Improving hydrologic forecasting using spaceborne soil moisture retrievals

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Abstract

Using existing data sets of passive microwave spaceborne soil moisture retrievals, streamflow and precipitation for 26 basins in the United States Southern Great Plains, a 5-year analysis is performed to quantify the value of soil moisture retrievals derived from the Tropical Rainfall Mission (TRMM) Microwave Imager (TMI) X-band (10.7 GHz) radiometer for forecasting storm event-scale runoff ratios. The predictive ability of spaceborne soil moisture estimates is objectively compared to that obtainable using only available rainfall observations and the antecedent precipitation index (API). The assimilation of spaceborne observations into an API soil moisture proxy is demonstrated to add marginal value to the forecasting of land surface response to precipitation.

1. INTRODUCTION

Within small and intermediate-scale basins, knowledge of antecedent soil moisture conditions provides a key source of skill for short-term (1- to 3-day) streamflow forecasting. Operational attempts to exploit this skill are usually hampered by a lack of reliable soil moisture information. In the near future, such information will be operationally available from remote sensing. Previous work examining the value of observed soil moisture for streamflow forecasting have considered observations derived from spaceborne radar (Pauwels et al. 2002; Francois et al. 2003), airborne passive (Goodrich et al. 1994; Jacobs et al. 2003), and *in situ* sensors (Aubert et al. 2003). Less work has been focused on soil moisture data estimates derived from passive spaceborne radiometers. Utilizing passive spaceborne observations for surface soil moisture retrievals presents a unique set of advantages (e.g. more frequent and spatially extensive observations than spaceborne radar, airborne passive, or ground-based observations and generally higher accuracy than spaceborne radar) and disadvantages (e.g. relatively poor spatial resolution). Examining the effect of these attributes on streamflow forecasting is further motivated by the expected windfall of global, passive-based soil moisture data expected from the upcoming Soil Moisture and Ocean Salinity (SMOS) (Kerr et al. 2001), Hydrospheric States (Hydros) (Entekhabi et al. 2004) and Conically Scanning Microwave Imager/Sounder (CMIS) (Chauban, 2003) spaceborne missions.

A critical benchmark for evaluating the value of such observations for hydrologic forecasting is whether their inclusion into a modeling system leads to marginal improvements above and beyond what is possible using existing observational resources. Within the context of rainfall-runoff modeling, the issue is whether remotely-sense soil moisture provides information concerning antecedent soil moisture that is more valuable for hydrologic forecasting than soil moisture proxies that are commonly available from observations of antecedent precipitation and simple soil moisture modeling.

Using long-term daily rainfall/runoff data sets collected as part of the MOdel Parameterization EXperiment (MOPEX), satellite-based precipitation observations from the Global Precipitation Climatology Project (GPCP), and nearly five years of remotely-sensed soil moisture derived from the 10.7-GHz band of the Tropical Rainfall Mission (TRMM) Microwave Image (TMI), this analysis examines the value of simple precipitation-based soil moisture proxies - derived with and without the assimilation of remotely sensed soil moisture observations - for the short-term (1-3 day) forecasting of storm event-scale runoff ratios (runoff/precipitation). The goal will be to definitely isolate the marginal value (if any) of spaceborne soil moisture retrievals for forecasting land surface response to precipitation.

2. DATA

MOPEX data sets provide high-quality, daily observations of streamflow, air temperature, and precipitation for a large number of intermediate-scale (500 to 10000 km^2) basins in the United States (Schaake et al. 2001). Prior to their inclusion into the MOPEX, individual basins are screened according to the quality (and density) of rain gauges observations in the basin and degree of anthropogenic diversion and impoundment. All MOPEX basins within a box extending from -99 to -90 degrees longitude and south of 39 degrees latitude (the maximum latitude of TRMM observations) are considered (Table 1). To the west of -99 degrees longitude, runoff magnitudes are generally too low (1 to 2% of annual rainfall) to obtain an adequate sample of storm events with significant streamflow responses, and the predominance of forested land cover east of -90 degrees latitude greatly complicates the remote retrieval of soil moisture. The retrieval of surface soil moisture observations from 10.7 GHz TMI observations is described in detail by Bindlish et al. (2003). Retrievals have a -3dB spatial resolution of 38^2 km^2. Due to TRMM orbital characteristics, overpass times vary, but retrievals are generally available on a daily basis. Satellite-based precipitation products are derived from one latitude/longitude degree daily (1DD) Global Precipitation Climatology Project (GPCP) product based on infrared retrievals from the Television Infrared Observation Satellite (TIROS) Operational Vertical Sounder (TOVS) and the Geostationary Operational Environmental Satellite (GOES) and passive microwave measurements from SSM/I (Huffman et al. 2001).

