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Utilizing satellite precipitation estimates for streamflow forecasting via adjustment of mean field bias in precipitation data and assimilation of streamflow observations

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SUMMARY

This study explores mitigating bias in satellite quantitative precipitation estimates (SQPE) and improving hydrologic predictions at ungauged locations via adjustment of the mean field bias (MFB) in SQPE and data assimilation (DA) of streamflow observations in a distributed hydrologic model. In this study, a variational procedure is used to adjust MFB in Climate Prediction Center MORPHing (CMORPH) SQPE and assimilate streamflow observations at the outlet of Elk River Basin in Missouri into the distributed Sacramento Soil Moisture Accounting (SAC-SMA) and kinematic wave routing models. The benefits of assimilation are assessed by comparing the streamflow predictions with or without DA at both the outlet and an upstream location, and by comparing the soil moisture grids forced by CMORPH SQPE against those forced by higher-quality multisensor quantitative precipitation estimates (MQPE) from National Weather Service. Special attention is given to the dependence of the efficacy of DA on the quality and latency of the SQPE, and the impact of dynamic correction of MFB in the SQPE via DA. The results show that adjusting MFB in CMORPH SQPE in addition to assimilating outlet flow reduces 66% of the bias in the CMORPH SQPE analysis and the RMSE of 12-h streamflow predictions by 81% at the outlet and 34–62% at interior locations of the catchment. Compared to applying a temporally invariant MFB for the entire storm, the DA-based, dynamic MFB correction reduces the RMSE of 6-h streamflow prediction by 63% at the outlet and 39–69% at interior locations. It is also shown that the accuracy of streamflow prediction deteriorates if the delineation of the precipitation area by CMORPH SQPE is significantly different, as measured by the Hausdorff distance, from that by MQPE. When compared with adjusting MFB in the CMORPH SQPE over the entire assimilation window, adjusting the MFB for all but the latest 18 h (i.e., the latency of CMORPH SQPE) within the assimilation window reduces the mean square error (MSE)-based skill score of streamflow predictions at the outlet by up to 0.08 and at interior locations by up to 0.13.

1. Introduction

Hydrologic forecasting requires timely and accurate quantitative precipitation estimates (QPE). In many parts of the world, however, access to high quality and low latency QPE (in situ and/or weather radar-based) is limited. In the US, considerable gaps exist in the coverage of the ground-based sensors for QPE (Zhang et al., 2013). Poor ground-based sensing for QPE along the US–Mexico border, for example, has been an issue for forecasting streamflow for the Rio Grande River Basin. These gaps may be filled by precipitation estimates from space-borne sensors (Kondragunta et al., 2005), which include the estimates based on brightness temperature observations from visible (VIS) and infrared (IR) sensors aboard geostationary satellites, radiance observations from passive microwave (PMW) sensors aboard low earth orbiters (LEO), and reflectivity observations from space-borne radars (Kidd and Levizzani, 2011). A number of techniques have been developed to fuse observations from multiple satellite platforms for generation of high-resolution QPE. They include the TRMM Multisatellite Precipitation Analysis (TMPA, Huffman et al., 2007), Self-calibrating Multivariate Precipitation Retrieval (SCaMPR, Kuligowski, 2002;

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Kuligowski et al., 2013), the Climate Prediction Center MORPHing technique (CMORPH; Joyce et al., 2004), the Lagrangian Model (LMODEL; Bellerby et al., 2009), and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Hsu et al., 1997).

The utility of satellite quantitative precipitation estimates (SQPE) for hydrologic applications has been examined in Hossain and Anagnostou (2004), Su et al. (2008), Bitew and Gebremichael (2011), Gebregiorgis and Hossain (2012), Lee et al. (2014) and others. Though SQPEs are playing an increasingly large role in hydrologic applications, their limited accuracy is a major challenge for operational hydrologic forecasting (Wilk et al., 2006; Boushaki et al., 2009; Vila et al., 2009; Tobin and Bennett, 2010; Kuligowski et al., 2013; Zhang et al., 2013; Lee et al., 2014). Large biases, false detection and overrepresentation of precipitation areas are among the issues with SQPE for streamflow prediction. In regions where streamflow and soil moisture observations are available, however, the above limitations may potentially be reduced by jointly utilizing SQPE and hydrologic observations. Though spatially sparse, streamflow observations are generally available in large river systems even in remote areas. In the Rio Grande River Basin, for example, stream gauge observations are readily available at downstream locations, which may be used to reduce uncertainty in streamflow prediction due to the paucity of ground-based precipitation observations in upstream parts of the basin.

