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Abstract

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Keywords (separated by '-') Satellite rainfall - Infrared - Passive microwave - Uncertainty

A Practical Guide to a Space-Time Stochastic Error Model for Simulation of High Resolution Satellite Rainfall Data

Faisal Hossain, Ling Tang, Emmanouil N. Anagnostou, and Efthymios I. Nikolopoulos

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1 Introduction

To the surface hydrologist, rainfall remains one of the most complex hydrologic variables exhibiting intermittency across scales of interest. Being a binary phenomenon (e.g. it is either raining or is completely dry), rainfall is one of the few natural variables whose lack of continuity in space and time dominates

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as scales become smaller (unlike stream flow or soil moisture). Although, the space-time structure of rainfall directly affects the response of dynamic terrestrial hydrologic processes such as runoff generation and soil moisture evolution, this scale-dependent complexity has remained a challenge to its mathematical modeling and a topic of much research the last few decades.

Models that simulate the rainfall generation process are aplenty. Using various discrete pulse-type probability distributions and/or the physics of the atmospheric process, these models can simulate the evolution of rainfall in the space-time continuum. The modeling of the rainfall process has been a much studied topic since the 1970s (see for example, Anagnostou and Krajewski, 1997; Rodriguez-Iturbe and Eagelson, 1987; Stewart et al., 1984; Bras and Rodriguez-Iturbe, 1976; Eagleson, 1972). For a review of currently available rainfall models, the reader is referred to Waymire and Gupta (1981) and Fowler et al. (2005).

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However, error models on rainfall, which are conceptually different from rainfall models because they simulate the measurement error of rainfall, are relatively less common, particularly if the focus is on space-borne platforms (Hossain, 2008). Satellite rainfall error modeling has a relatively shorter heritage than radar rainfall error modeling (see for example, Ciach et al., 2007 and Jordan et al., 2003). The issue of "error" (hereafter used synonymously with "uncertainty") arises when there is more than one source of data observing the same rainfall process, with one source having typically lower confidence than the other. Satellite rainfall, on account of being indirect "measurements" of the rainfall process are often linked with such lower levels of confidence than the more conventional measurement arising from ground networks such as weather radars and in-situ gages (Huffman, 2005). As satellite rainfall data become more easily available at higher spatial and temporal resolutions from multiple sources, a natural outcome will be an explosion of its use in surface hydrologic applications over regions where it is needed most. For applications that are very critical for society (such as flood/landslide monitoring or drought management), it is important therefore that users understand the uncertainty associated with satellite rainfall data prior to building decision support systems.

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The purpose of this chapter is to provide readers with a detailed practical guide on the use of a space-time satellite rainfall error model called SREM2D developed earlier by authors of this chapter – F. Hossain and E.N. Anagnostou ("A Two Dimensional Satellite Rainfall Error Model" *IEEE Transactions on Remote Sensing and Geosciences*, 44(6), pp. 1511–1522, 2006). In another work by Hossain (2008), titled *Error Models and Error Metrics*, a detailed overview on the history of error quantification of satellite rainfall data and its modeling is provided. Thus, other competing error models are not the subject of interest in this chapter.

Also, due to increased interest on SREM2D from users of various backgrounds, this practical guide is considered timely for advancing the application of high resolution (satellite) precipitation products (HRPPs) in surface hydrology (*hereafter, rainfall is used as a shorthand for precipitation*). At the time of writing this manuscript, users from the following organizations and institutions were identified as having expressed a direct interest or already begun using SREM2D in their analyses: (1) NASA Laboratory of Atmospheres, (2) NASA Data Assimilation Branch,

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(3) University of Oklahoma, (4) Mississippi State University's GeoResources Institute, (5) University of Mississippi Geoinformatics Center. Most error models described in literature are written for researchers engaged in development and assessment of satellite rainfall data. There is none, to the best of our knowledge, that aims to guide a user towards its practical use, calibration, limitations and interpretation of error model output. Hence, a motivation behind the compilation of this practical guide is that readers and users alike will learn to apply SREM2D recognizing simultaneously the pros and cons and thereby minimize any black-box or invalid applications for surface hydrology.