Table 1. Location, size, and long-term runoff ratios for basins used in the analysis.

Basin	USGS number	Lat/Long	Size [km^2]	Runoff Ratio
1	02486000	-90.178/32.281	7927	0.263
2	06908000	-93.196/38.992	2800	0.294
3	06913500	-95.256/38.616	3125	0.236
4	06933500	-91.977/37.929	7100	0.229
5	07019000	-90.591/38.505	9470	0.253
6	07052500	-93.461/36.805	2467	0.256
7	07056000	-92.745/35.983	2072	0.283
8	07057500	-92.248/36.622	1402	0.336
9	07058000	-92.304/36.626	1425	0.230
10	07067000	-91.014/36.991	4167	0.347
11	07068000	-90.847/36.621	5095	0.381
12	07144200	-97.387/37.832	3317	0.136
13	07144780	-97.935/37.844	1967	0.073
14	07147070	-97.012/37.795	1065	0.185
15	07147800	-96.994/37.224	4700	0.260
16	07152000	-97.277/36.811	4647	0.211
17	07172000	-96.315/37.003	1112	0.232
18	07177500	-95.954/36.278	2262	0.254
19	07183000	-95.430/37.890	9545	0.216
20	07186000	-94.566/37.245	2910	0.213
21	07196500	-94.920/35.921	2397	0.282
22	07197000	-94.838/35.921	767	0.270
23	07243500	-96.065/35.675	5045	0.195
24	07290000	-90.696/32.347	7030	0.340
25	07346000	-94.498/32.749	2125	0.244
26	08055500	-96.944/32.965	6147	0.103

3. SOIL MOISTURE PROXIES

Three different soil moisture proxies are calculated: the antecedent precipitation index (API), TMI-based surface soil moistures estimates (θ_{TMI}), and API updated with daily θ_{TMI} observations using a Kalman filter (API_{TMI}). API for day i is defined as

$$API_i = \gamma API_i + P_i \qquad (1)$$

where P_i is precipitation and γ is the loss coefficient. Both rain gauge data and satellite-based rainfall products will be used to estimate P.

Kalman filtering is used to update API predictions from (1) with remotely-sensed surface soil moisture from TMI. The relationship between API and TMI-derived surface soil moisture (θ_{TMI}), is derived by fitting a linear least-squares regression line (with slope b and intercept a) to daily scatter plots of each quantity. Due to the known sensitivity of this relationship to vegetation amount, separate fits are individually derived for each basin listed in Table 1. Using this measurement operator, the state update equation for the Kalman filter becomes

$$API^{+}_{TMI,i} = API^{-}_{TMI,i,} + Ki(\theta_{TMI,i} - a - b\, API^{-}_{TMI,i}) \qquad (2)$$

where K is the Kalman gain

$$K_i = b\, T_i^- / (b^2\, T_i^- + R), \quad (3)$$

T the dynamic error in forecasted API and R the error in θ_{TMI} retrievals. Between daily updates, the model state API^+_{TMI} is temporally updated using (1). Forecast error T is propagated in time using

