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Toward improving drought monitoring using the remotely sensed soil moisture assimilation: A parallel particle filtering framework

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ABSTRACT

Drought is the costliest hazard among all natural disasters. Despite the significant improvements in drought modeling over the last decade, accurate provisions of drought conditions in a timely manner is still a major research challenge. In order to improve the current drought monitoring skills, this study presents a land data assimilation system by merging the remotely sensed surface soil moisture with the model simulations with the use of a recently developed particle Markov chain Monte Carlo (PMCMC) method. To cope with the computational complexity, a modular parallel particle filtering framework (PPFF) is developed which allows a large ensemble size in PMCMC applications. The implementation of the proposed system is demonstrated with the 2012 summer flash drought case study over the Contiguous United States (CONUS). Results from both synthetic and real case studies suggest that the land data assimilation system improves the soil moisture predictions and the drought monitoring skills. Compared with the U.S. Drought Monitoring (USDM), the land data assimilation can better capture the drought onset on May 2012 and the drought severity in June and July 2012. This study recommends that the proposed land data assimilation system based on a high-performance computing (HPC) infrastructure can better facilitate the drought preparation and response actions.

1. Introduction

Drought is a complex natural hazard that affects hydrological, environmental, ecological, and social systems in many ways. Currently, no universal definition of drought exists (Lloyd-Hughes, 2014). Several drought definitions can be found in Wilhite (2000), Keyantash and Dracup (2002), Mishra and Singh (2010), Sheffield and Wood (2011), and Van Loon (2015). Generally, drought can be described as a deficiency in precipitation, soil moisture, or surface/ground water over an extended period, which can have significant negative impacts on agricultural, ecological, and socio-economic systems. A drought event can be short, lasting for just a few months, or it can persist for multiple years.

Among all natural disasters, drought is the most costly hazard (Sheffield et al., 2014). For example, the North American drought in 1988 resulted in nearly $62 billion loss, which was more than the cost of the 1993 Mississippi River flood and Hurricane Andrew combined (Ross and Lott, 2003). The 2012 summertime flash drought event across the Central U.S. caused a major curtailment in crop yields, and resulted in about $12 billion economic loss (Hoerling et al., 2014). One possible reason for such huge losses from a drought event is the lack of prompt preparation and effective response actions due to insufficient knowledge of the drought development behavior. Different from other natural disasters, drought has a slow onset and develops over large areas, which makes it difficult to detect until severe damage has already occurred (Wood et al., 2015). Therefore, a drought monitoring system that can detect drought conditions in a timely manner is essential for drought preparedness and risk reduction (Ahmadalipour et al., 2017; Andreadis et al., 2005; Hao et al., 2014; Maurer et al., 2002; Sheffield et al., 2014).

The current operational drought monitoring systems generally use the simulated soil moisture from hydrologic models to monitor drought conditions. For instance, the Climate Prediction Center (CPC) soil moisture data sets operationally used in the U.S. Drought Monitoring (USDM) (Svoboda et al., 2002) is based on a one-layer leaky bucket model. Although model simulations can provide consistent long-term soil moisture data sets at a continental scale, these soil moisture estimates are potentially biased due to the errors in model parameters, forcing data, and deficiencies in the model structure (Chaney et al., 2015; DeChant and Moradkhani, 2014; Moradkhani and Sorooshian, 2008; Samaniego et al., 2013; Yan and Moradkhani, 2016). As a result, the biased soil moisture may lead to sub-optimal drought monitoring skills.

A plausible approach to improve simulated soil moisture is to

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exploit the remotely sensed observations to update the soil moisture states in the model. This method of integrating observations and model simulations is referred to as data assimilation (DA) (Moradkhani, 2008). The assimilation of satellite soil moisture into a hydrologic model has received increasing attention and there have been numerous studies that have investigated the effects of assimilation of remotely sensed data on soil moisture predictions (Brocca et al., 2012; De Lannoy et al., 2007; Draper et al., 2012; Montzka et al., 2011; Reichle et al., 2008; Yan et al., 2015). While these studies have suggested improvements on soil moisture predictions, few of the studies actually quantified the improvements on the end-use application such as drought monitoring skill (Kumar et al., 2014a). Different from the studies focused on the soil moisture predictions, which can be performed at point or watershed scale, drought develops at regional to continental scales and therefore, it generally requires hydrologic modeling at large-scale (DeChant and Moradkhani, 2015; Hoerling et al., 2014). Compared to the model forward run, the large-scale DA is far more computationally expensive. Because of this computational complexity, the majority of previous large-scale satellite soil moisture DA studies were based on the ensemble Kalman filter (EnKF) with the use of small ensemble size ($12-20$) (Kumar et al., 2014b, 2009; Pan and Wood, 2010; Yin et al., 2015).