The paper is organized as follows. Section Two addresses the question *Why SREM2D?* and provides an overview of the philosophy behind SREM2D. Section Three dwells on the general modeling structure of the SREM2D error model. Section Four describes the formulation of SREM2D error metrics, followed by "Data Quality Control/Quality Assessment (QA/QC) and Error Metric Calibration" in Section Five. This section (Five) explains readers the computation of various error metrics of SREM2D from the data and the potential limitations that may be associated with the calibration approach. Section Six describes issues of SREM2D simulation and reproducibility of error statistics via ensemble generation of synthetic satellite data. Conclusions and the open issues needing closure regarding SREM2D are provided in Section Seven.

2 Why SREM2D?

Although existing rainfall error metrics and error models have undoubtedly advanced the application in terrestrial hydrology (Huffman, 1997; Gebremichael and Krajewski, 2004; Steiner et al., 2003; Ebert, 2008), some issues continue to remain open. Firstly, most error models treat error as a uni-dimensional (i.e., a single quantity) measure without an explicit recognition that rainfall is an intermittent process that can also affect the measurement accuracy. These models use the power law type relationships for estimating this aggregate error as a function of spatial and temporal sampling parameters. Such models may be acceptable for estimating the average error over large areal nd temporal domains (e.g 512 X 512 km^2, monthly or daily accumulations). However, there is no clear indication at this stage about the implication of using such coarse-grained error models for hydrologic error propagation experiments where the space-time covariance structure of the estimation error may not be preserved. For example, a satellite rainfall product with an error standard deviation of X mm/h can be generated from a multiplicity of distinct space-time patterns of rainfall. Each pattern, however, will have a different response in surface hydrology at fine space-time scales (see for example, Lee and Anagnostou, 2004).

Thus, there is a need to transition current error models to a level that recognizes at a minimum the need for preservation of covariance structure of the measured rainfall and the associated measurement accuracy as a function of space and time. With this need comes the recognition for a change in paradigm that single aggregate error metrics (such as error variance) are not sufficient metrics for error models that aim to simulate the hydrologically-relevant features of satellite rainfall uncertainty. SREM2D is one such error model developed for space-time generation of satellite rainfall fields in response to the limitations of current error models that tend to simplify the uncertainty.

3 General Modeling Structure Of SREM2D

SREM2D is designed as a collection of concepts, each having flexibility in modification or replacement with an alternative concept. The logical thought process behind the collection of concepts has already been outlined in a step by step manner by Hossain and Huffman (2008). For the convenience of our readers, we reiterate in this section the pertinent steps (Fig. 1) "as is" to highlight the general modeling structure of SREM2D. Hereafter, we use the term "reference" rainfall to refer to ground validation (GV) rainfall data that is corrupted by the error model to simulate less confident satellite-like observations of the rainfall process.

Recognizing that it is the intermittency of the rainfall process in space and time that dictates the variability of a hydrologic process overland, the SREM2D conceptualizes that the error metrics in three general dimensions. These are: (1) temporal dimension (*How does the error vary in time*?); (2) spatial dimension (*How does the error vary in space*?), and (3) retrieval dimension (*How "off" is the rainfall estimate from the true value over rainy areas*?). A given satellite grid-box can be rainy or non-rainy. When compared to the corresponding reference rainfall data, a satellite estimate may fall into one of four possible outcomes:

1) Satellite successfully detects rain (successful rain detection, or "hit").
2) Satellite fails to detect rain (unsuccessful rain detection, or "miss").
3) Satellite successfully detects the no-rain case (successful no-rain detection).
4) Satellite fails to detect the no-rain case (unsuccessful no-rain detection, or "false alarm").

The grid-boxes that are successfully detected as rainy may exhibit three additional properties or dimensions listed above (in space, time and scalar difference). Each of these properties may be considered fully or partially representative of the three general dimensions outlined earlier. At this stage, it is not clear how adequately these properties represent a given dimension. For example, the temporal variation of error probably results from a mixture of the true spatial and temporal correlations of the rain system in its Lagrangian (system-following) frame of reference, and the advection speed of that frame of reference. In SREM2D, the temporal dimension (*how does error vary in time?*) is modeled with a simple representation – assuming that only the mean field bias (systematic error) is correlated in time in an Eulerian (surface-based) frame of reference.

