Using a multi-dimensional satellite rainfall error model to characterize uncertainty in soil moisture fields simulated by an offline land surface model

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[1] In this study, we investigate the significance of using an improved error modeling strategy to characterize the spatio-temporal characteristics of uncertainty in simulation of soil moisture fields from an off-line land surface model forced with satellite rainfall data. We coupled a Two-Dimensional Satellite Rainfall Error Model (*SREM2D*) with the Common Land Model to propagate ensembles of simulated satellite rain fields for the prediction of soil moisture at depths of 5 cm (near surface) and 50 cm (root zone). Our investigations revealed that multi-dimensional error modeling captures the spatio-temporal characteristics of soil moisture uncertainty with higher consistency than simpler bi-dimensional error modeling strategies. The proposed error modeling strategy appears to have the potential for delineating a more robust framework for the optimal integration of satellite rainfall data into models towards the study of global water and energy cycle. **Citation:** Hossain, F., and E. N. Anagnostou (2005), Using a multi-dimensional satellite rainfall error model to characterize uncertainty in soil moisture fields simulated by an offline land surface model, *Geophys. Res. Lett.*, *32*, LXXXXX, doi:10.1029/2005GL023122.

1. Introduction

[2] Space-borne earth observations are increasingly becoming the prime source of hydro-meteorological forcing data for off-line land surface models (LSM) used to characterize land-vegetation-atmosphere interactions. Two widely used systems that rely on off-line LSMs and satellite data to provide high-resolution estimates of the land surface hydrologic state are the Global Land Data Assimilation System (*LDAS* [*Roddell et al.*, 2004]) and the Land Information System (*LIS* (S. V. Kumar et al., LIS—An interoperable framework for high resolution land surface modeling, submitted to *Environmental Modelling and Software*, 2004)). A recent study by *Syed et al.* [2004] has shown that most of the variability (70%–80%) of terrestrial hydrology is attributable to precipitation. Consequently, satellite rainfall estimation at regional and global scales and its error interaction with LSMs demand proper attention as being some of the most important input components dictating *LDAS*/*LIS* prediction accuracy.

[3] Satellite rainfall data takes greater importance when we consider the anticipated increased availability of passive microwave (PM) satellite sensor observations from the Global Precipitation Measurement mission (GPM [*Bidwell et al.*, 2002; *Yuter et al.*, 2003]). GPM observations combined with high-frequency rainfall estimates available from Geostationary IR sensors [*Joyce et al.*, 2004; *Tapiador et al.*, 2004; *Huffman et al.*, 2003] are expected to yield high-resolution global rainfall products of improved accuracy and consequentially expanded levels of utility. Another anticipated mission, the Hydrospheric State Mission—HyDROS (http://hydros.gsfc.nasa.gov)—is expected to provide soil moisture estimates at the 5-cm level with high accuracy. This mission therefore bears potential for constraining soil moisture predictions from off-line LSMs driven by satellite rainfall data.

[4] Although satellites provide the means for measuring rainfall over large-scale regions, their estimates are associated with error that is of complex nature [*Hossain and Anagnostou*, 2004, 2005a, 2005b]. Proper characterization of the error and its non-linear propagation in LSMs is therefore a critical priority. Developing probabilistic (ensemble) representations of the error propagation from satellite rainfall products to high-resolution hydrologic models can form the basis for studying the criteria for the optimal use of satellite rainfall data in the study of continental water and energy cycle [*Hossain and Anagnostou*, 2004, 2005a, 2005b].

[5] For the accurate modeling of satellite rain retrieval error, it is important to recognize that the desired progression to finer space-time scales in satellite rain estimation is counter-balanced by the increasing multi-dimensionality of the retrieval error. This scale dependence of rain retrieval error is associated with complex error propagation in hydrologic modeling through highly non-linear and fast-evolving land-atmosphere processes [*Anagnostou*, 2005; *Hossain and Anagnostou*, 2004, 2005a; *Hossain et al.*, 2004]. *Hossain and Anagnostou* [2005b] have recently provided evidence, on the basis of their Two Dimensional Satellite Rainfall Error Model (*SREM2D*), that a multi-dimensional decomposition of the satellite rainfall error structure with explicit formalization of the uncertainty in rainy/non-rainy area delineation can preserve the error structure of satellite rainfall estimates at higher scales of aggregation with significantly greater accuracy compared to simpler approaches.

