The Soil Moisture Analysis Rainfall Tool (SMART): Correcting Satellite-Based Precipitation Using Land Data Assimilation

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I. Introduction

Despite the obvious physical connection between precipitation over land and near-surface soil moisture, relatively little work to date has examined the mutual benefit of integrating information acquired from the remote estimation of both variables. Developing an effective synergistic strategy between these two geophysical retrieval types is especially important given the likely temporal overlap between the Global Precipitation Mission (GPM) and the NASA Soil Moisture Active Passive (SMAP) mission and known difficulties in obtaining satellite-based precipitation estimates over land of sufficient accuracy for critical water resource and natural hazard applications. Recent work in Crow et al. (2009) describes the development of a data assimilation system that uses remotely-sensed surface soil moisture retrievals to correct precipitation accumulation information derived from microwave satellite observations. This poster describes the baseline Crow et al. (2009) algorithm and methodological improvements to this baseline that have been integrated to create the Soil Moisture Analysis Rainfall Tool (SMART).

II. Crow *et al.* (2009) Baseline

The approach is based on an API model driven by uncertain daily precipitation accumulation P':

$$\mathrm{API}_{i,j} = \gamma_i \mathrm{API}_{i-1,j} + P'_{i,j} \quad (1)$$

At specific observations time, remotely-sensed surface soil moisture θ_{RS}:

$$\mathrm{API}^{+}_{i,j} = \mathrm{API}^{-}_{i,j} + K_{i,j}(\theta_{i,j} - \mathrm{API}^{-}_{i,j}) \quad (2)$$

where K is the Kalman gain:

$$K_{i,j} = T^{-}_{i,j}/(T^{-}_{i,j} + S_j) \quad (3)$$

and is θ_{RS} a soil moisture product that has been rescaled to match the long-term mean and standard deviation of open loop API predictions:

$$\theta_{i,j} = (\theta^{\circ}_{i,j} - \mu^{\theta}_j)\frac{\sigma^{\mathrm{API}}_j}{\sigma^{\theta}_j} + \mu^{\mathrm{API}}_j \quad (4)$$

Between observations, API forecasts are updated in time via (1) and the background error covariance are evolved following:

$$T^{-}_{i} = {\gamma_i}^2\, T^{+}_{i-1} + Q$$

Net additions and subtractions of water - or "analysis increments"- are dictated to th

$$\delta_{i,j} = \mathrm{API}^{+}_{i,j} - \mathrm{API}^{-}_{i,j} = K_i(\theta_{i,j} - \mathrm{API}^{-}_{i,j}) \quad (6)$$

Summing increments over 5-day periods, and rescaling by a temporally-fixed factor λ, provides an opportunity to additively correct for uncertain rainfall accu

$$[\widetilde{P'}]_{k,j} = [P']_{k,j} + \lambda_j[\delta_{k,j}]$$

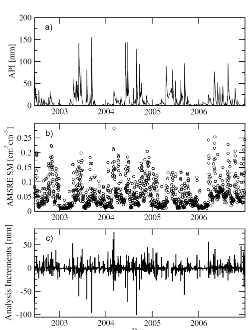

Figure 1. Over U.S. Southern Great Plains (SGP) region, sample daily times series of a) API, b) AMSR-E soil moisture (Single Channel Algorithm) and c) subsequent analysis increments.

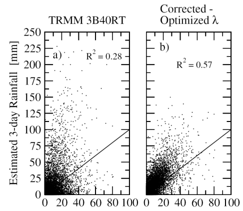

Figure 2. Over the U.S. SGP region, comparisons between corrected and un-corrected TMPA 3B40RT 3-day accumulation estimates.

Version	Domain	RMSE (mm)	R^2 (−)	FAR (−)	POD (−)
Original (λ = 0)	SGP	13.02	0.28	0.67	0.49
Estimated λ		9.15	0.53	0.60	0.77
Optimized λ		8.88	0.57	0.62	0.80
Default (λ = 1)		10.09	0.55	0.67	0.83
Default (λ = 0.5)		9.26	0.52	0.59	0.75
Original (λ = 0)	CONUS	11.78	0.30	0.62	0.37
Estimated λ		10.07	0.37	0.58	0.41
Optimized λ		9.66	0.37	0.57	0.41
Default (λ = 1)		13.07	0.19	0.72	0.32
Default (λ = 0.5)		10.17	0.32	0.57	0.37

Figure 3. Results in Figure 2 are for an optimized case where λ minimizes RMSE. Comparable results are found for an "estimated" case where λ minimizes differences with another satellite-only retrieval product (PERSIANN) and a "fixed" case of simply assuming λ = 0.50.

