Assessment of a Multidimensional Satellite Rainfall Error Model for Ensemble Generation of Satellite Rainfall Data

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***Abstract*—This letter presents preliminary insights from the pursuit of the following scientific query: "How realistic is ensemble generation of satellite rainfall data by a multidimensional satellite rainfall error model?" The authors first evaluated the scale-dependent multidimensional error structure for two satellite rainfall algorithms developed at the NASA Goddard Space Flight Center, namely: 1) the infrared (IR) estimates known as the 3B41RT product and 2) the combined passive microwave (PMW) and IR estimates known as the 3B42RT product. Ground radar (WSR-88D) rainfall fields from the Southern Plains of the U.S. were used as reference. Next, by reversing the definition of reference and corrupted rain fields produced by a multidimensional satellite rainfall error model (SREM2D, developed by Hossain and Anagnostou), the authors derived the inverse multidimensional error structure of WSR-88D rainfall fields with respect to the satellite rainfall estimation algorithms. SREM2D was then applied on actual satellite rainfall data with the pertinent inverse error parameters to generate an ensemble of most likely realizations of the reference WSR-88D rainfall fields. The simulated ensemble was then compared with that derived from a simpler (bidimensional) inverse error modeling approach. The accuracy of the SREM2D rainfall ensemble was observed to be higher than the simpler error-modeling scheme for the 3B41RT product. No tangible improvement was observed for the 3B42RT product, which is attributed to the heterogeneous nature of 3B42RT data statistics that was not accounted for in the inverse SREM2D approach. The overall conclusion is that a multidimensional error modeling approach such as SREM2D has the potential to generate realistic ensembles of satellite rainfall fields, which should be considered as an improvement over the more widely used simpler error-modeling scheme. A combined use of the multidimensional error model with a sequential error correction scheme could therefore potentially improve the diagnosis of satellite rainfall-based predictability of the global water and energy cycle.**

***Index Terms*—Ensemble satellite rainfall generation, global energy, infrared (IR), inverse model, multidimensional error structure, passive microwave (PMW), scale, water cycle.**

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I. Introduction

THE SATELLITE sensors [such as infrared (IR) and passive microwave (PMW)] that provide observations for rain estimation operate on distinct physical principles and exhibit different types of indeterminacy in estimation. This explains, to a large extent, the lack of unity and consistency among various types of satellite rainfall estimates [3]. As a natural consequence, numerous error studies have evolved on the quantification of the accuracy of various satellite rainfall estimation algorithms. Most of these studies, however, concentrate on rain estimation uncertainty issues associated with large spatiotemporal scales involving limited number of error statistics (such as [1], [8], [13], and [18], among others). Although useful for assessing the application of satellite rainfall data for long-term climatologic or water balance studies, these error statistics do not offer significant insight toward gauging the predictability of more dynamic and finer scale land surface hydrologic processes such as floods or soil moisture dynamics [9], [10]. Also, most satellite rainfall error models to date focus primarily on the sampling uncertainty arising from the low frequency of PMW sensor overpasses wherein the algorithm uncertainty has often been assumed a negligible component of the total rainfall error budget [2], [7], [24], [25]. However, with the anticipated abundance of PMW sensor rainfall data from the proposed global precipitation measurement (GPM) [23] mission that is expected to begin in 2010, it now appears critical to have the ability to accurately model the error structure of satellite rainfall at fine space–time scales ($< 0.1^\circ$ and 1–3 hourly) [10].

A problem encountered with application of satellite rainfall data at fine scales is the increasing frequency of mismatches (with the ground reference) that satellite rainfall data is progressively exposed to at these finer spaces and times. Under such a circumstance, simpler error statistics (such as root-mean-square error) have been found inadequate in distinguishing the physical consistency (or the lack of it) among satellite rainfall products [15]. Recent research also indicates that the desired progression to finer scales in satellite rain estimation is actually counterbalanced by an increasing dimensionality of the retrieval error, which has a consequentially complex effect on the propagation through land surface–atmosphere interaction simulations [4], [10]–[12]. In essence, this scale incongruity between meteorological data and its hydrologic application represents a competing tradeoff for lowering the satellite retrieval error versus modeling finest scale land–vegetation–atmosphere processes that is necessary. It is therefore obvious that if the predictability of the global water and energy cycle is to move forward on the basis of satellite rainfall data, then a generic system is needed that can address this scale-dependent incongruity without resorting to larger spatiotemporal averaging.