[6] In this study we seek to quantify the significance of this improved satellite rainfall error modeling strategy in terms of uncertainty in soil moisture fields derived from an

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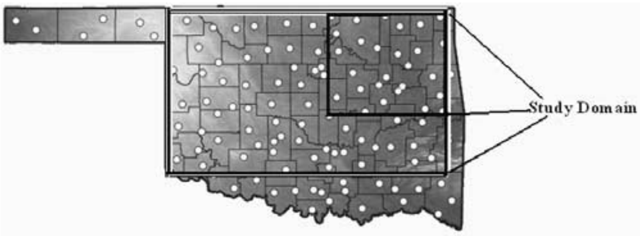

Figure 1. Study domain over the Oklahoma Mesonet (stations shown in circles). The larger box represents the domain used in *SREM2D* calibration, while the smaller domain is the effective area for CLM simulation of soil moisture fields.

off-line LSM driven by satellite rainfall data. Soil moisture is the main variable that controls water and energy fluxes between land surface and the atmosphere. Yet, little is known about the complex dependence of soil moisture accuracy on the error characteristics of precipitation. A point to note is that in this investigation we are not concerned with the absolute accuracy of soil moisture simulation *per se*, which is an entirely independent topic related to modeling structure and process conceptualization. We rather concentrate on the role of satellite rain retrieval error relative to the most definitive rainfall source (i.e., rainfall data from a rain gauge-calibrated ground weather radar system).

2. Data, Study Region and Methods

[7] The Two Dimensional Satellite Rainfall Error Model (*SREM2D*) of *Hossain and Anagnostou* [2005b] is used to model the multi-dimensional satellite retrieval error characteristics. This is currently the most detailed and modular error model comprising nine dimensions available for fine-scale assessment of satellite rainfall algorithms. The major algorithm components are: (1) the joint probability density function for characterizing the spatial structure of the successful delineation of rainy and non-rainy areas; (2) the temporal dynamics of rain estimation bias; and (3) the spatial structure of the random rain rate estimation error. We stress that satellite rain retrieval uncertainty is associated with correlated rain/no-rain detection and false alarm error characteristics, as well as systematic and random rain rate error components with long spatio-temporal correlation lengths. These components are explicitly characterized in *SREM2D*.

[8] In this study we used hourly IR rainfall data products as our satellite rainfall source, and coincident hourly radar rainfall fields as ground ''truth'' reference in *SREM2D*. In terms of IR retrievals, we selected the operational NASA product IR-3B41RT [*Huffman et al.*, 2003] available at 0.25 deg and hourly. Radar rainfall fields were derived from WSR-88D observations using National Weather Service precipitation estimation algorithm with real-time adjustments based on mean-field radar-rain gauge hourly accumulation comparisons [*Fulton et al.*, 1998]. To minimize effects due to complex terrain the calibration exercise was performed over the region of Oklahoma bounded by −100°W−95°W and 37°N−34°N (Figure 1). We selected a study period of four months (May 1, 2002 to August 31, 2002; 2952 hourly time steps each with 20 × 12 pixels at 0.25 degree resolution) to determine the *SREM2D* error parameters. The error modeling performance of *SREM2D* was compared against two simpler, but widely used, approaches of error modeling [see for example *Walker and Houser*, 2004]. We name those error-modeling approaches as *N1* and *N2*. In *N1*, we modeled the rain rate estimation error (assuming perfect delineation of rainy and non-rainy areas) without any coherent spatio-temporal structure. The systematic (mean) and random (variance) error parameters are the same with those used in *SREM2D* [*Hossain and Anagnostou*, 2005b]. In *N2* we also assume perfect delineation of rainy and non-rainy areas, but the rain rate estimation error was modeled with spatially and temporally correlated structure similar to that conceptualized in *SREM2D*. *Hossain and Anagnostou* [2005b] showed that both of these simpler approaches fare poorly with regards to preserving the error structure across scales. They underestimated the true sensor retrieval error standard deviation by more than 100% upon aggregation to coarser resolution, which, for *SREM2D*, was found to be less than 30%. Further details on the *SREM2D* calibration of error parameters are given by *Hossain and Anagnostou* [2005b].

[9] For simulation of soil moisture at two depths (near-surface - 5 cm and root zone −50 cm) we used the Common Land Model (CLM [*Dai et al.*, 2003]) over a 2-deg × 2-deg domain (Figure 1, smaller domain). All requisite hydro-meteorological data were derived from hourly in-situ measurements from the Oklahoma Mesonet network ([*Elliot et al.*, 1994] available at http://www.mesonet.ou.edu) or the NCEP reanalysis database. CLM was spun-up with 16 months of prior hydro-meteorological data to reach to an equilibrium state [*Cosgrove et al.*, 2003]. In each simulation run CLM was initialized with the equilibrium state variables, and subsequently run over the 4-month study period based on the rainfall fields derived from various sources: the WSR-88D and IR-3B41RT rain estimates, and the synthetic fields simulated by *SREM2D*, *N1* and *N2* satellite rainfall error models.