The successful rain or no-rain detection capability may exhibit a strong covariance structure (i.e., the probability of successful detection of a grid-box as rainy or non-rainy may be a function of the proximity to a successfully detected grid-box).

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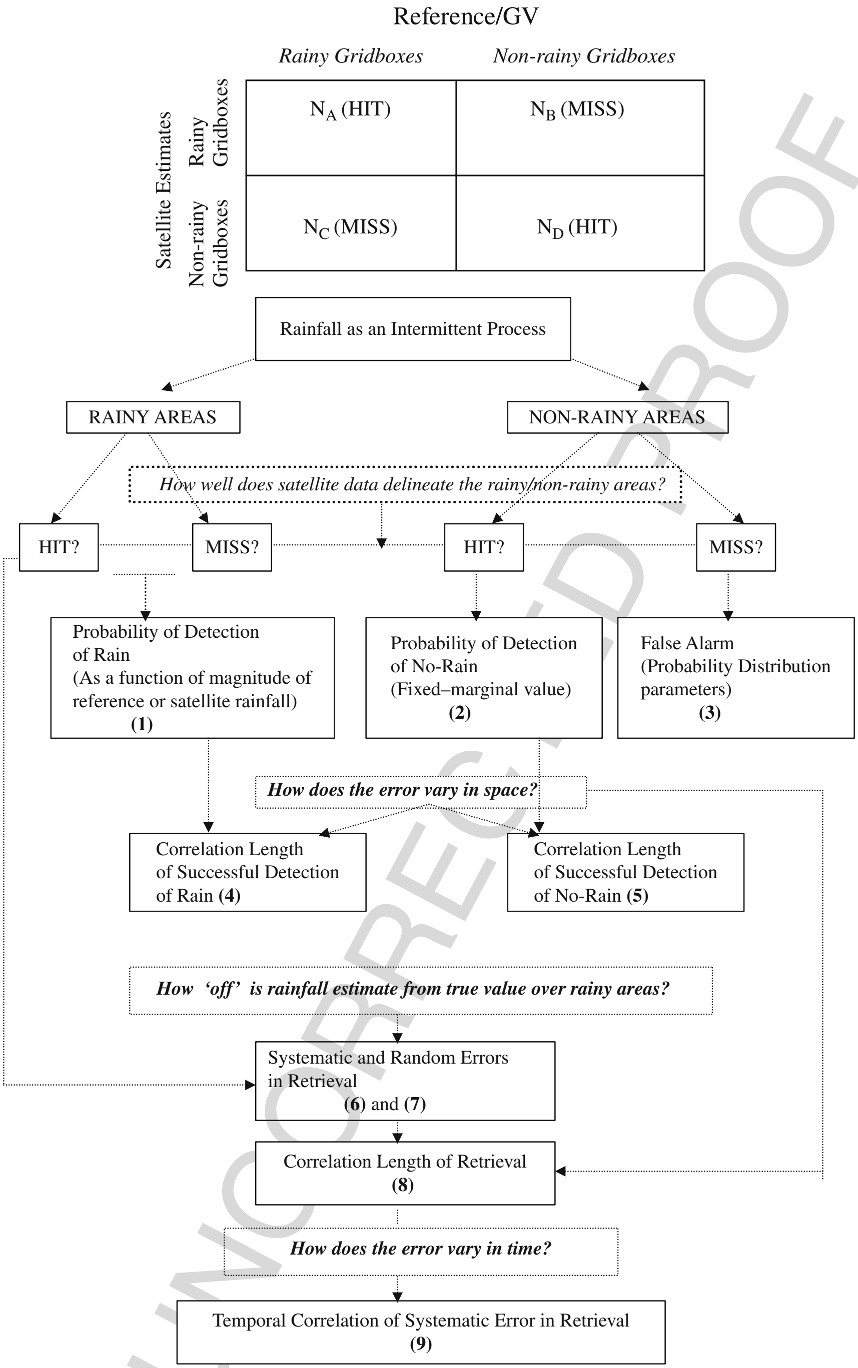

