Assimilation of Satellite Quantitative Precipitation Estimates and Streamflow into Distributed Hydrologic Models for Flood Prediction

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INTRODUCTION

We conduct experiments to examine the accuracy of flood prediction when satellite precipitation estimates and streamflow observations are assimilated into the distributed Sacramento Soil Moisture Accounting (SAC-SMA) model via a variational data assimilation (DA) framework. The DA technique, developed at Office of Hydrologic Development, National Weather Service, estimates hourly-varying mean field bias in the precipitation data and assimilates flow observations. These experiments are performed for a headwater catchment in Missouri using hourly CPC MORPH (CMORPH) QPEs at the HRAP scale (~16 km^2) as the forcing to the distributed SAC-SMA. The result of the experiments indicates that a) CMORPH data exhibit significant positive bias which leads to overprediction of discharge during flood events; b) streamflow assimilation greatly mitigates the bias in the streamflow analysis within the assimilation window; and c) the adjustment to the bias of CMORPH is limited by DA - the bias appears to be compensated by over-adjustment of soil moisture.

1: Motivations

NWS relies on accurate, low latency precipitation products for its flood and water resources predictions in the US. At present, such products are based mostly on ground gauge and radar data. Although radar and gauge coverage is relatively good over the CONUS. There are still conspicuous gaps (See Figs 1 and 2).

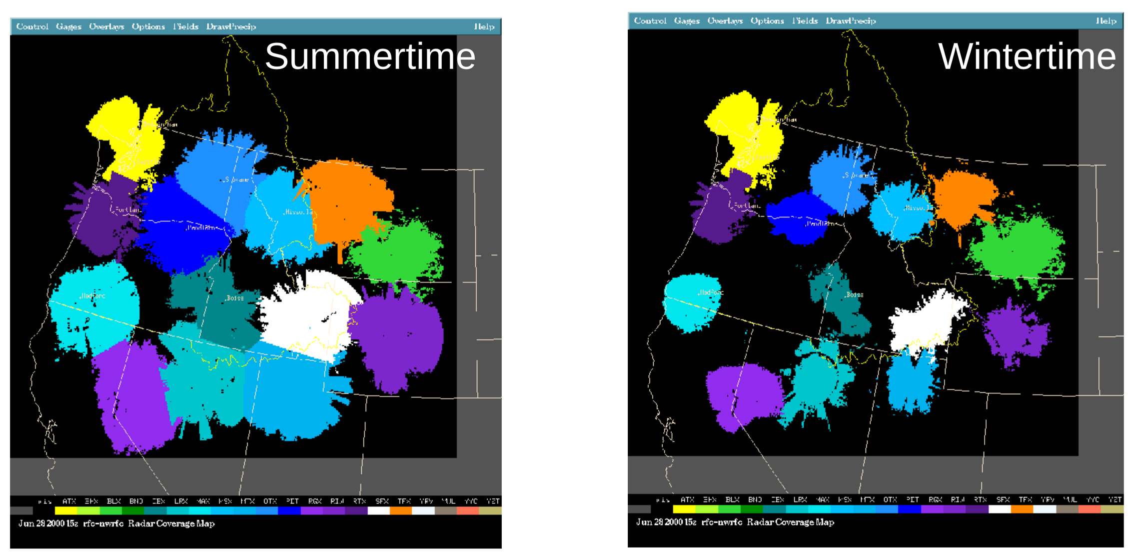

Fig 1: Coverage gaps of WSR-88Ds over the western US for summer and winter..

The launch of the Global Precipitation Measurement (GPM) satellite in 2014 is expected to greatly improve the accuracy and latency of satellite quantitative precipitation estimates (QPEs) and thereby enhance their potential utility in operational hydrologic predictions at National Weather Service.

In previous work, we have assessed the accuracy of satellite QPEs from the Self-calibrating Multivariate Precipitation Retrieval (SCaMPR) for operational hydrologic predictions, where we used SCaMPR QPEs before and after ingesting Tropical Rainfall Measuring Mission (TRMM) QPEs.