[10] For the error characterization of soil moisture fields we used as ''reference'' the CLM soil moisture simulations forced by the most definitive WSR-88D rainfall data. The assumption made here is that CLM may adequately represent the land surface hydrologic processes of the study area. Deviations of the ''reference'' soil moisture fields from those derived using satellite rainfall input define the satellite error propagation in soil moisture. The satellite error propagation in soil moisture prediction (defined as ''true'' error) is determined here for the 3B41RT rainfall dataset. We compare the spatio-temporal characteristics of the ''true'' soil moisture error fields to those stochastically derived from synthetic satellite rainfall fields generated by the different error-modeling approaches. Specifically, the aforementioned satellite error models are used to generate multiple realizations of synthetic satellite rainfall fields by corrupting the most accurate WSR88D rainfall fields over a 2-deg area (Figure 1). The synthetic rainfall fields are then used to force CLM and produce synthetic soil moisture fields. In total, we generated 15 Monte Carlo (MC) realizations of *SREM2D*, *N1* and *N2* through CLM to understand the soil moisture prediction uncertainty. Numerical consistency checks conducted by *Hossain and Anagnostou*

Table 1. Standard Deviation of Error for Simulated Soil Moisture Fields by Various Rainfall Input Scenarios[a]

Rainfall Input	Std. Deviation (cm^3/cm^3) 0.25 degree	Std. Deviation (cm^3/cm^3) 0.5 degree	Std. Deviation (cm^3/cm^3) 1.0 degree
IR-3B41RT	0.037	0.035	0.031
SREM2D	0.036	0.028	0.022
N1	0.037	0.026	0.019
N2	0.037	0.029	0.024

[a]Note: For error modeling strategies (*SREM2D, N1, N2*) we report the mean of the 15 Monte Carlo realizations.

[2005b] have shown that 15 realizations are adequate to converge to the true error statistics in the case of long time series (2952 time-steps).

3. Results and Discussion

[11] Statistical comparisons of the marginal soil moisture error statistics (standard deviation) of the three error models with those of the "true" soil moisture error are shown for three scales (0.25, 0.5 and 1.0 degree) in Table 1. It is observed that the marginal error statistics in terms of standard deviation are comparatively similar across the three different error models and reasonably consistent with the scaling behavior of "true" error. In Figures 2a and 2b we show the temporal correlogram (auto-covariance function) of soil moisture error at depths of 5 and 50 cm for scales of aggregation up to one degree. The dashed lines represent the range of variability associated with the 15 realizations. It is evident from Figures 2a and 2b that *SREM2D*-derived soil moisture error fields have higher consistency in enveloping the spatio-temporal dependency (solid line) of the satellite-derived soil moisture error characteristics. The simpler error propagation schemes (*N1* and *N2*) have a tendency to systematically underestimate the pattern of spatio-temporal variability of error at all examined scales. In addition, they appear to predict a faster rate of dissipation of soil moisture error than what is indicated by the "true" error statistics. In terms of spatial error correlation, Figure 3 shows a similar behavior. Namely, the spatial error correlation of actual satellite rain retrievals is bounded reasonably well by the *SREM2D* synthetic fields, while the two simpler methods significantly underestimate the spatial error auto-correlation.

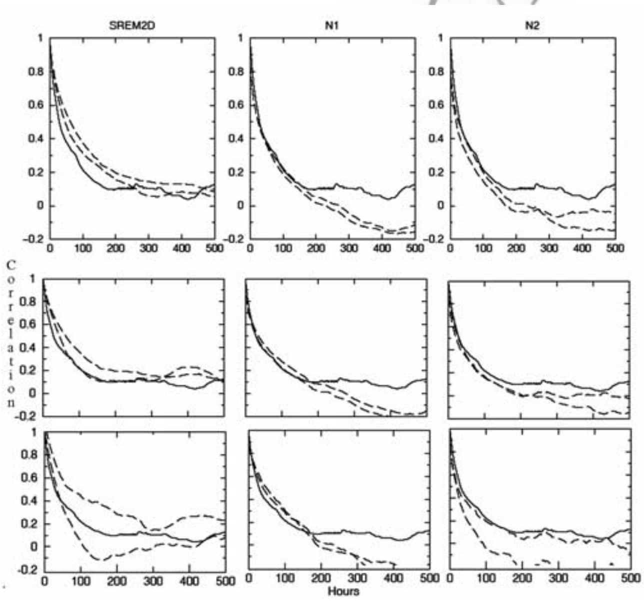

Figure 2a. Temporal correlogram of simulated near surface (5 cm) soil moisture error fields at three scales−0.25 degree (Uppermost panel), 0.5 degree (middle panel) and 1.0 degree (lowermost panel). The solid lines show the correlograms of "true" error determined from actual satellite data; dashed lines represent the upper and lower bounds of error correlograms derived from the 15 MC realizations of simulated satellite error fields.