In the spirit of tackling this scale-dependent incongruity, Hossain and Anagnostou [9]–[12] have demonstrated that a detailed decomposition of the satellite rainfall error structure to a multidimensional stochastic hyperspace can indeed distinguish the various facets of physical consistency among satellite rainfall products and consequently improve our understanding of the utility of satellite rainfall data for predicting dynamic hydrological processes. The two-dimensional satellite rainfall error model (SREM2D) is one such stochastic multidimensional error modeling approach developed and verified by Hossain and Anagnostou [10]. SREM2D corrupts reference rain fields (of higher accuracy) to generate an ensemble of equiprobable traces of satellite-like estimates, which can subsequently be used to construct scientific inquiries on advancing the satellite-based predictability of the global water and energy cycle (see [11] and [12] for an example). Herein, the term "multidimensional" refers to the multiple facets (> 2) of satellite rainfall estimation that extend beyond the simpler aspects ($=2$) of systematic and random retrieval error components, whereas the term "two dimensional" coined with SREM2D refers to the spatial nature (x, y) of satellite rain fields simulated by the error model. A nonexhaustive list of the multiple facets of satellite rainfall estimation could be as follows: 1) the probability of successful detection/delineation of rainy and nonrainy areas with coherent spatial structures; 2) the probability distribution of false rain rates over nonrainy areas; 3) the temporal dynamics of rain estimation bias, etc. We provide a more exhaustive elaboration of these multiple facets of SREM2D model in the latter section of this letter.

In this letter, we therefore share our preliminary insights with the research community (comprising the satellite data producers and users) from an ongoing pursuit of the following scientific query: "How realistic is ensemble generation of satellite rainfall data from a multidimensional satellite rainfall error model?" We particularly focus on ensemble generation because of two reasons: 1) ensemble quantitative precipitation forecasting (QPF) is a well-established protocol nowadays among the scientific community and operational data producers [5]; and 2) ensemble generation allows the assessment of hydrologic error propagation in probabilistic terms, thereby relaxing the common assumption of satellite rainfall estimation as being a deterministic process [28]. In addressing our question, we used reference rain fields from rain gauge-calibrated ground radar (WSR-88D) measurements in the Southern Plains of the U.S. to evaluate the multidimensional error structure for two contrasting satellite-based rain retrieval algorithm developed at NASA Goddard Space Flight Center. Next, we derived the inverse (retrieved) multidimensional error structure of ground radar rain fields with respect to the algorithm by reversing the definition of reference and corrupted rain fields (produced by SREM2D). SREM2D was then applied on actual satellite rainfall data with the pertinent inverse error parameters to simulate realization of reference rain fields.

It is appropriate to highlight at this stage that SREM2D is conceptually different from the recently emergent body of work on quantifying the scale-dependent uncertainty of satellite rainfall estimates (see [26]–[28], among others). SREM2D has been conceptualized with the following three design objectives: 1) it should function as a filter wherein the hydrological implications of fine-scale components of the satellite precipitation error structure can be explicitly determined by coupling it with a hydrological/land surface model; 2) it should be modular in design with the capability to allow uncertainty assessment of any satellite rainfall algorithm; and, finally, 3) the error parameters of SREM2D should be such that their hydrologic implications are physically interpretable by the data producers and thus provide better focus to the development of next generation multisensor algorithms in anticipation of GPM. To the best of our knowledge, other frameworks on the scale-dependent error quantification, although useful in their unique ways, do not possess all these three attributes simultaneously in one single package. We would also like to highlight that the approach adopted herein does not address satellite rainfall estimation *per se*. Furthermore, our work should also not be construed as a suggestion of redundancy of the physically based breakthroughs in satellite precipitation remote sensing. The singular focus of our study is on advancing our ability to extract more useful hydrologic information from satellite rainfall data by harnessing knowledge of its scale-dependent multidimensional error structure. In the following section, we briefly describe SREM2D, the datasets, study region, simulation experiment, and, finally, the insights extracted from our study.