Fig. 1 Generalized framework for building error metrics and error models, (taken from – Hossain and Huffman(2008), "Investigating Error Metrics for Satellite Rainfall at Hydrologically Relevant Scales, Journal of Hydrometeorology vol. 9(3), pp. 563–575")

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For grid-boxes that are detected as non-rainy, satellite rainfall data can be characterized by a marginal probability of no-rain. However, for grid-boxes that are detected as rainy, the probability of successful detection may depend on the magnitude of the rainfall rate. The functional dependency of probability of detection of rain may be tagged with reference (GV) or the estimated rain rate. For surface hydrology, users would likely be interested in the probability of rain detection benchmarked with respect to ground validation data. On the other hand, according to Hossain and Huffman (2008), the data producers may find it almost impossible to tag the probability of detection of the satellite estimates in a likewise manner for the hydrologist on an operational basis due to lack of global scale GV data and hence, choose to use satellite estimates instead.

Collecting all these components, and by following the logical modeling steps outlined in Fig. 1, the SREM2D set of error metrics (e.g. in lieu of a single error metric concept) is: (1) Probability of rain detection (and as a function of rainfall magnitude) – POD_{RAIN}; (2) Probability of no-rain detection – POD_{NORAIN}; (3) First and second order moments of the probability distribution during false alarms; (4) Correlation lengths for the detection of rain-CL_{RAIN}, and (5) no rain–CL_{NORAIN}; (6) Conditional systematic retrieval error or mean field bias (when reference rain > 0); (7) Conditional random retrieval error or error variance; (8) Correlation length for the retrieval error (conditional, when rain >0.0) – CL_{RET}; and finally, (9) Lag-one autocorrelation of the mean field bias. In the following section, we dwell on the mathematical formulation of each of these nine error metrics. For more details, the reader can refer to Hossain and Huffman (2008) or Hossain and Anagnostou (2006).

4 Formulation of SREM2D Error Metrics

4.1 Probabilities of Detection (Rain and No-Rain) (Metrics 1 and 2)

Consider first, the following contingency matrix for hits and misses associated with satellite rainfall estimates:

The probabilities of detection for rain and no-rain are defined as follows,

$$\text{Probability of Detection for Rain (PODRAIN):} \frac{N_A}{N_A + N_C} \tag{1}$$

$$\text{Probability of Detection for No Rain (PODNORAIN):} \frac{N_D}{N_B + N_D} \tag{2}$$

We also define the (successful) rain detection probability, POD_{RAIN}, as a function of rainfall magnitude of either the reference rainfall or satellite estimate. The functional form is usually identified through calibration with actual data (see Hossain and Anagnostou, 2006). Based on observations with actual satellite data, SREM2D models the dependency of the probability of rain detection in the form of a logistic regression model as follows:

$$\text{PODRAIN (RREF)} = \frac{1}{A + \exp(-BR_{REF})} \tag{3}$$

Subscript "REF" refers to reference rainfall (A and B are logistic parameters). The use of an idealized rain detection efficiency function may have its demerits when the empirical detection property deviates significantly from the logistic form. Users are therefore encouraged to verify the form and consider modeling POD_{RAIN} from an empirical look-up table (discussed in detail in Section Five).

The $\text{POD}_{\text{NORAIN}}$, is the unitary probability that satellite retrieval is zero when reference rainfall is zero, which is also determined on the basis of actual satellite and reference rainfall data (Eq. 2).

4.2 False Alarm Rain Rate Distribution (Metric 3)

A probability density function (D_{false}) is defined to characterize the probability distribution of the satellite estimates when there are misses over non-rainy areas. This function is also identified through calibration on the basis of actual sensor data. Hossain and Anagnostou (2006) have reported that this D_{false} probability density function typically tends to appear exponential. Hence, both the moments (first and second) can be defined using only one parameter (a SREM2D metric) of the distribution, λ. This can be computed using the chi-squared or maximum likelihood method. We must however stress that it is up to the user to verify the assumption of exponential distribution and use the appropriate probability distribution for sampling these false alarm rain rates.