A potential mechanism for optimally combining hydrometeorological and hydrologic information is data assimilation (DA), which is able to factor in the uncertainties in the observations and the model in a dynamic fashion (Liu and Gupta, 2007). Assimilating streamflow observations into rainfall–runoff models using ground-based forcing data has been a popular study topic (Weerts and El Serafy, 2006; Clark et al., 2008; Seo et al., 2009; Lee et al., 2011, 2012; Rakovec et al., 2012; McMillan et al., 2013 and references therein). Despite the presence of this large body of literature, however, there were few attempts that examined the efficacy of DA as a tool for improving the quality in QPE – most of the published DA studies employed streamflow as the main verification variable (Clark et al., 2008; Seo et al., 2009; Lee et al., 2011, 2012; McMillan et al., 2013). In addition, utilizing SQPEs in a DA procedure presents new practical challenges not seen in the case of using ground sensor products, as SQPEs are known to be subject to large bias, wide uncertainties caused in part by spatial displacement, and have relatively long latency (Sorooshian et al., 2011). On the other hand, the effects of assimilating streamflow downstream on the predictive accuracy over interior points were largely overlooked, in spite of the fact that many smaller catchments are ungauged and the prediction over these locations has been one of the key practical challenges. Rakovec et al. (2012) showed that assimilating discharge observations at additional upstream locations would improve streamflow prediction at the outlet, but the work does not explicitly address the efficacy of DA for improving flow predictions at interior points, an important issue for regions with sparse stream gauge networks. Moreover, it remains unclear how much improvement in streamflow prediction can be attained by DA when the model is forced by highly uncertain SQPE, and whether assimilation of streamflow would yield meaningful improvement to the quality of SQPE given the fact that DA seeks solutions in a highly underdetermined system.

The aim of this paper is to assess the impact of adjusting bias in SQPE in addition to assimilating outlet flow observations on the accuracy of adjusted SQPE, updated soil moisture and predicted streamflow over the outlet, and, more importantly, interior points from a distributed hydrologic model. To this end, we carry out a set of assimilation experiments in which outlet flow observations are assimilated into the NWS distributed hydrologic model for a catchment in Missouri, and base model results are compared with DA results at the outlet and, more importantly, interior points with observed streamflow data. In this study, the operational radar–gauge multisensor QPE (MQPE) and MQPE-driven soil moisture and streamflow without assimilation are used as the benchmarks. The work reported herein is similar in spirit with Crow and Ryu (2009) in that we seek to improve skill in the prediction of streamflow and soil moisture through jointly utilizing multiple sources of hydrometeorological and hydrologic observations within a DA framework. It, however, offers new insights into the efficacy of the assimilation approach in relation to the bias and spatial displacement of SQPE, and data latency. Since stream gauge data is potentially more accurate and frequent than satellite-based data at a number of basins in the world, our study results can suggest the utility of assimilating streamflow data in order to reduce bias in SQPEs at a fine time scale – this enhances the utility of SQPEs for flood prediction for fast-responding headwater basins outside of the coverage of weather-radars or rain gauges. Contrasting to off-line correction of bias in the precipitation data such as Adjoint-Based OPTimizer (AB_OPT, Seo et al., 2009), real-time-based correction of SQPEs via a variational assimilation technique used in this study will assess the operational utility of SQPEs for flood forecasting. The 4D Variational method used in this study allows us to account for the lag time between precipitation and discharge and therefore avoid excessive, non-physical adjustment of state variables (Li et al., 2013; McMillan et al., 2013).

The remainder of the paper is organized as follows. Section 2 describes the methodology used in this study, including the hydrologic model, the assimilation technique, QPE data, DA issues investigated, evaluation metrics adopted, and the study area. Section 3 documents the results and discussion and Section 4 summarizes findings and a concluding remark.

2. Methodology

In this section, we describe the hydrologic models and the assimilation technique used along with CMORPH SQPE and MQPE. Described subsequently in the rest of this section are DA issues investigated, evaluation metrics adopted, and the study area used.

2.1. Hydrologic model

The rainfall–runoff and routing model used is the distributed Sacramento Soil Moisture Accounting (SAC-SMA; Burnash et al., 1973) and kinematic-wave routing models, respectively, as implemented in the Hydrology Laboratory Research Distributed Hydrologic Model (HL-RDHM, Koren et al., 2004). The distributed SAC-SMA model (Koren et al., 2004) is a gridded version of the conceptual lumped SAC-SMA model used operationally by most River Forecast Centers (RFC) in the US. The distributed SAC-SMA model generally operates on the so-called Hydrologic Rainfall Analysis Project (HRAP; Reed and Maidment, 1999) grid mesh, which is about 4-km in size and it is also the default grid mesh of NWS radar and multisensor QPE. The model resolution can be adjusted depending on the availability of fine-resolution precipitation input and model parameters. The runoff in each grid box is computed based on surface and subsurface flows generated from two subsurface storages, namely, the Upper Zone (UZ) and the Lower Zone (LZ). The LZ is generally much thicker than the UZ and supplies moisture to the atmosphere to meet the evapotranspiration demands (Koren et al., 2014). Soil moisture states in the UZ and LZ are represented by tension and free water contents as summarized in Table 1. Tension water contents (UZTWC and LZTWC) are related to soil moisture bounded to soil particles defined as the difference between field capacity and wilting point and can be removed only by evapotranspiration. Free water contents