III. The Soil Moisture Analysis Rainfall Tool (SMART)

The Crow et al. (2009) algorithm has been extensively tested within the Contiguous United States (CONUS) and evaluated in terms of its net effect on the RMSE, R^2 and categorical accuracy of the TMPA real-time retrieval products versus the CPC Unified rain gauge analysis. While results are generally positive, three areas of degradation are observed: 1) the slight decrease in R^2 over heavily vegetated areas, 2) the increase in False Alarm Ratio (FAR) for low thresholds and 3) a slight decrease in Probability of Detection (POD) for high accumulation thresholds. To address these shortcomings, three modifications were made in Crow et al. (2011): 1) the forecast variance Q is conditioned to be a linear function of P'^2, 2) the observation error covariance S has been made a linear function of MODIS-based Evaporative Vegetation Index retrievals, and 3) the rescaling of AMSRE-based soil moisture retrievals have been modified to operate individual on individual 31-day periods. The combination of these changes with the original C09 algorithm are referred to as the Soil Moisture Analysis Rainfall Tool (SMART).

IV. SMART Results

Relative Magnitude of SMART Improvement Versus Other Measurements

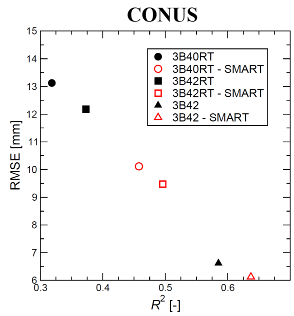

Figure 4. R^2 and RMSE for 1º, 3-day TMPA 3B40RT, 3B42RT and 3B42 accumulation products with (red) and without (black) application of SMART. Results are averaged across the Contiguous United States (CONUS).

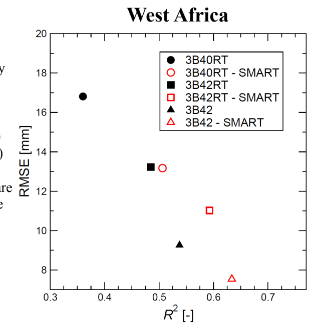

Figure 5. R^2 and RMSE for 1º, 3-day TMPA 3B40RT, 3B42RT and 3B42 accumulation products with (red) and without (black) application of SMART. Results are averaged across West African AMMA supersites in Benin, Niger and Mali.

Global Correction of 2002-2010 TMPA 3B40RT

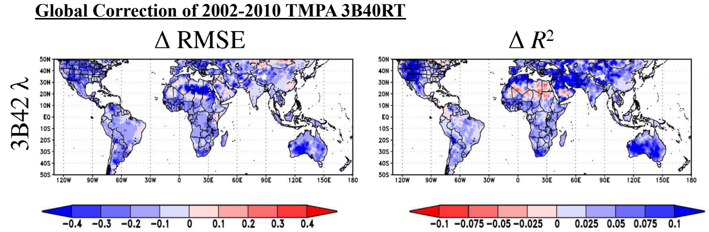

Figure 6. Global SMART R^2 and RMSE improvements for 1º, 3-day TMPA 3B40RT accumulation products versus a (gauge-corrected) TMPA 3B42 baseline. Blue is improvement and red is degradation.

Global Correction of 1979-1987 PGFD Precipitation

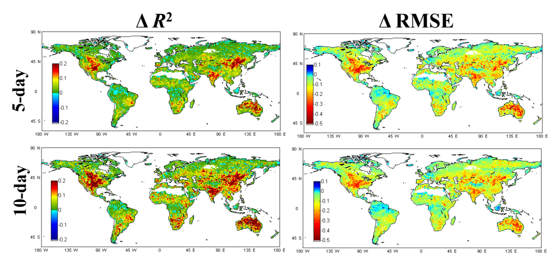

Figure 7. Application of the SMART algorithm to correction of the Princeton Global Forcing Dataset (PGFD) based on NCEP reanalysis as primary input and adjusted to match the CRU monthly totals and long-term rain-day statistics. Corrections are based on 1979- 1987 SMMR surface soil moisture retrievals acquired using the LPRM soil moisture algorithm and improvements are verified against the global Climate Prediction Center rain gauge analysis. Plots show changes in PGFD RMSE and R^2 evaluation metrics (for both 5- and 10-day accumulation periods) realized upon the application of SMART. The study is part of an ongoing project to create a 20-year (1979-1998) global corrected PGFD precipitation dataset using SMMR (01/1979 – 08/1987) and SSM/I (09/1987 – 12/1998) surface soil moisture retrievals.

Work Cited:

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• Crow, W.T. M.J. van den Berg, G.F. Huffman and T. Pellarin, "Correcting rainfall using satellite-based surface soil moisture retrievals: The Soil Moisture Analysis Rainfall Tool (SMART)," *Water Resources Research*, 47, W08521, doi:10.1029/2011WR010576, 2011.
• Chen, F. and W.T. Crow, "Correcting reanalysis-based precipitation datasets using remotely-sensed surface soil moisture," *IEEE Selected Topics in Applied Earth Observations and Remote Sensing*, in preparation, 2011.