4.3 Correlation Lengths (Metrics 4, 5 and 8)

To identify the correlation lengths of error (i.e., *how does the error vary in space*) a simple exponential type auto-covariance function is assumed in SREM2D (users may opt for more sophisticated approaches if necessary). The correlation length (the separation distance at which correlation $= \frac{1}{e} = 0.3678$) is thus determined on the basis of calibration with actual data over a large domain. For identifying the spatial correlation length of rain detection, CL_{RAIN} (or, no-rain detection – CL_{NORAIN}) from data, all successfully detected rainy (non-rainy) pixels are assigned a value of 1.0 while the rest has a value of 0.0. The empirical semi-variogram is then computed as follows:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} (z(x_i) - z(x_i + h))^2 \tag{4}$$

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where $z(x_i)$ and $z(x_i + h)$ are the binary pixel values (0 or 1) at distance x_i and $x_i + h$, respectively and h is the lag in km. n represents the number of data points at a separation distance of h. The term $\gamma(h)$ is the semi-variance at separation distance h. Assuming that the empirical variogram is best represented by an exponential model, the functional parameters describing the spatial variability can be fitted as follows,

$$\gamma(h) = c_0 + c(1 - e^{-h/CL}) \tag{5}$$

where c_0 represents the nugget variance, c is the sill variance and CL is the distance parameter known as "correlation length" (a SREM2D metric). Conversely, the correlation function is modeled as, C = EXP(–h/CL), where C is the correlation.

For identifying the correlation length for retrieval error (i.e., when both satellite and reference rainfall simultaneously register HITs), CL_{RET}, a similar set of steps are adopted as above for rain/no rain detection, with the exception that the binary values (0–1) are no longer pertinent. Instead, one computes the correlation length in terms of retrieval error defined as the logarithmic difference between reference and satellite estimate.

4.4 Conditional Rain Rate Distribution (Metrics 6 and 7)

The conditional (i.e., reference rainfall > threshold unit) non-zero satellite rain rates, R_{SAT}, are statistically related in SREM2D to corresponding conditional reference rain rates, R_{REF}, as,

$$R_{SAT} = R_{REF}.\varepsilon_S \tag{6}$$

where the satellite retrieval error parameter, ε_S, is assumed to be log-normally distributed. This assumption has its pros and cons. The advantage of such an assumption is that a log transformation [log(R_{SAT})–log(R_{REF})] of Eq. 6 allows the ϵ_S to be mapped to a Gaussian $N(\mu, \sigma)$ deviate, ε (hereafter referred to as "log-error"), where μ and σ are the mean and standard deviation, respectively. On the other hand, the assumption of log-normality implies that data on log-error is homoscedastic (i.e., the variance remains the same regardless of the magnitude of the log-error). Hence, it is the user's responsibility to verify the assumption of log-normality and homoscedasticity and assess if log-normality is sufficient to model the skewness expected from non-zero and positive rainfall rates. Skewness of rainfall is known to diminish at longer space-time accumulations (from hourly to monthly). Thus, for a particular application, such as optimizing satellite rainfall-based irrigation schedule at weekly timescales, there may not be any need to account for skewness in the satellite rainfall. Vice-versa, skewness will be important for assessing the use of half-hourly real-time satellite rainfall data for flash-floods forecasting.

Another aspect to highlight is the definition of the threshold rainfall rate to distinguish rainy events from non-rainy (dry) events. This is particularly