II. SREM2D

The major dimensions of error structure in satellite estimation modeled by SREM2D are as follows: 1) the joint probability of successful delineation of rainy and nonrainy areas accounting for a spatial structure; 2) the temporal dynamics of the conditional rainfall estimation bias (rain > 0 unit); and 3) the spatial structure of the conditional (rain > 0 unit) random deviation. The spatial structure in SREM2D is modeled as spatially correlated Gaussian random fields, whereas the temporal pattern of the systematic deviation is modeled using a lag-one autoregressive process. The spatial structures for rain and no-rain joint detection probabilities are modeled using Bernoulli trials of the uniform distribution with a correlated structure. This correlation structure is generated from Gaussian random fields transformed to the uniform distribution random variables via an error function transformation. In total, SREM2D models the satellite rainfall error structure via nine parameters (and hence a nine-dimensional stochastic hyperspace). These SREM2D error parameters are as follows: 1) probability of successful detection of rain pixels (as a function of reference rainfall); 2) probability of successful detection of nonrainy pixels; 3) second-order moments of the probability density function of false satellite rain rates over nonrainy pixels; 4) conditional rainfall retrieval bias (multiplicative); 5) standard deviation of conditional rainfall retrieval error (multiplicative); 6) correlation length for the successful delineation of rainy areas; 7) correlation length for the successful delineation of nonrainy areas; 8) correlation length for the conditional retrieval error (multiplicative); and 9) lag-one time-step autocorrelation of rainfall estimation bias. For more details on

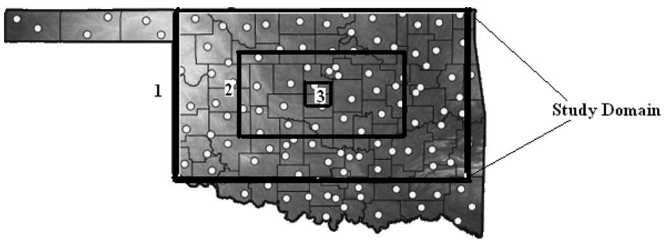

Fig. 1. Study region in the Southern Plains bounded between $-100°$W and 95°W and 37°N and 34°N. At 1/4° resolution, the domain comprises 20×12 pixels. The boxed areas represent the three spatial integration area domains used in the study. The solid circles show locations of the Oklahoma Meso-network meteorological stations.

SREM2D, the reader is referred to the formulation and validation assessment provided in [10].

III. Data, Study Region, and Methods

We selected two satellite rainfall data products and corresponding ground radar rainfall fields as the reference input for corruption by SREM2D. In terms of the satellite retrievals, we selected the following two algorithms: 1) hourly IR estimates with homogeneous statistics known as the 3B41RT product and 2) three hourly combined PMW and IR estimates with heterogeneous statistics known as the 3B42RT product. Both these products are produced at NASA Goddard Space Flight Center at the 0.25° spatial resolution and are publicly available in pseudo real time on a best effort basis [14]. Radar rainfall fields were derived from WSR-88D observations using the National Weather Service multicomponent precipitation estimation algorithm with real-time adjustments based on mean-field radar-rain gauge hourly accumulation comparisons [6], [21], [22]. To minimize effects due to complex terrain and range effects, the calibration exercise was performed over the region of Oklahoma bounded by $-100°$W to 95°W and 37°N to 34°N (Fig. 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° resolution) to determine the SREM2D error parameters for 3B41RT. For determination of the SREM2D error parameters for the three hourly 3B42RT product, we considered radar rain fields at the corresponding three hourly time scales. The error modeling performance of SREM2D was compared against a simpler but more widely used version of error modeling (examples of such models can be found in [19] and [29]). We name this error-modeling approach as SIMP where we modeled the rain rate estimation error (assuming perfect delineation of rainy and nonrainy areas) without any coherent spatiotemporal structure. This means that the SIMP methodology employed mainly two error parameters, namely: 1) systematic (mean) and 2) random (variance) errors. These two parameters were assumed the same as those used in SREM2D. Further details on the SREM2D calibration of error parameters over the study region can be found in [10].