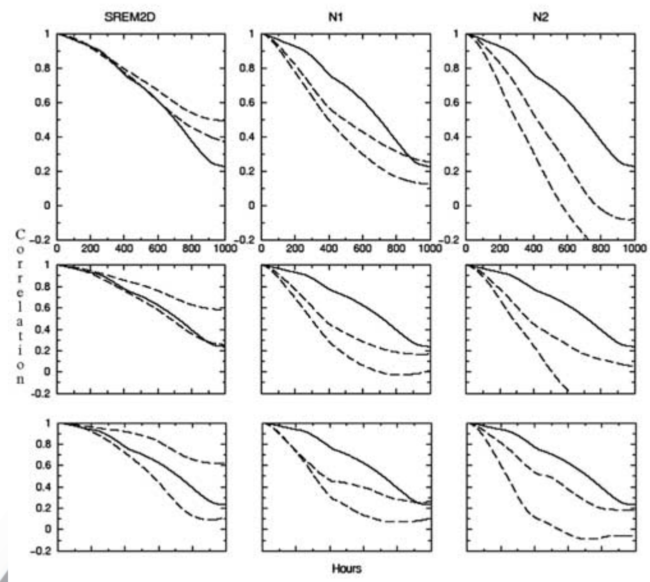

Figure 2b. Same as in Figure 2a, but for simulated root zone (50 cm) soil moisture fields.

[12] The demonstrated differences between multi-dimensional and simpler (bi-dimensional) error modeling strategies impact the assessment of satellite rainfall algorithms (current or proposed) with regard to their optimal integration in off-line LSMs. For example, a *SREM2D* based error propagation study can delineate more accurately the updating (or assimilation) frequency required for an LSM forced by a current (or proposed) satellite rainfall product. More specifically, *SREM2D* can identify the time required for simulated soil moisture error to decorrelate to the white noise level. A longer decorrelation time (and hence slower dissipation of error) would be indicative of greater divergence in LSM predictions due to continued accumulation of

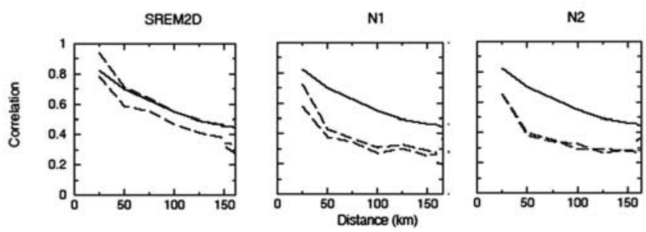

Figure 3. Same as in Figure 2, but for the spatial correlogram of near-surface (5 cm) soil moisture error fields at daily temporal aggregation.

bias in the model predictions. This in turn would demand more frequent updating of soil moisture with observations to constrain the model predictions to realistic levels. Consequently, *SREM2D*'s improved capability to provide a more accurate characterization of the spatio-temporal error structure would strengthen our ability to define optimality requirements for integration of satellite rainfall data in *LDAS*.

4. Conclusions

[13] Our preliminary investigations show that a multi-dimensional error modeling strategy such as the one formalized by *Hossain and Anagnostou* [2005b] can provide a more accurate assessment of the spatio-temporal make-up of uncertainty in soil moisture fields derived from LSM forced with satellite rainfall data. This greater accuracy was manifested in our study as a consistent ability of the generated error propagation ensembles to envelope the observed uncertainty characteristics from real sensor data. On the other hand simpler error modeling strategies such as the two bi-dimensional methods assessed herein, which are the backbone of conventional error propagation studies, revealed a systematic underestimation in predicting the spatio-temporal patterns of soil moisture simulation error. In anticipation of future water cycle and climate missions such as GPM and HyDROS, it is hoped that our proposed multi-dimensional error modeling strategy will trigger, at least in concept, detailed investigations to study the optimal integration of space-based rainfall and near-surface soil moisture retrievals in *LDAS/LIS* systems.

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