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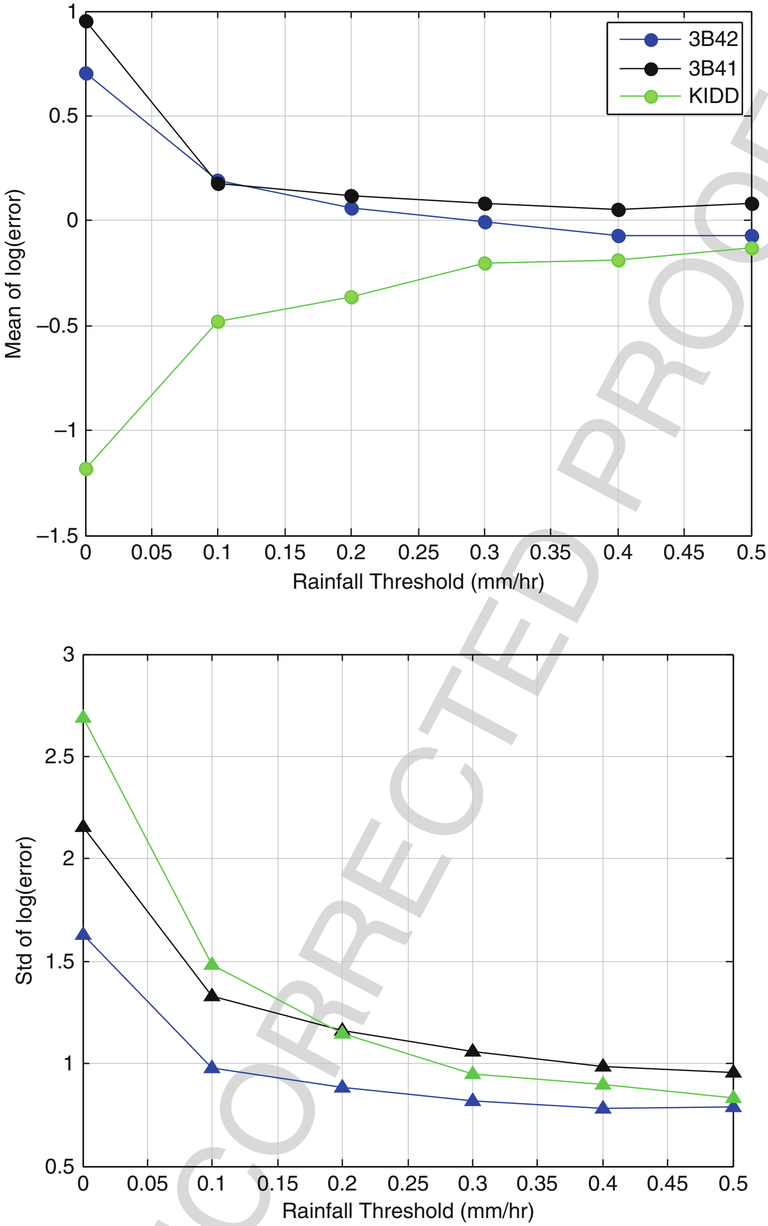

Fig. 2 Impact of reference rainfall threshold on the derivation of the mean and standard deviation of log-error for SREM2D for three high resolution satellite rainfall products (3B41RT, 3B42V6 and KIDD) over Northern Italy. Here, KIDD is a IR-based satellite rainfall product by Kidd et al. (2003)

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important because of the multiplicative and log-transformed nature of the error model. A zero threshold can result in unrealistically high Gaussian standard deviation and bias because of exceedingly high multiplicative ratios that are obtained at near-zero reference rain rates. Figure 2 shows how the <ι>μ</ι> and σ of log-error varies as a function threshold for three existing satellite rainfall products remapped at 0.25° and 3 hourly timescales over Northern Italy. The reference GV data was derived from a dense gauge network. Our general recommendation is that the threshold be constrained to 0.1 mm/h or be subjectively decided after checking for reproducibility of SREM2D error statistics (discussed later in Section Six).

4.5 Lag-One Temporal Correlation (Metric 9)

The retrieval error parameter ε is both spatially and temporally auto-correlated and this space-time structure is accounted for in SREM2D. The spatial aspect has already been discussed earlier in Section 4.3. For temporal correlation, an autoregressive function is used to identify the temporal variability of <ι>μ</ι> (i.e., conditional satellite rainfall bias),with the pertinent metric being the lag-one correlation. This makes the treatment of temporal dependence of error in SREM2D somewhat subjective as the lag-one correlation will be dictated by the temporal resolution of data. A more robust treatment may be to incorporate the correlation length in time (i.e., the e-folding time of the temporal correlogram) in modeling of the temporal correlation of error. Again, this issue is for the user to verify depending on how adequately SREM2D captures the full spectrum of error at hydrologically relevant scales. More details on the temporal aspect is provided in the next section (Section Five).