Next, we derived the multidimensional SREM2D error parameters in the inverse mode. In this mode, the actual satellite rainfall retrievals were assumed as our "reference" for derivation of the multidimensional deviation of the reference WSR-88D rain fields. By applying SREM2D with these inverse "error" parameters on actual satellite data, we simulated

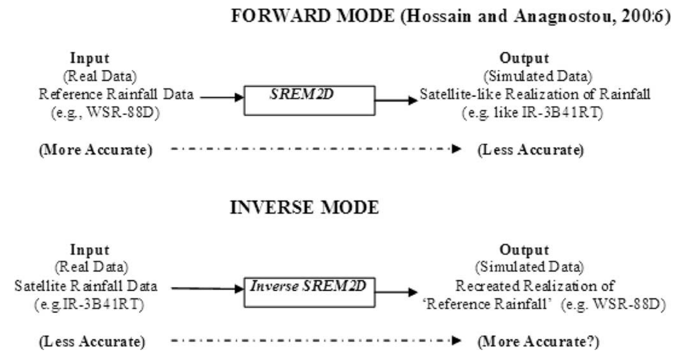

Fig. 2. Two modes of SREM2D error parameter estimation. The forward mode (upper panel) is an already demonstrated concept used in recent error propagation studies by Hossain and Anagnostou [10]–[12]. The inverse mode is proposed as a way to provide ensembles of satellite rainfall fields calibrated to reference rainfall observations.

TABLE I
Forward and Inverse SREM2D Error Parameters Evaluated at 0.25° Resolution for 3B41RT and 3B42RT

Mode	3B41RT		3B42RT	
	Forward[1]	**Inverse[2]**	**Forward[1]**	**Inverse[2]**
Multiplicative Bias	2.20	0.35	1.22	1.09
Gaussian Std. Deviation	1.27	0.84	0.73	0.73
False Alarm mean $(\frac{1}{\lambda})$[3]	1.43 mm/hr	1.70 mm/hr	2.02 mm/hr	1.50 mm/hr
Probability of Detection parameters A(B)[3]	1.1(1.5)	1.1(1.25)	1.05(1.5)	1.05(1.25)
Probability of No Rain Detection (%)[3]	95.60	95.0	97.0	95.0
Retrieval Error Correlation Length (Spatial)[3]	170.0 km	50.0 km	25.0 km	25.0 km
Successful No-rain Detection Correlation Length (Spatial)[3]	220.0 km	200.0 km	40.0 km	40.0 km
Successful Rain Detection Correlation Length (Spatial)[3]	170.0 km	120.0 km	50.0 km	50.0 km
Lag-one (hourly) Correlation of retrieval error (temporal)[3]	0.62	0.65	0.95	0.94

1 - WSR-88D rainfall is reference;

2 – Satellite rainfall data (3B41RT or 3B42RT) is assumed as reference;

3 – Based on calibration according to [10].

realizations of WSR-88D rain fields. In this way, this inverse approach allowed us to evaluate the ability of SREM2D to further improve the accuracy and precision (discussed next) of ensemble of satellite rainfall data by exploiting knowledge of its scale-dependent multidimensional error structure. The inverse approach of SREM2D was next compared with the inverse approach of SIMP with the same pertinent inverse error parameters. Fig. 2 summarizes schematically the inverse approach undertaken in this letter and presents it in perspective of the more usual forward approach used for error propagation studies. In Table I, we summarize the SREM2D error parameters for both the forward and inverse approaches that were computed according to [10]. Significantly lower bias and standard deviation of conditional retrieval error is observed for 3B42RT as compared with 3B41RT, which can be attributed to the merging of the more accurate PMW rainfall estimates with the IR rainfall data. The lower spatial correlation lengths reported for the 3B42RT product is possibly a manifestation of the heterogeneous statistics of the data due to the merging of PMW instantaneous rain rates with IR estimates [14]. Twenty Monte Carlo (MC) simulations were run for the inverse SREM2D and

