic treatment of land-atmosphere coupling, one that considers the co-evolution of snow properties, cloud forcing, temperature, relative humidity, precipitation, wind, and boundary layer growth. On the Canadian Prairies, for example, the monthly variability of temperature and relative humidity in the warm season is dominated by shortwave cloud forcing, and as a result, both equivalent potential temperature and the lifting condensation level, which drive moist convective development, depend strongly on cloud forcing (Betts et al. 2013a, 2015, 2016). This has implications for seasonal predictability, given the uncertainties in predicting daily cloud forcing in numerical forecast models. Betts et al. (2017) provide a set of coupling coefficients between the near-surface diurnal cycle of the moist thermodynamic variables, cloud forcing and lagged precipitation for model evaluation. Another challenge for seasonal predictability is the dynamic coupling between vegetation phenology, precipitation anomalies, soil water extraction, and evapotranspiration. The intensification of cropping increases evapotranspiration and cools the summer climate both in the US Midwest (Mueller et al. 2016) and the Canadian Prairies (Betts et al. 2013b), and the extraction of soil water during the growing season appears to damp precipitation anomalies (Betts et al. 2014b) and perhaps contributed to the onset of 2012 Great Plain drought (Sun et al. 2015).

The Global Land Atmosphere System Study (GLASS) panel of the Global Energy and Water Exchanges (GEWEX) project has focused recently on the definition and evaluation of land-atmosphere coupling processes in models and observational data (Santanello et al. 2011) with a particular focus on the hydrologic cycle. The reader is directed to the website http://cola.gmu.edu/dirmeyer/Coupling_metrics.html for an evolving summary of land-atmosphere coupling metrics and associated references.

#### 2.4.2 Examples from the Symposium

Symposium papers addressed several facets of land-atmosphere coupling, including the attribution of the sources of the coupling strength simulated by an Earth system model and the evaluation of simulated coupling characteristics with relevant observational datasets. Figure 11 shows recent results from the analysis of Canadian Prairies data, in the context of the aforementioned holistic approach to analyzing land-atmosphere interaction.

### 2.5 Hydrological prediction

#### 2.5.1 Recent Literature

Again, a key motivation for studying hydroclimatic variability is improvement in the skill of hydrological predictions – skillful predictions can allow society to prepare itself better for upcoming hydrological variations. One highly relevant tool for this is the extended-range forecast system, a coupled ocean-atmosphere-land modeling system that provides, among other things, forecasts of temperature and rainfall over continents weeks to months in advance. Doblas-Reyes et al. (2013) provide a review of the state-of-the-art in seasonal forecasting with such systems, Yuan et al. (2015) provide a review of climate model-based seasonal hydrological forecasting, and Robertson et al. (2015) and Vitart et al. (2016) describe emerging operational subseasonal-to-seasonal (S2S) forecast systems. Regarding the overall accuracy of seasonal forecasts, Roundy and Wood (2015) use statistical models to examine how such forecasts may be limited by biases in their treatment of land-atmosphere coupling, and Yuan and Wood (2012) address critical questions regarding the combination of forecasts from different systems – whether redundancies amongst the systems can be properly accounted for when developing a multi-model forecast.

In essence, forecast skill in a subseasonal-to-seasonal forecast system is derived from the information content inherent in the system's initialization. Therefore, considerable effort has been directed toward improving this initialization, for example, through the improvement of Bayesian (Kalman and particle filters) and variational (1D-4D) data assimilation methods as applied to the initialization of high-dimensional models (e.g. Li et al. 2015; van Leeuwen, 2015). A promising strategy is based on combining advantageous characteristics of both paradigms (e.g., the probabilistic estimates for Bayesian methods and the broader evaluation window for variational ones), as demonstrated by, for example, Bruehner et al. (2010) and Noh et al. (2011).

While the initialization of ocean states has long been considered key for the coupled forecast systems (NRC, 2010), there is growing recognition that the initialization of various land states may be just as critical to extracting otherwise unattainable facets of skill (e.g., Dirmeyer and Halder 2017). Soil moisture impacts on subseasonal forecast skill is quantified across a broad range of systems in the Global Land-Atmosphere Coupling Project (Koster et al. 2011; van den Hurk et al. 2011); impacts are found to be much larger on temperature forecast skill, but impacts on precipitation forecast skill are significant in places, particularly when considering the strongest initial soil moisture anomalies. A positive impact of snow initialization on seasonal temperature forecast skill is demonstrated by Peings et al. (2011) and Lin et al. (2016); the latter show that the assimilation of satellite measurements improves the initialization, with concomitant impacts on the forecast skill. Koster and Walker (2015) show that when a dynamic plant phenology model is used in a forecast system, initializing the vegetation state (e.g., the leaf area index) has a positive impact on temperature forecasts but not on precipitation forecasts. Subsurface temperature is another variable to consider; Xue et al. (2016) demonstrate that initializing these temperatures in an atmospheric modeling system can improve the simulation of subsequent drought. As shown by Dirmeyer et al. (2013c), the predictability of meteorological variables (the theoretical maximum forecast skill that can be derived from an initialization) may change as the climate changes.

Drought forecasting in particular has been a focus of much recent work. In sub-Saharan Africa, an advanced drought monitoring and forecasting system based on hydrological modeling, remote sensing, and seasonal forecasts has been developed and implemented, for example, at regional weather and climate centers in Niger and Kenya (Sheffield et al., 2014). Regarding the skill of seasonal drought forecasts, results are mixed. Yuan and Wood (2013), in an analysis of multiple seasonal forecast systems, uncover significant limitations in the ability of such systems to forecast drought. Quan et al. (2012), however, using a specific seasonal forecast system, demonstrate that the sea surface temperatures produced in the system, particularly those associated with ENSO, do add some skill to drought prediction over the United States. Roundy et al. (2014) demonstrate that apparent deficiencies in the simulated land-atmosphere coupling behavior of a forecast system can limit its ability to predict and maintain drought.

