SMAP SOIL MOISTURE ASSIMILATION TO ENHANCE STREAMFLOW ESTIMATES ACROSS SOUTH ASIA

Jawairia Ahmad[1,*], *Barton Forman*[1], *Augusto Getirana*[2,3], *Sujay Kumar*[2]

[1]Department of Civil and Environmental Engineering, University of Maryland, College Park, MD, USA
[2]Hydrological Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt, MD, United States
[3]Science Applications International Corporation, Greenbelt, MD, United States

ABSTRACT

Streamflow estimation across areas facing water scarcity is important considering the evolving climatic conditions. In this study, the impact of assimilating Soil Moisture Active Passive (SMAP) soil moisture retrievals on the modeled streamflow across three main river basins in South Asia is explored. Model estimated runoff was hydraulically routed using the HYMAP routing model within the NASA Land Information System (LIS) framework. Streamflow estimates via soil moisture assimilation highlighted the potential improvements in streamflow across low-flow river tributaries in irrigated regions. Limited relative change was noted along high-flow river tributaries. Modeled streamflow tended to underestimate the flow magnitude at upstream stations and overestimated the streamflow at downstream stations within the Indus basin due to missing physics related to reservoir operation. Improvement of the modeling systems representativeness of the ground conditions by the inclusion of water management information would potentially improve the current streamflow modeling capability across South Asia.

Index Terms— SMAP, soil moisture, streamflow, NASA Land Information System, South Asia, data assimilation

1. BACKGROUND AND MOTIVATION

Streamflow estimation is important for irrigation planning [1], estimation of expected agricultural yield [2], water resources management [3], and water security forecasts [4]. Soil moisture and streamflow are linked through the infiltration capacity of a watershed [5]. Unsaturated soils generally yield low streamflow due to high infiltration capacities. In contrast, soils that are saturated prior to rainfall events yield high lateral flows which results in greater streamflow magnitudes [6].

Previous attempts at leveraging data assimilation to improve soil moisture and streamflow estimation have primarily focused on the assimilation of Soil Moisture and Ocean Salinity (SMOS) observations in land surface models [7, 8]. The relatively recent Soil Moisture Active Passive (SMAP [9]) observations outperform all prior satellite-based soil moisture observations [10]. In this study, the SMAP observations have been assimilated in a land surface model to improve soil moisture and streamflow estimates across a significantly irrigated region, i.e., South Asia. Streamflow estimation is particularly difficult across this domain as the surface water is primarily managed through a network of storage reservoirs, dams, and irrigation canals. The operation of the water management infrastructure is subjectively controlled and is dependent on the changing hydrologic as well as geopolitical conditions.

Contemporary studies have attempted streamflow estimation across South Asia by tracking downstream river flow via correlated satellite data [11], and quantifying river discharge that originates from different sources such as snow, rainfall, and glacier melt [12]. While these studies have made important contributions to streamflow estimation in South Asia, there is a lack of a consistent dataset that can provide streamflow estimates at a fine resolution ($\leq$5 degree) across the major basins in South Asia. The presented study is motivated by these knowledge gaps.

2. STUDY DOMAIN

The study domain comprises three main river basins located within South Asia, i.e., Indus, Ganges, and Brahmaputra, Figure 1. The freshwater provided by these rivers is critical for the local population [3]. There are three main contributing sources to the river runoff, i.e., snowmelt, glacier melt, and rainfall. The percentage of contribution of the former two sources is greater for the Indus river, whereas rainfall is the primary source of freshwater in the Ganges and Brahmaputra rivers [3].Irrigation is a prominent component of the local hydrological cycle across croplands. Figure 2b maps the percentages of irrigated-equipped area within each grid cell based on the Food and Agriculture Organization's global map of irrigated areas (GMIA).

3. ASSIMILATION FRAMEWORK

The NASA Land Information System (LIS) framework [14] was used to implement the assimilation experiments. The model-only, ensemble-based simulation is defined as the open loop (OL). The Noah-Multiparameterization (MP)- version