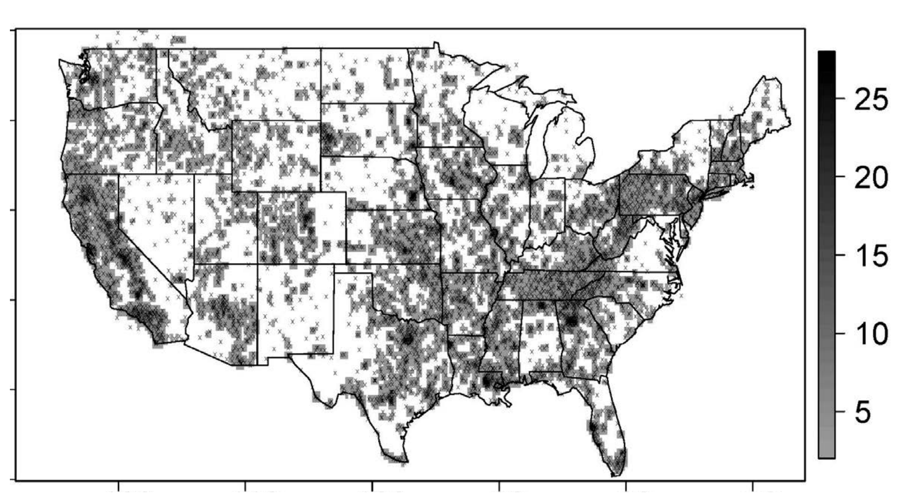

Fig 2: Density of 1-h reporting gauges in CONUS, left blank are areas where SCaMPR with TRMM ingest may outperform gauge-only analysis at 1-h scale.

NWS has developed **a data assimilation (DA)** framework that automatically adjusts model states and forcing inputs on the basis of streamflow and soil moisture observations, and prescribed error characteristics. It is important to understand the performance of GPM-era satellite QPEs when they are used in a data assimilation context when limited observations of streamflow is available.

2: Science Questions and Experimental Design

2.1 Science questions

i) How good are streamflow simulations from a distributed hydrologic model driven by a satellite QPE?

ii) Does assimilating streamflow at outlet and QPE data improve the simulations of a distributed model at interior points?

iii) Does assimilation properly adjust the QPE and soil moisture states that reflect the physical reality?

2.2 Experimental Design

We perform a set of hindcast experiments for Elk River near Tiff City (TIFM7), MO, with a drainage area of 2258 km^2 . Its tributary LANAG has a drainage area of 619 km^2.

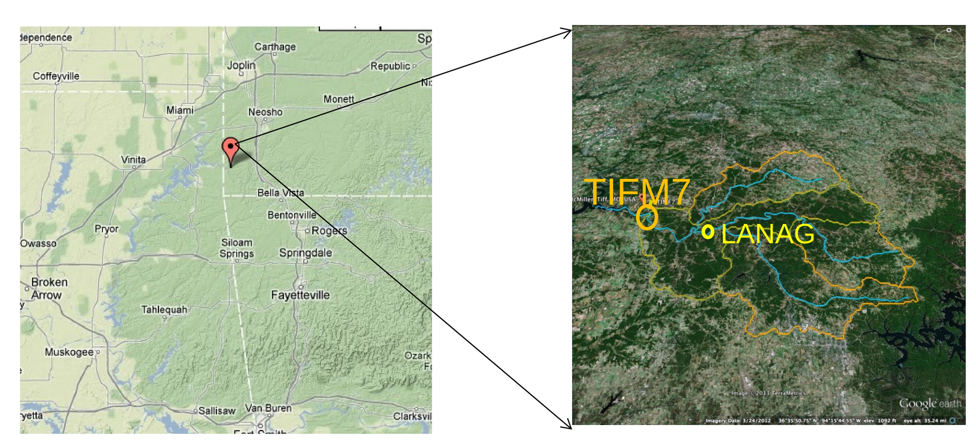

Fig 3: Study catchments: TIFM7 and its tributary, LANAG.