Streamflow forecasting has obvious relevance to water resources management, and relative to drought forecasting, it can rely less on dynamical seasonal forecasts given the strong connection between streamflow and, for example, snow storage at the start of a forecast period. Koster et al. (2010) and Mahanama et al. (2012), without using a dynamical forecast model, produce accurate streamflow forecasts at seasonal leads based solely on initial snow and soil moisture information. This said, seasonal climate forecasts (perhaps combined with medium-range weather forecasts, as described by Yuan et al. [2014]) can add skill to long-term streamflow forecasts (Yuan et al. 2013).

Demargne et al. (2014) describe in detail the operational Hydrologic Ensemble Forecast Service, which provides, through integration of multiple inputs (including meteorological forecasts), streamflow forecasts at leads from 6 hours to 1 year. Pagano et al. (2014) outline the challenges faced by forecast agencies around the world in developing an operational river forecasting system that is suitably effective.

#### 2.5.2 Examples from the Symposium

Forecast-related presentations at the symposium include a description of a data assimilation approach called OPTIMISTS (Optimized PareTo Inverse Modeling through Integrated Stochastic Search), which combines features from Bayesian and variational methods for the initialization of highly distributed hydrological models (Figure 12). The idea that the US operational forecast model underestimates land-atmosphere coupling is inferred from the fact that observed precipitation rates are more closely related to antecedent soil moisture than model simulated rates (Figure 13; Dirmeyer 2013).

**3. Summary**

The present paper provides an overview of some recent research (roughly since 2010) on the subject of hydrological variability and predictability, with particular focus on the spatial as well as temporal aspects of variability and with an eye toward large-scale prediction. Given the wealth of research on the subject, this overview does not pretend to be comprehensive, even for the recent period; it is perhaps best considered a starting point for those interested in pursuing this multi-faceted topic further. The specific examples shown in the figures were culled from relevant presentations made at the Symposium in Honor of Eric Wood: Observations and Modeling Across Scales. These examples are representative of the breadth of today's research on this topic.

Hydrological variations, as exemplified by floods and droughts, have substantial societal impact on a range of spatial and temporal scales. Much recent work has shown that the characteristics of droughts and floods are evolving with the climate. To address such issues, physically-based dynamical models incorporating more than just the hydrologic cycle are beginning to supplant lumped models, particularly at multi-basin scales. Given the potential benefits to society of predicting hydrological variations well in advance, large-scale, climate-oriented hydrological variability studies will undoubtedly continue to be a vibrant component of Earth system science.

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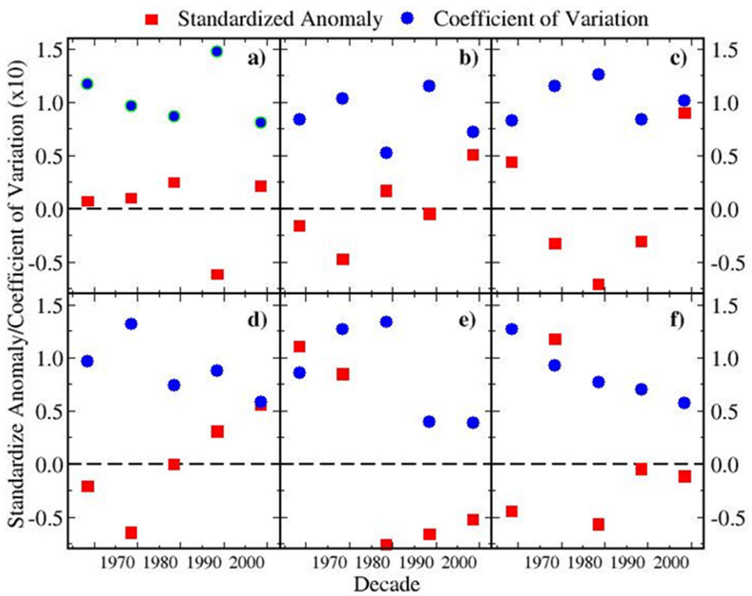


**Figure 1: Decadal variations in the standardized mean (i.e., standardized anomalies in the decadal mean) and coefficient of variation of total river discharge for six drainage basins of northern Canada: a) Bering Sea; b) Western Arctic Ocean; c) Western Hudson and James Bay; d) Eastern Hudson and James Bay; e) Eastern Arctic Ocean (Hudson Strait/Ungava Bay); and f) Labrador Sea. The decades of interest are 1964-1973, 1974-1983, 1984-1993, 1994-2003, and 2004-2013. Note that values of the coefficient of variation have been multiplied by 10. [Contact: Stephen Dery.]**

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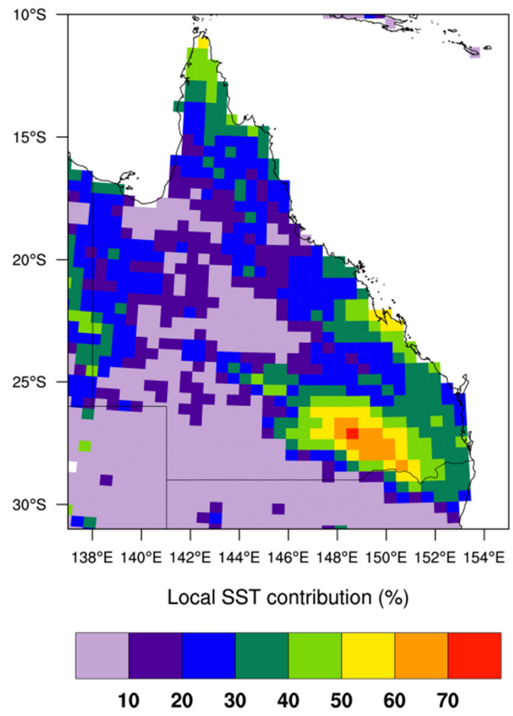


Figure 2. The contribution of local SSTs to major flooding that occurred between 10 and 20 December 2010 in Queensland, Australia. In many places the high local SSTs (within a few hundred km of the coast) accounted for more of the precipitation than the prevailing La Niña conditions did. This demonstrates limitations in hydrological predictability based on large-scale climate modes such as ENSO. Results were obtained by comparing 40-member ensembles of WRF runs using observed SSTs with an ensemble using SSTs associated with previous La Niña events but the same atmospheric circulation conditions. [Contact: Jason Evans. See Evans and Boyer-Souchet (2012) for further information.]