Although the successful applications of the EnKF have been reported in the above studies, the EnKF technique has some inherent features resulting in sub-optimal performances in hydrologic applications (Abbaszadeh et al., 2018; DeChant and Moradkhani, 2012; Dong et al., 2015; Leisenring and Moradkhani, 2011; Lorentzen and Naevdal, 2011; Yan et al., 2017). First, the EnKF uses only the first- and second-order statistical moments and assumes the model and observation error distribution to be Gaussian, which is violated in the nonlinear and non-Gaussian hydrologic system. Second, the updating step within the EnKF is based on a linear equation. As is the case in most hydrologic models, the observation model (or observation operator) is nonlinear, therefore, such an updating rule may not be correct since the posterior ensemble is not a sample from the posterior probability density function resulted from the Bayes' law (Lorentzen and Naevdal, 2011). Third, the EnKF technique violates mass conservation (not preserving the water balance) because water is removed from or added to the model by the updating formulation, which may lead to non-physical model state values. For drought applications, the closure of the water balance is especially important because a moderate change of soil water due to imbalanced water budget can result in a category change of drought severity. The use of small ensemble size (12–20) in these studies further deteriorates the EnKF performances in drought monitoring because such small ensemble size is insufficient to represent the posterior distributions.

To overcome the above EnKF problems, data assimilation by means of particle filter (PF) has been recommended as an alternative approach in hydrologic applications (Dong et al., 2015; Montzka et al., 2011; Moradkhani et al., 2012; Noh et al., 2011; Plaza et al., 2012; Yan et al., 2017). In comparison to the EnKF, the PF can preserve the water balance and relaxes the Gaussian assumption of error distributions, which allows the PF to potentially characterize skewed or multimodal posterior distributions. This is accomplished by resampling the model state or state-parameter ensemble, as opposed to the linear updating rule of the EnKF. In other words, the PF can lead to a more complete representation of the posterior distribution for a nonlinear and non-Gaussian hydrologic system. In the literature, a few studies have compared the effectiveness and robustness of the EnKF and PF in hydrologic predictions, and they suggested that the PF is a more effective and robust data assimilation technique. For instances, Leisenring and Moradkhani (2011) examined the performances of EnKF and PF on snow water equivalent (SWE) predictions with the assimilation of SNOTEL observations. They found out that the PF reduced the root-mean-square-error (RMSE) of SWE predictions from the EnKF by about 33%. DeChant and Moradkhani (2011) assessed both the EnKF and PF techniques on SWE predictions with the assimilation of satellite brightness temperature data. Their results suggested that PF provided more accurate predictions than EnKF. Van Delft et al. (2009) compared the use of EnKF and PF on streamflow predictions and suggested PF approach led to a lower RMSE value. Pasetto et al. (2012) found out that PF is a more robust method in soil moisture assimilation because Gaussian approximation in the EnKF led to a state estimation that is inconsistent with the physics of the model. DeChant and Moradkhani (2012) further provided a comprehensive robust assessment between the EnKF and PF on streamflow predictions. They demonstrated that the PF is a more robust technique because the streamflow predictions from the EnKF were consistently overconfident, and occasional filter divergence was also identified in the EnKF.

Despite the advantages of PF, few satellite soil moisture DA studies used PF approach and the majority of these PF studies were limited to point to watershed scale (Montzka et al., 2011; Plaza et al., 2012; Yan et al., 2015; Yan and Moradkhani, 2016), and fewer have attempted to implement PF for large-scale drought analysis (e.g., Yan et al., 2017). The main obstacle for the PF to be applied in large-scale drought application is the limited computational power of modern computers, which means that we cannot have enough model ensembles to simulate the posterior distributions and avoid weight degeneration (filter collapse due to few particles having significant weight). Compared to the EnKF method, the successful application of PF requires a larger ensemble size. The current EnKF based large-scale drought monitoring system (with the use of small ensemble size) is already compute-intensive; while the PF needs to increase that demand by 1–2 orders of magnitude. One possible solution allowing the use of PF in large-scale drought applications is to benefit from the parallel computing technique in a high-performance computing (HPC) cluster infrastructure, which requires the parallel implementations of DA algorithm. Currently, open source parallel DA library is available in the community such as the Parallel Data Assimilation Framework (PDAF) (Nerger and Hiller, 2013). The PDAF is developed at the Computing Center of the Alfred Wegener Institute based on Fortran code compilable in the Unix/Linux environment and provides fully implemented and optimized data assimilation based on the Kalman filtering algorithms (Ridler et al., 2014). Although the PDAF can provide parallel simulation for large-scale DA applications on a HPC cluster, the PF technique is not included in the PDAF up to date.

Given the above discussions, the main motivation of this study is to advocate the use of PF approach in large-scale drought applications by using the parallel computing technique in the HPC cluster. Specifically, a parallel PF modular is needed to be compatible with modern HPC infrastructure. Therefore, the goals of this study are to:

1. develop a modular parallel particle filtering framework (PPFF) which allows a large ensemble size in large-scale (continental to global scale) drought applications;
2. examine the effectiveness of PPFF by comparing its soil moisture predictions to the results from the EnKF based data assimilation system; and
3. implement the large-scale assimilation of remotely sensed soil moisture into a distributed hydrologic model and provide a quantitative assessment of its impact toward drought monitoring skills with the use of PPFF."

The remaining of the paper is organized as follows: Section 2 describes the framework of the proposed PF based drought monitoring system, which includes the dynamical hydrologic modeling, the DA algorithm, and the parallelization of the DA. Section 3 assesses the drought monitoring system over the Contiguous United States (CONUS) for both synthetic and real case studies. Finally, Section 4 concludes the paper.