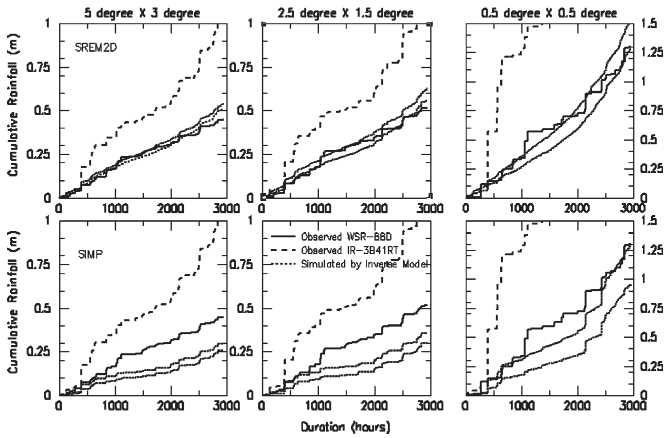

Fig. 3. Ensemble envelopes of satellite-retrieved cumulative hyetographs (dotted lines) for two error-modeling schemes, namely: 1) SREM2D (upper panel) and 2) SIMP (lower panel). Solid line represents the ground reference WSR-88D cumulative hyetograph. Long-dashed line is the actual 3B41RT cumulative hyetograph used as input to the inverse error models.

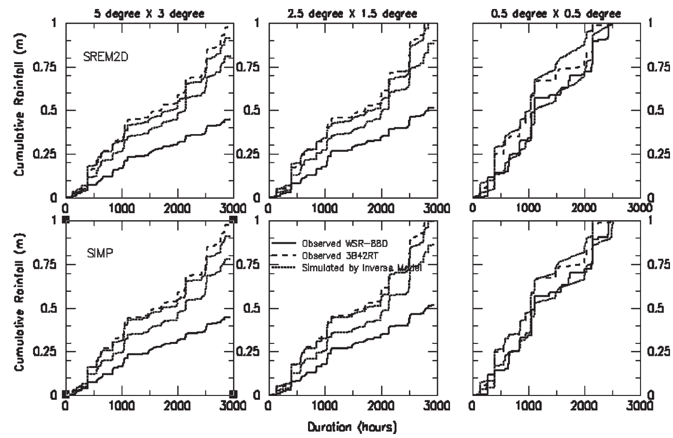

Fig. 4. Same as Fig. 3, but for the 3B42RT product.

SIMP approaches. Hossain and Anagnostou [10] have reported that about 15 MC runs are usually adequate to converge to the global error statistics for the study region. The corresponding prediction range (maximum and minimum) of the cumulative rainfall hyetograph (over the whole study period) were then derived from the ensemble of simulated rain fields averaged in three areal domains (see Fig. 1): 1) $5^\circ \times 3^\circ$ (20×12 pixels), 2) $2.5^\circ \times 1.5^\circ$ (10×6 pixels), and 3) $0.5^\circ \times 0.5^\circ$ (2×2 pixels).