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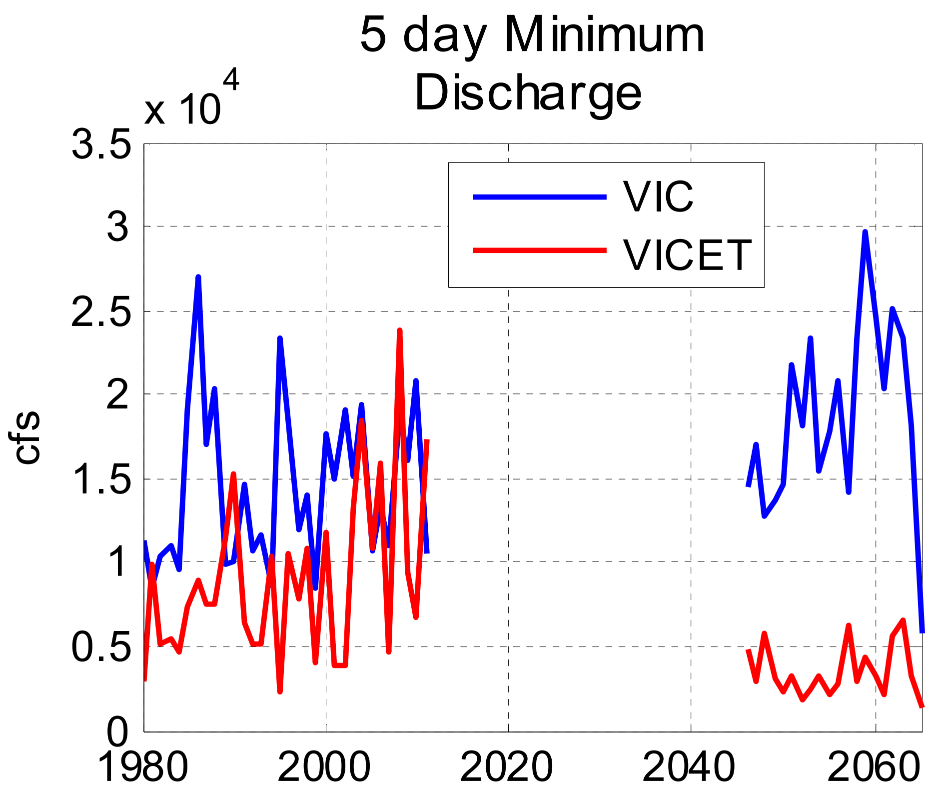


Figure 3. The 5-day minimum discharge at the Thompsonville station on the Connecticut River Basin, as simulated by the default VIC model and the version of VIC with bias-corrected evapotranspiration (VICET). The historical simulations were driven with NLDAS-2 meteorological forcing (Xia et al., 2012), and future projections were driven with the bias-corrected NARCCAP projection following the approach of Ahmed et al. (2013) using NLDAS-2 as the observational reference. [Contact: Guiling Wang. See Parr et al. (2015) for further information.]