$$T_i^- = \gamma\ 2\ T_{i-1}^+ + Q \quad (4)$$

and then adjusted at measurement times via

$$T_i^+ = (1 - b\, K_i)\, T_i^- \quad (5)$$

The filter requires that two error parameters, Q and R, be set equal to the variance of daily error in API calculations and θ_{TMI} retrievals, respectively. Based on validation results for θ_{TMI} in Bindlish et al. (2003) and the known sensitivity of R to vegetation amount, R is assumed to be $(2\%)^2$ volumetric for basins in the lightly vegetated western portion of the region (west of -97 degrees latitude), $(4\%)^2$ for heavily vegetated eastern portions of the basin (east of -92 degree latitude) and $(3\%)^2$ for basins located in between. Following Dee (1995), modeling error is calculated by tuning Q such that normalized filter innovations - $(\theta_{TMI,i} - (a+b\ API^-_{TMI,i}))^2/(b^2 T_i^- + R)$ - have a temporal mean of one. During tuning, all basins are lumped together to obtain a single calibrated Q value.

4. APPROACH

For each of the 26 basins described in Table 1, API, θ_{TMI} and API_{TMI} were calculated on a daily basis between December 1997 and September 2002. Each moisture proxy was then used to estimate moisture levels on the day prior to the start of a storm event. The value of various soil moisture proxies for runoff forecasting were intercompared based on the Spearman-rank correlation coefficient (S_R) calculated between their pre-storm value and the subsequent time-integrated runoff ratio (total streamflow/total rainfall) observed during the event. A storm event is initiated when at least 2 mm of rainfall is recorded on single day and lasts for the next 7 days or until a day of above-threshold rainfall is recorded following a day of below-threshold rainfall. To limit the impact of convoluted streamflow responses from closely following storms, only events lasting 5 days or more were considered and any event proceeded by streamflow greater than 2 mm day^{-1} was deemed too close to the proceeding event and dropped from the analysis. To minimize the impact of frozen precipitation, events beginning on days in which the average of minimum and maximum temperature was below 0 C were also masked. For the remaining events, rainfall and streamflow were summed over individual events and used to calculate a storm-scale runoff ratio (total streamflow/total precipitation) for each event. Since base flow rates are generally low in the region, no base flow separation was performed.

5. RESULTS

Figure 1 shows time series of θ_{TMI}, API and API_{TMI} proxies for a single basin (USGS number 07243500) between July 2000 and June 2001 and, for storms between December 1997 and September 2002, scatter-plots of pre-storm values of each proxy versus subsequent storm-scale runoff ratios. All three proxies demonstrate a positive and statistically significant Spearman-rank correlation coefficient (S_R) between their pre-storm values and subsequent storm-scale runoff ratios. A higher correlation coefficient is obtained for the merged API_{TMI} proxy (Figure 1f) than for either θ_{TMI} or API in isolation (Figures 1b and 1d). Figure 2a repeats the analysis for all 26 basins in Table 1 and plots S_R values calculated between the pre-storm value of proxies and subsequent event-scale runoff ratios. S_R values for θ_{TMI} and API are generally comparable with correlation levels for θ_{TMI} exhibiting more basin-to-basin variability. However, the merger of θ_{TMI} into API to form API_{TMI} increases the observed correlation for all 26 basins (Figure 2a).