∗ Now at Centre for Water Informatics and Technology, LUMS, Pakistan

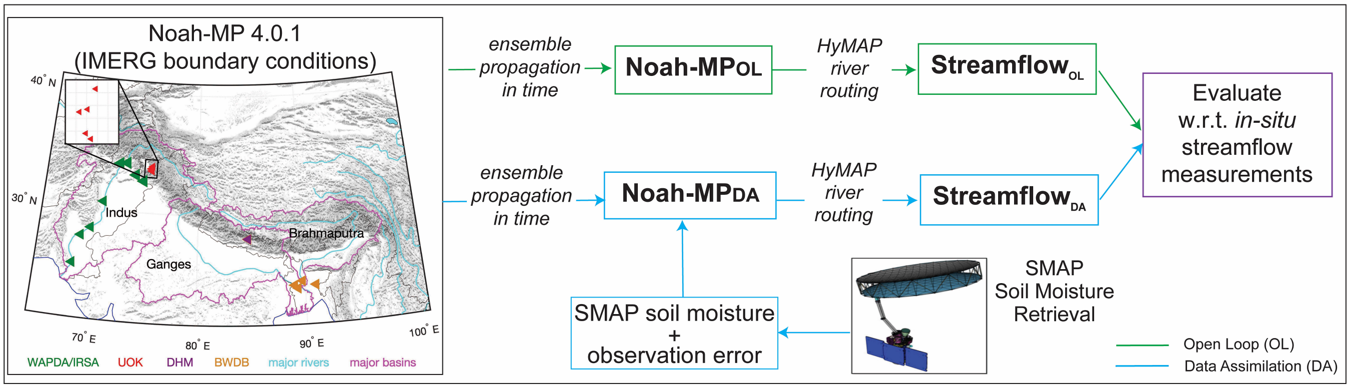

Fig. 1: Overview of the Noah-MP open loop (OL) and data assimilated runs (DA). IMERG= Integrated Multi-satellitE Retrievals for Global Precipitation Measurement [13]. The triangular makers located within the relief map of the study domain show the location of the ground stations used for streamflow evaluation in Section-4. WAPDA= Water and Power Development Authority Pakistan, IRSA= Indus River System Authority, UOK= University of Kashmir, DHM= Department of Hydrology and Meteorology Nepal, and BWDB= Bangladesh Water Development Board.

4.0.1 [15] land surface model was used to model the hydrologic cycle within LIS over the three main South Asian basins. Noah-MP simulations were carried out on a 0.05° equidistant cylindrical grid using a 15 minute timestep. It is important to note that irrigation was not explicitly modeled within Noah-MP. Precipitation boundary conditions were provided by the Integrated Multi-satellitE Retrievals for Global Precipitation Measurement (IMERG) [13], while all other meteorological forcing fields were defined by the Modern-Era Retrospective analysis for Research and Applications - Version 2 (MERRA2) dataset [16].

LIS includes a river routing model which was used to hydraulically route the modeled runoff through a pre-defined network of streams. The Hydrological Modeling and Analysis Platform (HyMAP) [17] is a flow routing model that estimates river flow characteristics such as water level, discharge, and storage. It includes modeling routines that represent time delays in flow, river and floodplain interaction, flow of water through river channels and across floodplains, and evaporation from open water bodies. The kinematic wave configuration within HyMAP was used to route the flow at a 15 minute timestep.

The Ensemble Kalman Filter (EnKF) assimilation method is used to assimilate the SMAP soil moisture retrievals into the Noah-MP modeled estimates. EnKF has two main steps, i.e., 1) the state propagation forward in time, and 2) state update based on the difference between the modeled estimate and the observed value. SMAP soil moisture retrievals [18] were assimilated into Noah-MP modeled soil moisture to obtain data assimilated (DA) simulations. Assimilation was carried out by computing innovations for the top soil layer ($\sim$5 cm) considering the emission depth of L-band radiation. The initial conditions for both the OL and DA simulations are provided by a model spin-up run. Therefore, the only difference between the OL and DA simulations is the assimilation of SMAP soil moisture retrievals. Figure 1 provides an overview of the experimental methodology. Further details regarding the assimilation framework are provided in Ahmad et al. [19].

The simulation experiments span from 2015 to 2020 due to the availability of SMAP observations from 2015 onwards. The SMAP soil moisture retrievals have gaps in areas with frozen soils, snow cover, dense vegetation or radio frequency interference. The spatial resolution of the product used in this study is 36 km.

4. STREAMFLOW ANALYSIS

Station guage data from several networks was used to evaluate the OL and DA streamflow estimates. Figure 1 shows the locations of the individual stations used to compute the results in Sections 4.2 and 4.3. Section 4.1 describes the relative change in streamflow associated with assimilation.