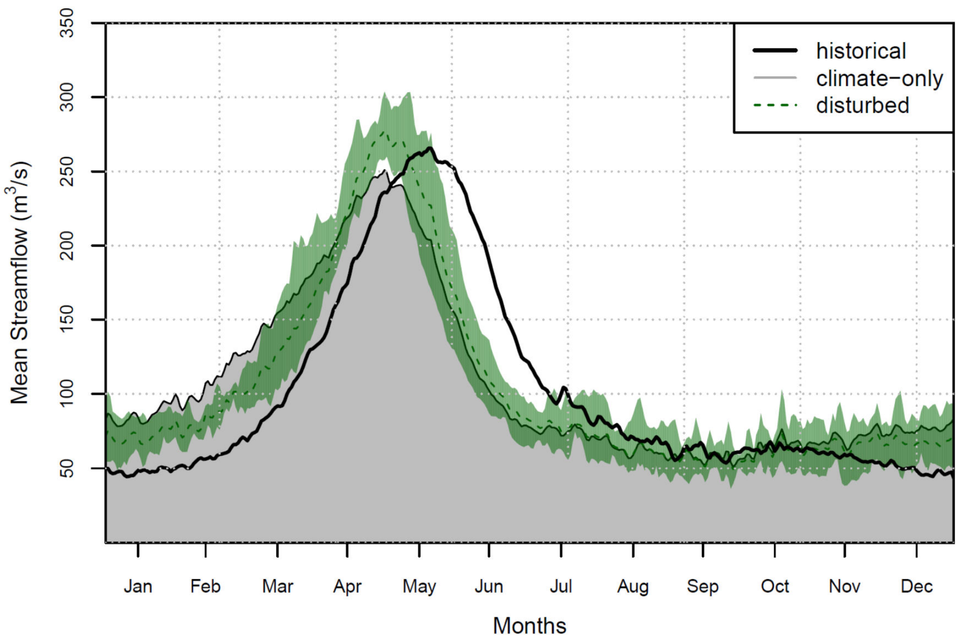


Figure 4. San Juan River basin streamflow for historical (1970-1999) and future (2070-2099) Variable Infiltration Capacity model simulations. The average historical flow conditions are represented by a black line. Future flow conditions are based on downscaled earth system models (ESM) from the IPCC's CMIP5 database run with climate-only changes (grey) and for a disturbed vegetation (green). The climate-only scenarios are run with projected changes in temperature and precipitation, while the disturbed vegetation scenarios include changes in temperature and precipitation and forest mortality close to 90% by the 2080s, based on work from McDowell et al. (2016). The range of responses across four ESMs for the disturbed is shown with a green envelope, and the mean is given with a dashed green line. We see that for the San Juan River basin, a major tributary to the Colorado River basin, spring freshet is projected to occur earlier in the season, shifting from mid-May to the end of April. Flows are projected to be higher during late fall, winter and early spring, and lower during late spring, summer and early fall. Compared to the climate-only scenario, the disturbed vegetation scenarios result in a different pattern of streamflow, with lower flows in early spring and then higher peakflow, with lower recessional summer flows due to the differences in how regrowth vegetation (i.e. shrubs) partitions water and snowpack. Without a consideration of changes to vegetation dynamics in studies on climate change, results may be misleading or could underestimate impacts (Bennett et al. in prep).

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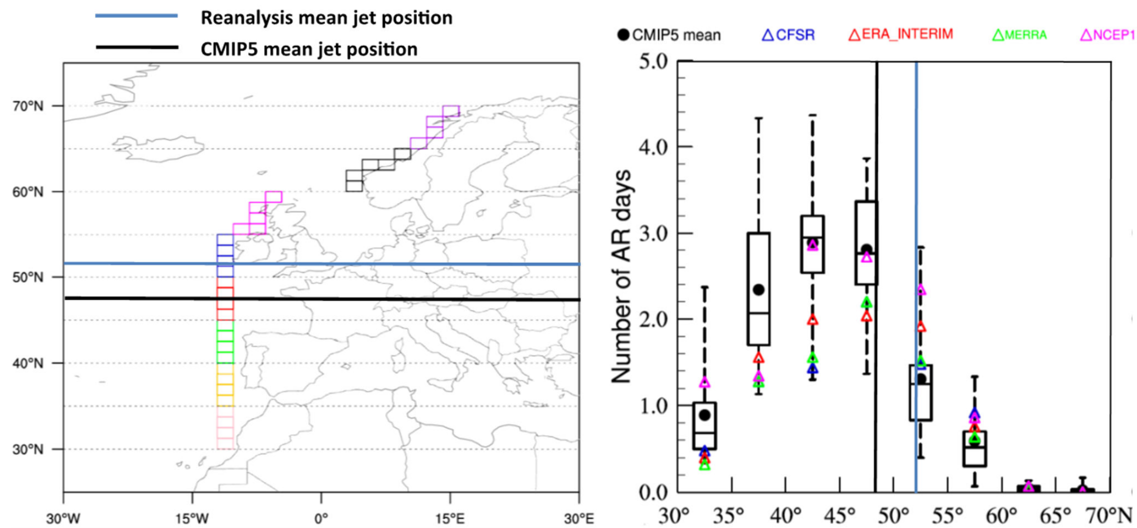


Figure 5. Left: Grid boxes (colored) used to detect North Atlantic atmospheric rivers making landfall in Europe. Right: The number of winter (December-February) atmospheric rivers making landfall at different latitudes based on four global reanalyses and simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5). The box-and-whisker plots show the CMIP5 multi-model mean (dot), median (horizontal bar), 75% and 25% percentiles (upper and lower boundaries of the box), and the highest and lowest values (whiskers). The black and blue lines on the left (horizontal) and right (vertical) panels show the CMIP5 and reanalysis mean jet position, respectively. The CMIP5 models are seen here to simulate a mean jet stream position that is equatorward of that in the reanalysis, probably due to their relatively coarse resolution (e.g., Lu et al. 2015); as a result, CMIP5 models simulated too few (too many) atmospheric rivers poleward (equatorward) of the observed jet position in the North Atlantic. This is important because atmospheric rivers are responsible for over 90% of the moisture transport to the extratropics (Zhu and Newell 1998) and heavy precipitation in many regions worldwide (e.g., Ralph et al. 2006). [Contact: Ruby Leung. See from Gao et al. (2016) for more information.]