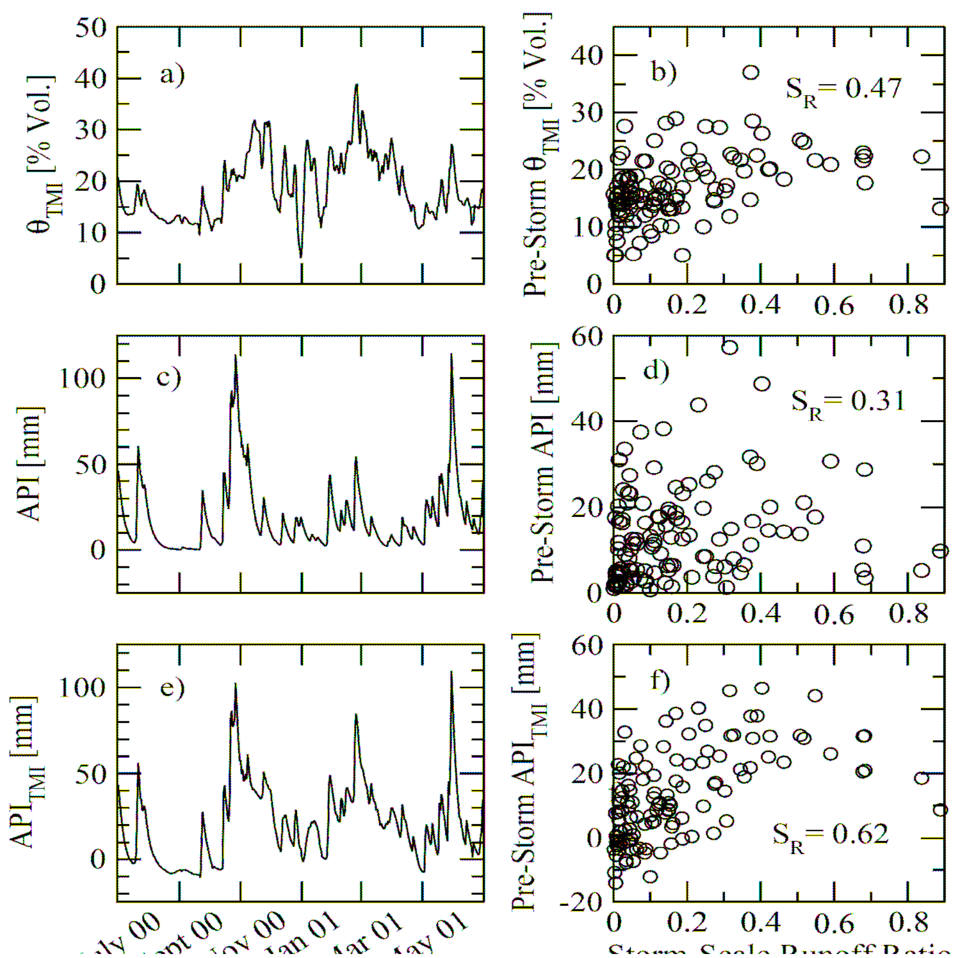

Figure 1. For a single basin (USGS number 07243500), 1-year time series of soil moisture proxies and scatter plots (for all five years) of proxies on the day prior to precipitation events versus subsequent storm event-scale runoff ratios. Each circle represents a separate event. Spearman-rank correlation coefficients (S_R) are given for each scatter plot.

Results in Figure 2a reflect storm events of all magnitudes. Modifying the approach to examine proxy skill for only large storm events (total magnitudes above 75 mm) does not qualitatively change results. When limiting the analysis to storms above 75 mm, the inclusion of TMI soil moisture observations improves the forecasting of runoff ratio in 21 out of 26 basins (as opposed to 26 out of 26 basins for all storm magnitudes) and results in an average increase in S_R of about 0.15 (not shown). Unfortunately, the length of the TMI soil moisture data set (5 years) prevents the adequate sampling of larger storm thresholds. Consequently, it is not possible to definitely isolate marginal skill for storm-events associated with even modest flood return intervals (2 to 5 years).