IV. Results and Discussion

Figs. 3 and 4 (upper panels) show the ensemble envelope of the simulated rainfall hyetographs produced by the inverse SREM2D approach for the three areal domains. This is compared with the ensemble envelope produced by the inverse SIMP approach in the lower panels of Figs. 3 and 4. The following two considerations are used to compare the two ensemble error simulations. If the ensembles (i.e., uncertainty limits) are too narrow, and the whole ensemble envelope is biased (i.e., WSR-88D rainfall hyetograph is outside the upper/lower bounds), it suggests that the inverse error modeling approach lacks the statistical consistency to constrain/improve the uncertainty of satellite rainfall estimates. On the other hand, if the ensemble envelope is too wide, it could be concluded that the inverse approach has inadequate predictive ability. The dual paradigms of statistical consistency and predictive ability are analogous to the notions of accuracy and precision of the ensemble simulation. We observe significant differences in the hyetograph ensemble ranges between the inverse SREM2D and SIMP for the 3B41RT product. Inverse SREM2D envelops consistently the observed rainfall hyetograph of WSR-88D in all scales of aggregation, whereas inverse SIMP is found to be inadequate (Fig. 3). The inverse SREM2D and SIMP ensemble envelops are comparable in terms of width (SREM2D is slightly wider), whereas the width changes consistently with scale. However, the inverse SREM2D approach is found to impart no tangible improvement for ensemble generation of the 3B42RT product (Fig. 4). We attribute this behavior to the absence of homogeneous statistics in 3B42RT data [14] that possibly rendered the inverse SREM2D approach ineffective. We speculate that the adoption of separate statistics for the PMW and IR rainfall pixels could have potentially resolved this issue. However, detailed feasibility assessment is required to identify the algorithm modifications necessary for the inverse SREM2D approach to be suitable for data with heterogeneous statistics. Overall, findings from this study indicate that modeling the rainy/nonrainy area delineation and spatiotemporal correlation of error in the inverse mode can considerably improve the accuracy satellite rainfall estimates with homogeneous statistical distribution without compromising the predictive capability (precision) of the algorithm.

One implication of the above-observed difference between multidimensional and simpler (bidimensional) error modeling strategies could be on the potential amelioration of satellite rainfall products to make them more suitable for advancing the predictability of the water cycle at fine space–time scales. This amelioration could be achieved for any satellite rainfall product via the inverse SREM2D approach and knowledge of the regional/seasonal variability of the error model parameters. A very important issue that concerns the operational precipitation producer in this regard is the development of an on-line error-correction scheme to adjust the near real-time precipitation products from operational systems at instantaneous timescales. Currently, there is a wide body of literature on successful application of instantaneous sequential techniques for dynamic updating of time varying parameters (see [17] for an exhaustive list). Although beyond the scope of this letter, findings from our work demonstrate that there is merit in pursuing the development of a real-time dynamic error correction scheme for realistic ensemble generation of satellite rain fields on the basis of inverse SREM2D. The improved ensembles of satellite rainfall data from a real-time inverse SREM2D could then be integrated in a more optimal fashion in off-line land surface models. Two widely used systems that rely on off-line LSMs and satellite rainfall data to provide high-resolution estimates of the land surface hydrologic state are the Land Data Assimilation System (LDAS) [20] and the Land Information System (LIS) [16].

V. Conclusion

Our preliminary investigations showed that a multidimensional error modeling strategy such as that formalized by

Hossain and Anagnostou [10] can provide progressive answers to the question that we posed earlier in this study, namely, "How realistic is ensemble generation of satellite rainfall data from a multidimensional satellite rainfall error model?". Our overall conclusion is that a multidimensional error modeling approach such as SREM2D has the potential to generate realistic ensembles of satellite rainfall fields with homogeneous statistics, which should be considered as an improvement over the more widely used simpler error-modeling scheme. The greater accuracy was manifested by the use of inverse SREM2D through generating satellite rain ensembles capable of enveloping the reference rain fields derived from the more definitive ground radar observations. On the other hand, a simpler error modeling strategy, such as a stochastic error field generator with no acknowledgement of rainy/nonrainy area delineation and spatiotemporal error structure, revealed limited capability in producing realistic ensembles from satellite rainfall data and constrain them it to the ground truth. In anticipation of future water cycle and climate missions such as GPM and HyDROS, it is our hope that the multidimensional error modeling strategy of SREM2D proposed herein will trigger detailed investigations to study ways to improve satellite rainfall estimation for hydrologic and water cycle applications on the basis of an *a priori* knowledge of the multidimensional error structure at the region of application. Such investigations could potentially provide further insights into the optimal integration of satellite rainfall and near-surface soil moisture retrievals in land data assimilation systems. One immediate extension of our work in this regard is to explore the combined use of our multidimensional error model with a sequential error correction scheme to improve the diagnosis of satellite rainfall-based predictability of the global water and energy cycle. We hope to report our findings on this aspect to the scientific community when we complete these extended investigations.

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