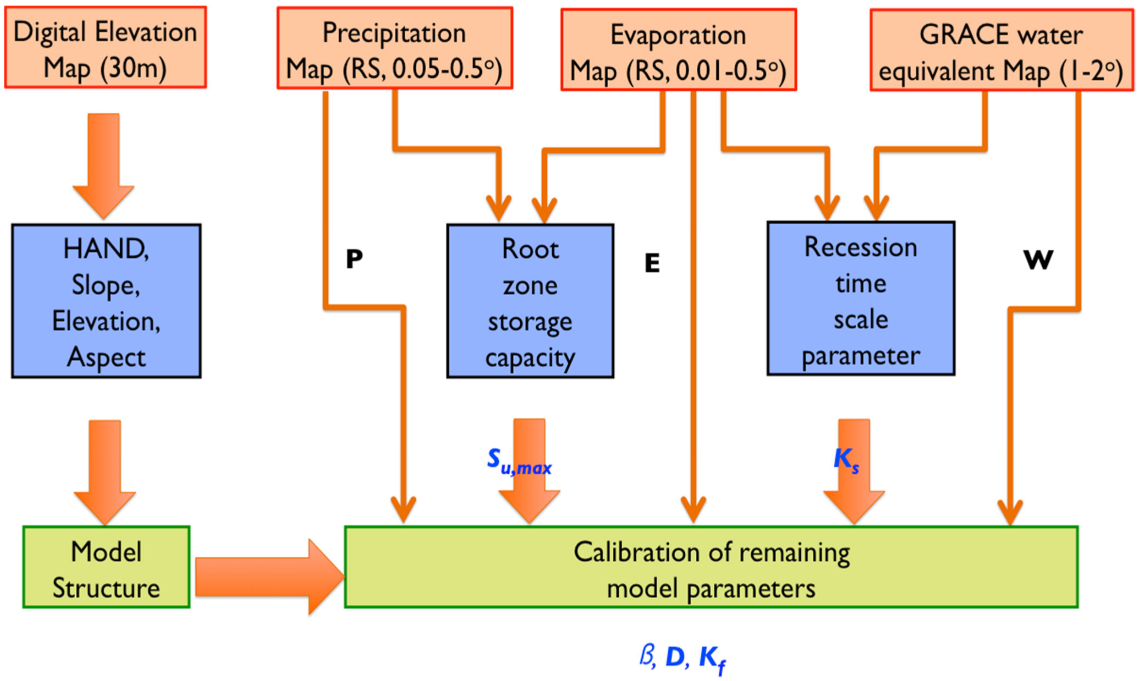


Figure 6. Readily available remote sensing products can be used to constrain hydrological models in a way that allows prediction in ungauged basins. The key parameter in the rainfall-runoff process is the root zone storage capacity of ecosystems, which is the product of an active and living 'agent'. From historical time series of precipitation and evaporation we can derive the storage capacity that the ecosystem created and then connect this to the ecosystem's survival strategy (Gao et al., 2014). This approach is also a way to investigate how ecosystems will adjust their storage capacity in response to climatic change and, hence, how rainfall-runoff relations will change. [Contact: Hubert Savenije. See Savenije and Hrachowitz (2016, 2017) and for more information.]

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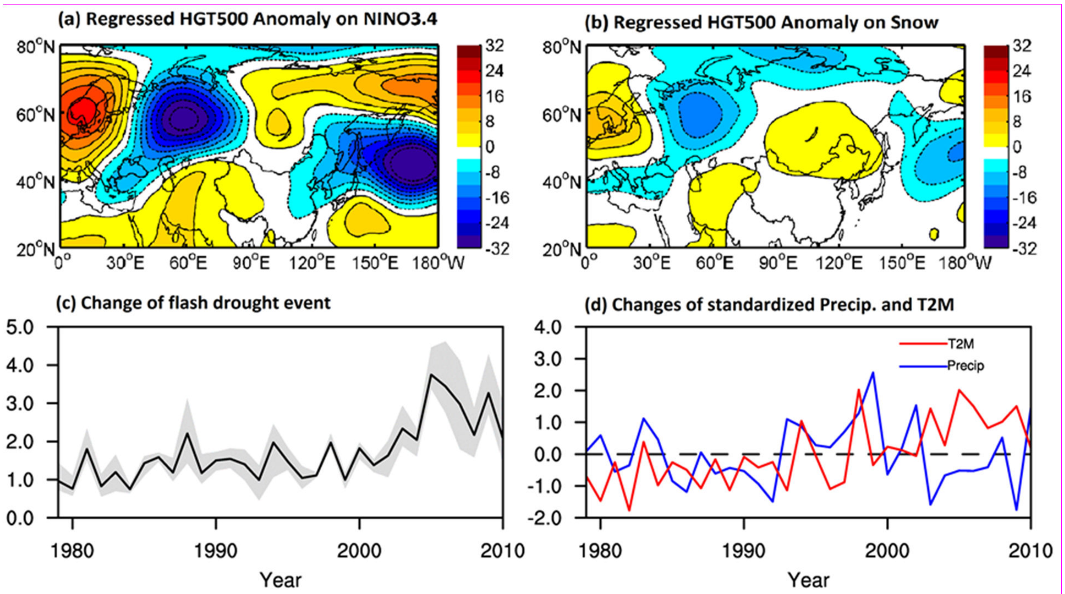


**Figure 7.** Predictability of seasonal drought and change of flash drought in China. (a-b) Distributions of July-August 500 hPa geopotential height regressed against detrended July NINO3.4 index and negative March Eurasian snow cover, showing the relationships between ENSO/Eurasian snow cover and the Eurasia teleconnection (EU) pattern that are responsible for summer droughts in northern China (modified from Wang et al., 2017). Note that a seasonal climate forecast model usually shows higher forecast skill during ENSO years; the CFSv2 model, for example, predicted the 2015/16 El Niño and roughly captured the devastating North China drought in the summer of 2015. However, a strong El Niño does not necessarily result in an extreme drought in North China; it depends on whether the El Niño evolves synergistically with Eurasian spring snow cover reduction to trigger a positive summer Eurasian teleconnection (EU) pattern (a-b) that favors anomalous northerly air sinking over North China (see Wang et al. 2017 for more information). (c-d) Changes of flash drought events, precipitation and surface air temperature averaged over southern China. The increasing trend in flash drought over southern China (c) suggests that the probability of concurrent heat extreme, soil moisture deficit and positive evapotranspiration anomaly is increasing (see Wang et al., 2016 for more information). [Contact: Xing Yuan]