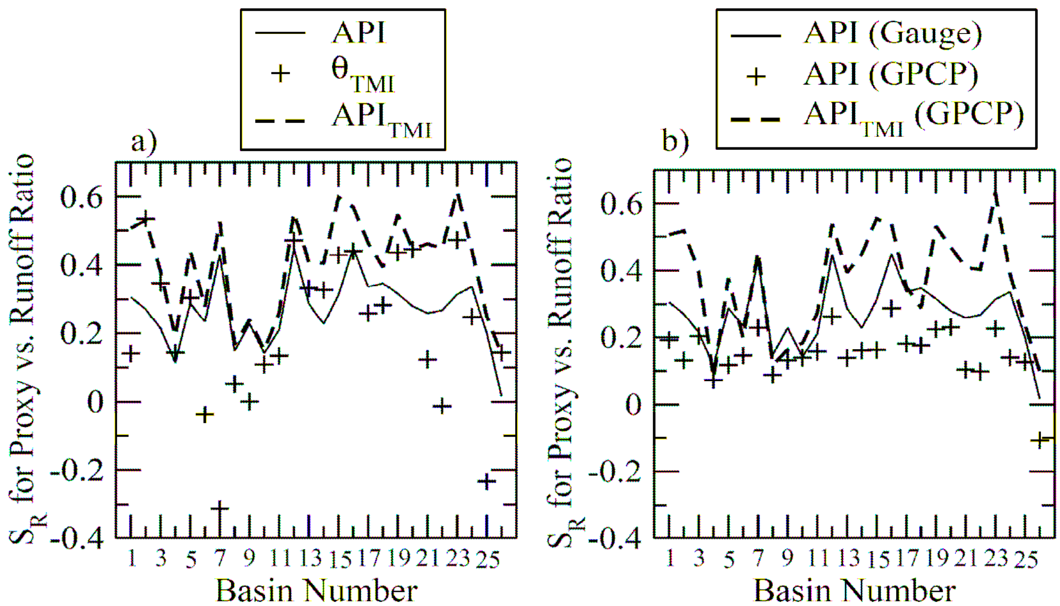

Figure 2. a) Comparison of S_R calculated between pre-storm values of soil moisture proxies versus storm event-scale runoff ratios using gauge-based precipitation and API, θ_{TMI} and API_{TMI} proxies. Basin numbers on the x-axis correspond to the first column of Table 1. b) Same as a), except proxies are gauged-based API (API(Gauge)), satellite-based API (API(GPCP)), and the merged proxy based on the assimilation of θ_{TMI} into API(GPCP) (API_{TMI}(GPCP)).

6. IMPACT OF SATELLITE-BASED PRECIPITATION

Only basins with sufficiently dense ground-based gauge data were included into the MOPEX data set. Consequently the reliability of daily rainfall accumulations used to derive API values in Figures 1 and 2 is very high and not globally representative of typical rainfall accuracies. The results in Figure 2b are based on modifying the analysis in Figure 2a by using satellite-based GPCP-1DD daily rainfall estimates instead of rain gauge data to estimate P in (1). Switching between gauge- and satellite-based precipitation products leads to a reduction in the ability of API to forecast runoff-ratios (Figure 2b). However, when TMI observations are assimilated into API(GPCP) to form

API_{TMI}(GPCP), the increase in S_R is large enough to fully compensate for the deficiencies of the GPCP-1DD precipitation forcing (Figure 2b). That is, an appropriate combination of satellite-based precipitation and TMI soil moisture observations provides as much (or more) land surface information than high quality rain gauge-based API predictions lacking any soil moisture assimilation.

7. CONCLUSIONS

Relative to the skill obtainable through consideration of only gauge-based antecedent precipitation, the assimilation of TMI-based soil moisture estimates (θ_{TMI}) into a simple API model leads to an enhanced ability to predict next-day storm runoff ratios (i.e. an enhanced Spearman-rank correlation between soil moisture proxies and runoff ratios) for all twenty-six of the basins listed in Table 1 (Figure 2a). The marginal value of TMI observations is enhanced when lower quality, but more readily available, satellite-based precipitation data sets are used to drive API predictions. In fact, Kalman filter-based assimilation of θ_{TMI} into an API model driven by satellite-based GPCP precipitation data leads to runoff-ratio forecasting skill that is slightly better than API models driven by high-quality ground-based gauge data (Figure 2b). That is, for this particular application, TMI-based soil moisture estimates are capable of compensating for the relative deficiency of satellite-based precipitation products versus higher-quality (but less readily available) rain gauge observations.

It is also worth noting that, relative to the 10.7 GHz TMI observations utilized here, future spaceborne surface soil moisture missions (i.e.. SMOS and Hydros) will be based on lower frequency observations capable of improved retrieval accuracy and deeper soil sampling volumes. These improvements will almost certainly enhance the value of remotely sensed surface soil moisture products for hydrologic applications including flood forecasting.

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