4.1. Relative change

The relative change in streamflow is calculated as:

$$\text{Relative change} = \frac{\text{Streamflow}_{DA} - \text{Streamflow}_{OL}}{\text{Streamflow}_{OL}} \quad (1)$$

where Streamflow_{DA} and Streamflow_{OL} are streamflow estimated by the assimilation run (DA) and model-only (OL) simulation, respectively. Figure 2a highlights the spatial performance of assimilation across grid cells of different landcover types. Magnitude of relative change is quite high (>0.7) for areas that are irrigated. Figure 2b shows the GMIA-based irrigated area map for reference. The grid cells with large percentages of irrigated areas generally coincide with areas of high relative change in Figure 2a. This is particularly visible across the lower Indus Basin. Increases in soil moisture via assimilation across irrigated areas effectively alters the contribution of irrigation to the local water balance. A similar

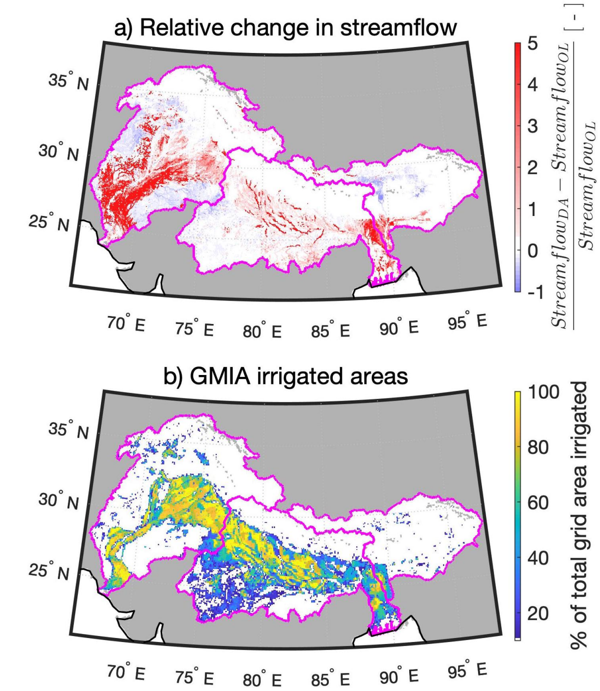

Fig. 2: Spatial map of relative differences between the OL and DA estimated streamflow. Large positive values are observed across the lower Indus Basin indicating higher streamflow estimated via assimilation.

spatial pattern is observed for regions where high precipitation magnitudes occur such as the downstream confluence of the Ganges and Brahmaputra rivers.

Another important feature present in Figure 2a is the minimal relative change in streamflow across rivers with high average flows. The peak magnitude of streamflow through the main river tributaries is quite large ($\geq$2000 m^3/s). The majority of the differences between the DA and OL streamflow estimates are $\leq$ 250 m^3/s. In comparison to the magnitude of peak streamflow, the differences between the DA and OL estimated streamflow are not considerable enough to show large relative change across high-flow river tributaries.

4.2. Timeseries

The SMAP soil moisture dataset used in the assimilation experiments has gaps across regions of complex terrain, partially or completely frozen soil, intense precipitation events, and densely vegetated areas. Considering the data gaps due to frozen soil conditions and the location of WAPDA's upstream stations and the UOK and DHM networks, assimilation instances across these locations are limited in number, and thus, it is expected that the OL and DA streamflow estimates at these stations will be similar. For the BWDB network, SMAP data gaps are prevalent during the monsoon season and over densely vegetated areas. Therefore, the evaluation of the OL versus DA streamflow estimates using publicly-available station measurements is inherently limited.

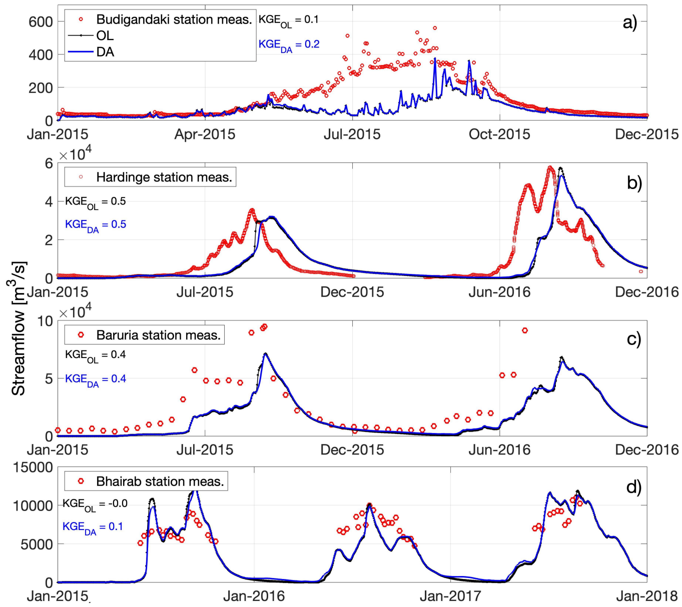

Fig. 3: Timeseries of the OL and DA estimated and station measured streamflow for four stations located within the Ganges and Brahmaputra basins. OL= Open Loop; DA= Data Assimilated run; KGE= Kling-Gupta efficiency.