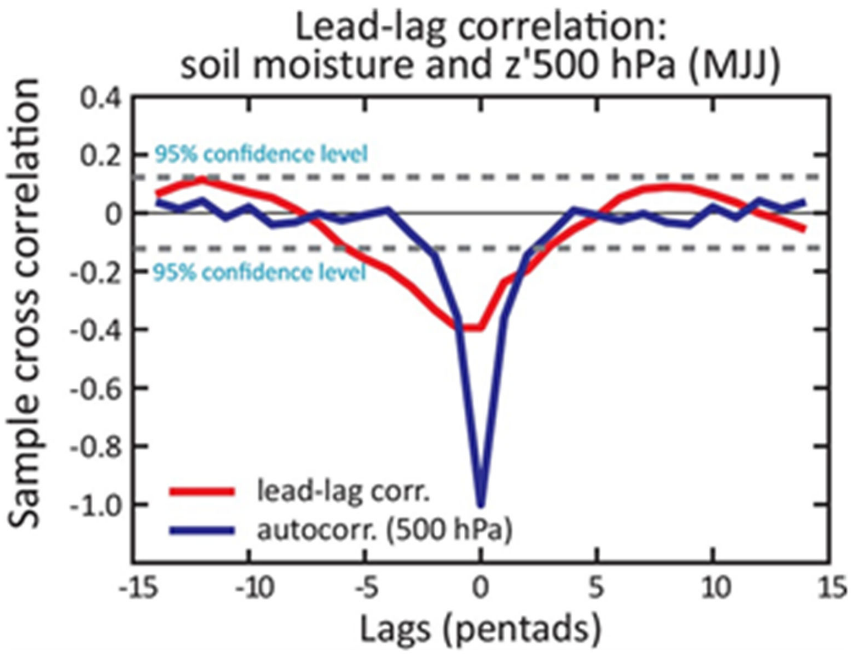


Figure 8. Lead-lag correlation (red curve) between pentad soil moisture anomalies and 500 hPa geopotential height anomalies during May-July (MJJ) over the south-central United States over the period 1981-2012. The blue line depicts the autocorrelation function (ACF) of the pentad 500 hPa geopotential height anomalies of MJJ for the same region and period. The ACF values have been multiplied by -1 for easy comparison with the red curve. The 95% confidence bounds are derived as the standard deviations divided by the square roots of N, where N is the effective number of independent samples. The original sample size is n=612, whereas N=139 after accounting for autocorrelation in the time series. The fact that the red curve lies below the blue curve (and is significant) for -1 to -6 pentads indicates that positive large-scale mid-tropospheric geopotential height anomalies (which are characteristic of circulation patterns associated with drought) are more correlated with soil moisture deficits 5-30 days earlier than with earlier height anomalies, suggesting that the patterns may be influenced more by soil moisture than by the memory of the large-scale atmospheric circulation (either remotely forced by SSTA or through memory provided by the internal atmospheric variability). This result provides observational evidence of soil moisture feedback on large-scale drought circulation in summer over the south central US (or southern Plains). The responses of both clouds and rainfall to soil moisture deficits contribute to such observed soil moisture influence on the atmospheric circulation. [Contact: Rong Fu. Figure taken from Fernando et al. (2016); see this reference for more information.]

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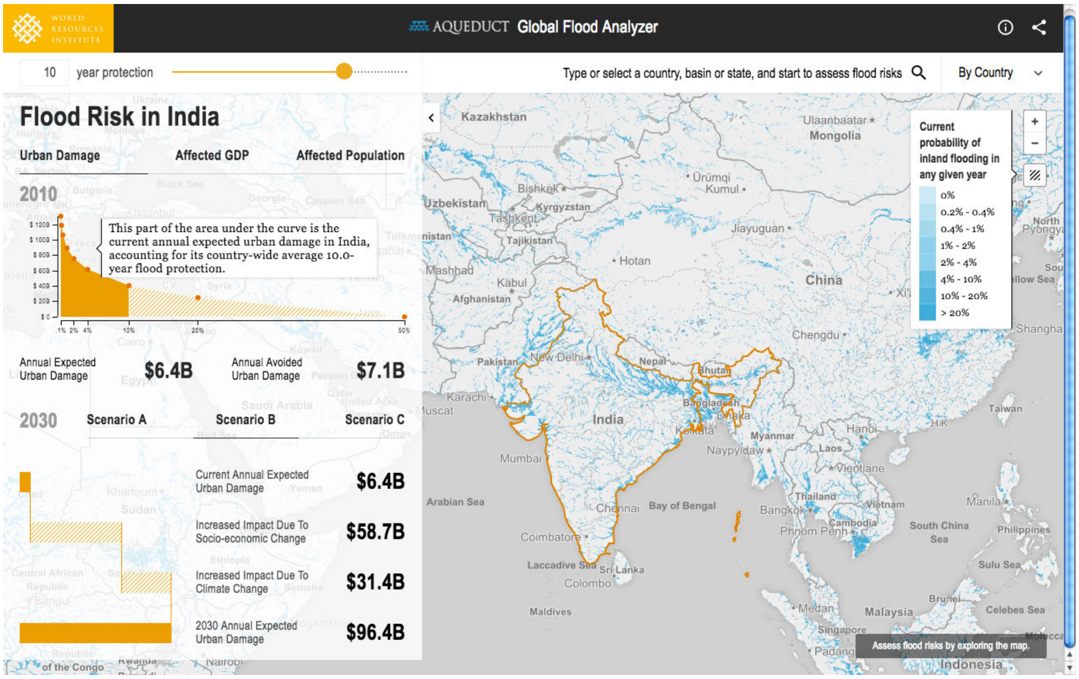


Figure 9. The Aqueduct Global Flood Analyzer is a web-based interactive platform that estimates river flood risk in terms of urban damage, affected GDP, and affected population at the country, state, and river basin scale across the globe. The Analyzer enables users to estimate current flood risk for a specific geographic unit, taking into account existing local flood protection levels. It also allows users to project future flood risk under climate and socio-economic change and separately attribute change in flood risk to each of these drivers. Finally, for each flood protection level, high-resolution maps of yearly flooding probability are provided. The basis for the analyzer is the global hydrology and water resources model PCR-GLOBWB (Van Beek et al., 2011). The methodology behind the tool is described extensively in Ward et al. (2013) and Winsemius et al. (2015). (Adapted from Bierkens [2015]. Contact: Marc Bierkens)