We collected CMORPH QPE (30-minute, 8-km) for 2003-2005, hourly, 4-km multisensor QPE (MPE) from Arkansas Red River Basin River Forecast Center (ABRFC), and streamflow observations from USGS. We conducted two sets of streamflow simulations for 2003-2005 using the Hydrologic Laboratory – Research Distributed Hydrologic Model (HL-RDHM).

Baseline: No assimilation
Control: Assimilation of streamflow at TIFM7, QPE and potential evapotranspiration (PET)

4D-Var

$$\text{Minimize} \quad J_k = \frac{1}{2}[\mathbf{Z}_q - \mathbf{H}_{qq}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)]^T \mathbf{R}_{qq}^{-1}[\mathbf{Z}_q - \mathbf{H}_{qq}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)] + \frac{1}{2}[\mathbf{Z}_\theta - \mathbf{H}_{\theta\theta}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)]^T \mathbf{R}_{\theta\theta}^{-1}[\mathbf{Z}_\theta - \mathbf{H}_{\theta\theta}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)]$$

$$+\frac{1}{2}[\mathbf{Z}_p - \mathbf{H}_{pp}\mathbf{X}_p]^T \mathbf{R}_{pp}^{-1}[\mathbf{Z}_p - \mathbf{H}_{pp}\mathbf{X}_p] + \frac{1}{2}[\mathbf{Z}_e - \mathbf{H}_{ee}\mathbf{X}_e]^T \mathbf{R}_{ee}^{-1}[\mathbf{Z}_e - \mathbf{H}_{ee}\mathbf{X}_e] + \frac{1}{2}[\mathbf{Z}_b - \mathbf{H}_{bb}\mathbf{X}_{s,k-l}]^T \mathbf{R}_{bb}^{-1}[\mathbf{Z}_b - \mathbf{H}_{bb}\mathbf{X}_{s,k-l}]$$

$$\text{subject to} \quad \mathbf{X}_{s,j} = \mathbf{F}(\mathbf{X}_{s,j-1}, \mathbf{X}_{p,j}, \mathbf{X}_{e,j}), \quad j = k-l+1,...,k$$

$$X_{s,i}^{\min} \le X_{s,k,i} \le X_{s,i}^{\max}, \quad j = k-l,...,k; \quad i = 1,...,6$$