Figure 3 presents the OL and DA estimated streamflow for four stations belonging to the DHM and BWDB networks in the eastern part of the study area. The Kling-Gupta Efficiency (KGE) is used to evaluate the performance of the OL and DA modeled streamflow. It is seen in Figure 3 that the KGE values for the OL and DA estimates are quite similar. Minimal improvement is observed for subplot a) and d). All of the stations presented here have large peak flows and show limited influence of SMAP retrieval assimilation. Figure 3a shows that the model is underestimating the flow during the summer months of May to September when the temperatures are high and bulk of the rainfall occurs. For Figures 3b and 3c, there is a time lag present in the occurrence of the peak flow as compared to the station measurements. There are a number of gaps present in the station data as well which further limits the evaluation of the modeled streamflow. It is expected that the influence of soil moisture assimilation will be greater for areas with higher percentages of SMAP retrievals available for assimilation. Lack of publicly-available ground measurements from 2015 onwards across the low-flow areas in the Indus and Ganges basins limits the validation of streamflow estimates.

The result presented here are similar to the conclusions presented by Lievens et al. [7] in terms of potentially improved streamflow after assimilation, but differ in the magnitude of change observed after assimilation across low flow river tributaries. These results are primarily different due to the bias correction method used, the retrievals being assimilated, and the prevalence of intensive irrigation across the study domain.

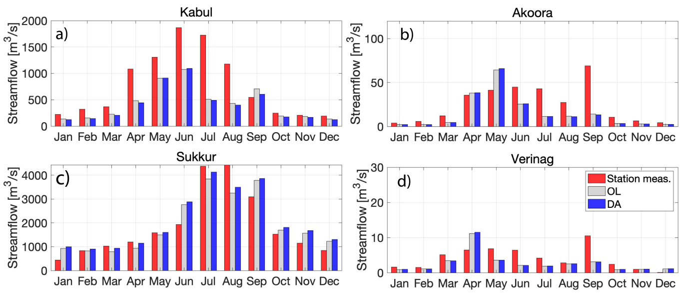

Fig. 4: Annual hydrographs of four stations along the Indus river. Subplot a) shows upstream high flows while subplot c) represents a high-flow downstream location. Subplots b) and d) show upstream low-flow tributaries that are considerably contributed to by snow and ice melt.

4.3. Annual Hydrographs

Annual hydrographs for four stations along the Indus river where streamflow data was available for multiple years are presented in Figure 4. Subplot a), which represents a high-flow upstream location, shows the underestimation of the modeled streamflow, especially in terms of the peak flow. This bias could be due to: 1) operation of upstream reservoirs, and 2) bias in the precipitation boundary conditions and the subsequent snowmelt. The estimation accuracy is much improved for the high-flow downstream location (Figure 4c). The difference between the OL and DA streamflow remains consistent throughout the year with an increase during the peak monsoon months of July and August. The two low-flow streams have similar streamflow magnitudes as compared to the station measurements, apart from the peak in September which the model underestimates. However, the flow magnitudes are low for these two stations, and therefore, any bias in the modeling framework could result in large differences between the station measurements and OL/DA estimated streamflow.

5. CONCLUSION

This study attempted to quantify the influence of SMAP soil moisture retrieval assimilation on modeled streamflow across three large river basins in South Asia. SMAP soil moisture retrievals were assimilated into Noah-MP modeled surface soil moisture. Large relative changes were observed across low-flow streams in irrigated areas. However, limited influence was noted for high-flow river tributaries and upstream locations where SMAP soil moisture retrievals were missing. The lack of publicly-available in-situ measurements within low-flow river tributaries limited a thorough evaluation of the modeled results. However, it is expected that improving the representativeness of the river flow by including regional reservoir operation within the modeling framework will improve the accuracy of estimated streamflow.

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