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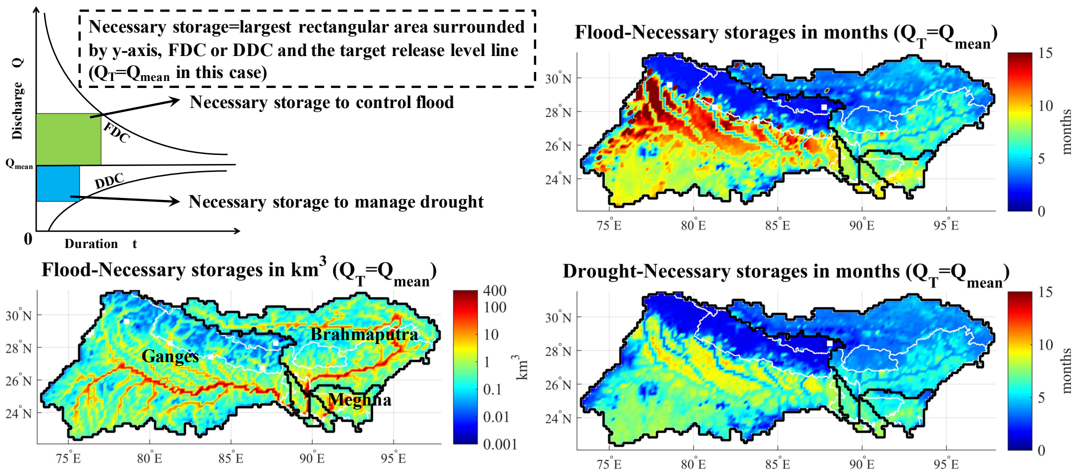


Figure 10: Storage is the only way to smooth out hydrological variation associated with floods and droughts. Spatial variability in hydrological storage, however, remains relatively unstudied – so far there is no global map showing the storage needed to ameliorate floods and droughts, either for the present climate or under climate change. Using the Ganges-Brahmaputra-Meghna basin as an example, the storage is calculated with a new method: intensity-duration-frequency curves of flood and drought (flood duration curve and drought duration curve: FDC-DDC) assuming the target release ($Q_T$) for smoothing is, for simplicity, the long term mean discharge ($Q_{mean}$) at each grid (for details see Takeuchi and Masood, 2016). The figure shows a typical FDC-DDC curve for a grid and an illustration of how to calculate necessary storage (top left), the spatial distribution of storage ($km^3$) needed to smooth floods (bottom left), and the spatial distribution of storage (months) needed to smooth flood (top right) and drought (bottom right). Storages expressed in months are calculated by dividing the necessary storage volume by the local $Q_{mean}$ for 1979-2003. Remarkable differences are seen between the $km^3$ (bottom left) and months (right) expressions which would indicate a potential use of mean residence (or renewal) time as an indicator of hydrological heterogeneity. Also, the geographical distribution of necessary storage reflects hydrological heterogeneity associated with meteorological inputs, topography, geology, soil, vegetation, landuse, and so on. Quantifying the relationships between spatially distributed necessary storages and the geographical distribution of hydro-climatological, geological and land cover conditions can lead to improved hydrological analysis and produce useful information for water resources managers. (Contact: Muhammad Masood )

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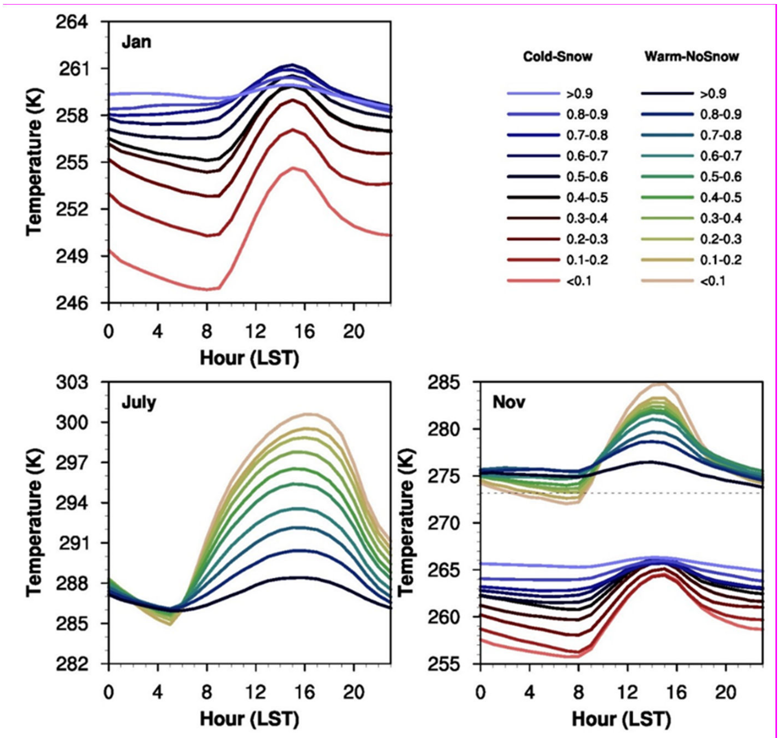


Figure 11. Coupling between opaque cloud fraction and distinct cold and warm season diurnal climatologies in January, July and the fall transition month of November. Days are binned by daily mean cloud fraction in tenths, with a different color scheme for cold days with mean temperature <0$^{o}$C and snow cover, and days >0$^{o}$C and no snow cover. Background: trained observers in the Canadian Prairies recorded hourly, since 1953, the fraction of the sky covered by opaque reflective cloud, providing daily shortwave and long-wave cloud forcing (SWCF and LWCF) on climate timescales when calibrated against baseline surface radiation measurements (Betts et al. 2015). In the warm season the diurnal cycle of temperature and relative humidity is dominated by SWCF on both daily and monthly timescales and temperatures rise under clear skies. In the cooler months the presence or absence of reflective snow cover switches the land-surface-cloud coupling between two non-overlapping climates. The mean climate on the Prairies is 10K colder with snow cover and temperatures fall under clear skies as LWCF dominates (Betts et al. 2014a, 2015). November, the fall transition month, shows both these distinct climatologies. [Contact: Alan Betts. Adapted from Betts and Tawfik (2016).]