3: Preliminary Results

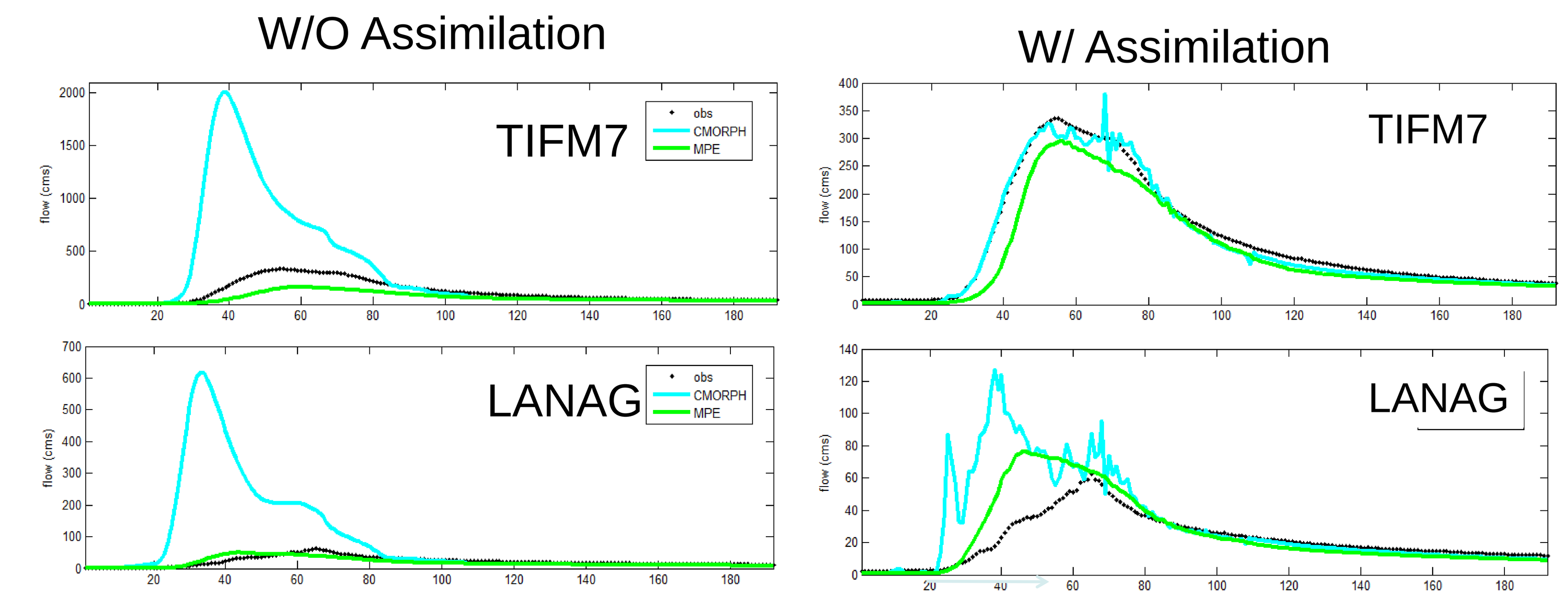

Fig 4: Base-line and control simulations (without and with assimilation, respectively) for TIFM7 and LANAG for the 3-10 Mar 2004 flood. The positive bias in CMORPH-based simulations is evident without assimilation.

CMORPH QPE shows a positive bias around 2.0 (versus MPE), The resulting streamflow has a bias ranging between 5-7 for the two catchments. MPE-driven results fared better but are negatively biased at TIFM7.

After assimilating QPE and streamflow at the outlet of TIFM7, streamflow results (at forecast issue time) at both the outlet and the interior points were greatly improved. However, there is still a positive bias from CMORPH-based simulations at LANAG.

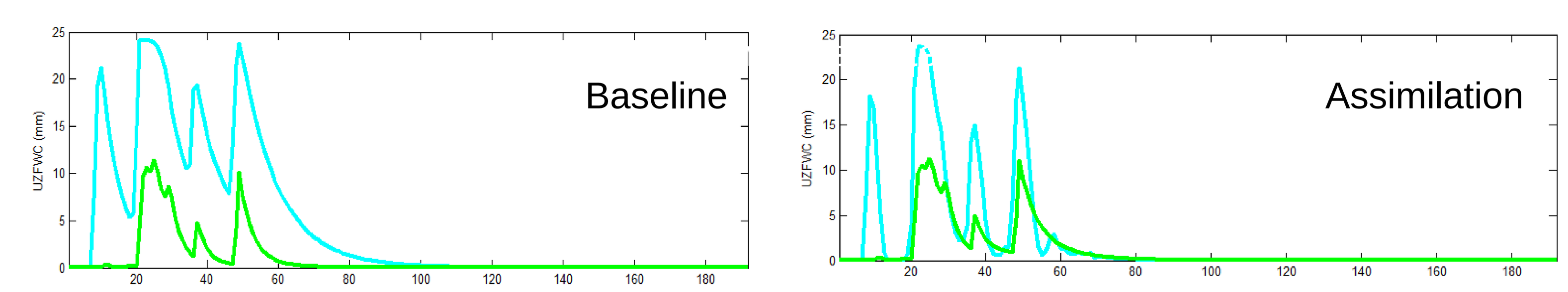

Fig 5: Time series of soil moisture state with and without assimilation for the 3-10 Mar 2004 flood. Shown is the upper zone free water from SAC-SMA.

Assimilation has a larger impact on the CMORPH-based results, mostly because of the positive bias in CMORPH. It appears that the model over-adjusts model soil moisture states to compensate for this bias.

4: Conclusions

Satellite QPE may suffer from large biases and errors. Assimilation of limited streamflow downstream and other observations may help mitigate these issues. However, whether the adjusted soil moisture states better mimic the physical reality needs to be closely investigated. These issues will be further explored in future studies.