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| | **Bayesian** | **Variational** | **OPTIMISTS** |
|---|---|---|---|
| **Resulting state-variable estimate** | Gaussian (KF, EnKF), Non-Gaussian (PF) | Deterministic (unless adjoint model is used) | Non-Gaussian |
| **Solution quality criteria** | High likelihood given observations | Minimum cost value (error, consistency) | Minimum error, maximum consistency with history |
| **Assimilation time step** | Sequential | Sequential (1D-3D) or entire window (4D) | Flexible |
| **Search method** | Iterative Bayesian belief propagation | Convex optimization | Coupled belief propagation/multi-objective optimization |
| **Model dynamics** | Linear (KF), non-linear (EnKF, PF) | Linearized to obtain convex solution space | Non-linear (non-convex solution space) |

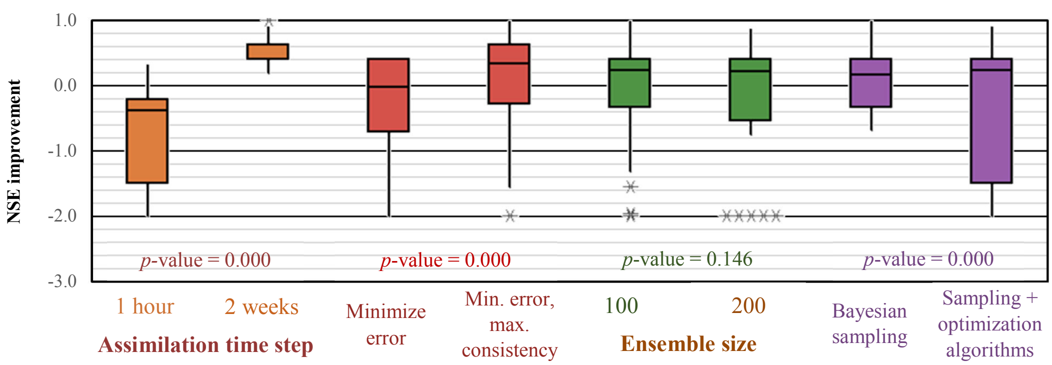

Figure 12. (Top) Comparison between standard Bayesian data assimilation algorithms (KF: Kalman Filter, EnKF: Ensemble KF, PF: Particle Filter), variational data assimilation, and OPTIMISTS. Some of the features selected for OPTIMISTS, such as non-Gaussian probabilistic estimation and support for non-linear model dynamics, are considered advantageous (van Leeuwen, 2015); flexible configurations are available for other features (e.g., the choice of optimization objectives or the analysis time step) for which no consensus has formed. (Bottom) Boxplots of streamflow forecasting improvements (y-axis: change in Nash-Sutcliffe Efficiency coefficient, with positive values indicating improvement over a control that uses no data assimilation) achieved using different configurations of OPTIMISTS (along x-axis). Asterisks on the boxplots indicate outliers. The tests were conducted with the Distributed Hydrology Soil Vegetation model (DHSVM) using 1,472 cells with over 30,000 state variables. Three features provided statistically significant advantages (demonstrated by the p-values from the ANalysis Of VAriance): (i) setting the analysis time step equal to the entire two-week assimilation period; (ii) maximizing the consistency of the states with the background (and not only minimizing the error); and (iii) using only Bayesian sampling to generate new members/particles. While using an ensemble of size 100 rather than 200 led to better forecasts, the difference was not statistically conclusive. [Contact: Xu Liang.]

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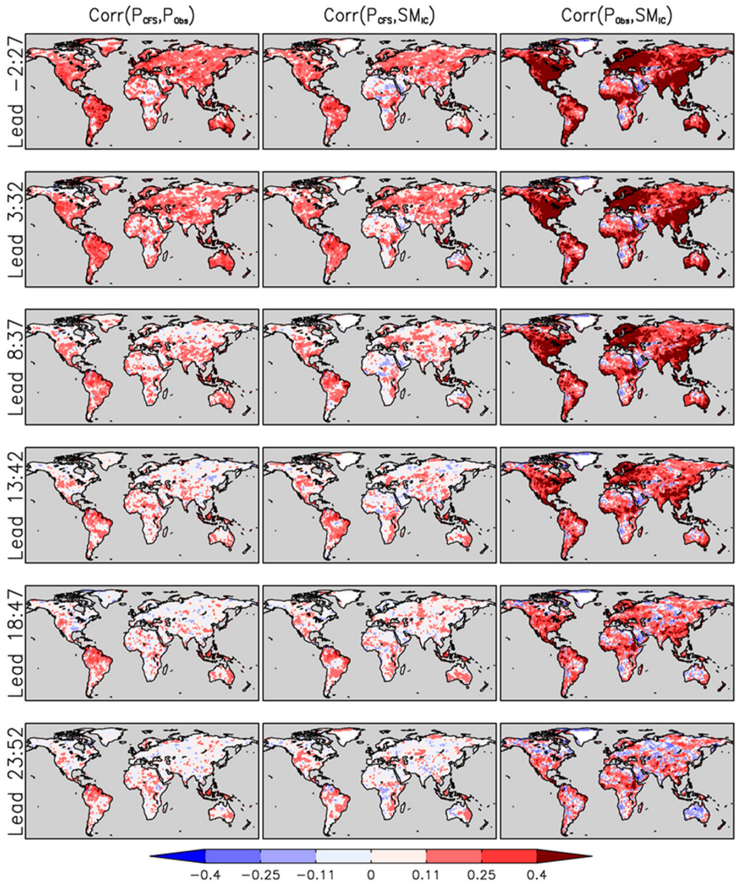


Figure 13. Pair-wise correlations between monthly CFSv2 reforecast precipitation ($P_{CFS}$), observed precipitation ($P_{Obs}$) and reforecast initial soil moisture in layer 2 (10-40cm depth; $SM_{IC}$), as indicated above each column, for forecasts validating during JJA, grouped by forecasts leads in days as indicated to the left of each row. Dark colors (beyond ±0.11) are significant at the 95% confidence level. The fact that observed precipitation rates are more closely related to antecedent soil moisture than are model simulated rates suggests that the US operational forecast model underestimates land-atmosphere coupling. [Contact: Paul Dirmeyer; see Dirmeyer (2013) for further information]