5 Data QA/QC and Calibration of Metrics for SREM2D

5.1 Quality Assessment and Quality Control

SREM2D uses as input, a time-series of reference rainfall fields. This time-series is then corrupted in space and time according to the nine error metrics outlined in Section Four. The user needs to calibrate these nine SREM2D error metrics for a specific satellite rainfall product that he/she plans to assess. Collectively, these nine metrics represent the multi-dimensional error structure of the satellite data product under investigation. For calibration of SREM2D metrics, a sufficiently long period of synchronized rainfall fields (from a sufficiently large areal domain) of reference and satellite sources is required. The definition of “sufficiently long” is subjective. For example, 5 year of hourly reference and satellite rainfall data over the Upper Mississippi basin may yield a “climatologic” average SREM2D metrics for a specific satellite rainfall product that has matured in algorithmic formulation (such as Global Precipitation Climatology Project product available at 1° -Daily resolution).

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On the other hand, 3 month-long hourly data during summer may be more informative of metrics a user should employ for simulation of satellite observation of thunder storms and other shorter-duration convective rain systems.

An important aspect of QA/QC during SREM2D calibration is that there should not be any missing data in space and time and that both sets (satellite and reference) must be synchronized very accurately. Users should resolve this QA/QC issue because most real-time HRPPs available today at sub-daily time scales are produced on a best-effort basis with a non-negligible portion of data often reported missing. We recommend the following two strategies for replacement of missing data: (1) if the percentage missing is small (< 5%), then reference rainfall may be substituted with minimal effect on the computation of error metrics; (2) if percentage of missing is considerably larger (∼5–15%), persistence of preceding satellite data over missing periods may be considered. The argument for #2 is that in a real-world scenario, the user would have to continue using the last available satellite observation over ungauged regions until the next satellite overpass or data downlink.

A major problem arises when both satellite and reference data are missing in significant portions. For such cases, we recommend that the period of data not be included in SREM2D error metric calibration. As an example, Table 1 shows missing data statistic for one particular data set of Stage IV NEXRAD radar rainfall data over the United States spanning six years (2002–2007). The Northwestern region appears to have a significant amount missing data (mainly east of the Cascade Mountains) that can result in spurious error calibration of SREM2D if attempted.

Table 1 Missing data statistics for Stage IV NEXRAD data over different regions of the United States spanning 6 years (2002–2007) at 4 km and 1 hourly scale

	ALL	Northwest	Southwest	Midwest	Northeast	Southeast
% Missing	11	32%	9.1%	0.8%	1.3%	12.7%

Because the primary motivation of an error modeling technique is to understand how erroneous a satellite rainfall product is compared to a reference GV dataset both in rainfall and in hydrologic simulation, SREM2D does not account for the possible effects of errors in the "reference" rainfall estimates. However, users must also recognize that the SREM2D estimation technique of the nine error metrics will incorporate the uncertainties arising from both the satellite and reference rainfall.

5.2 Error Metric Calibration

After proper QA/QC of calibration data, the user needs to calibrate the nine metrics that serves as input to the SREM2D error model. In this section, we show examples of calibration for four global satellite HRPPs at 0.25^{o} 3 hourly scales over the United States spanning two regions (Florida and Oklahoma; Fig. 3) and four seasons in 2004 (Winter, Spring Summer, and Fall). These four satellite products are: (1) 3B41RT; (2) 3B42RT; (3) CMORPH and (4) PERSIANN. Literature on

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Fig. 3 Two regions (Oklahoma and Florida) in the United States selected for SREM2D calibration of error metrics for four global satellite rainfall products (*shown in boxes*)

the first two products (hereafter referred to as 3B41RT and 3B42RT) are available from Huffman et al. (2007), while readers can refer to details on CMORPH and PERSIANN from Joyce et al. (2004) and Hong et al. (2005), respectively. The reference GV data pertained to NEXRAD (Stage III) rainfall product. The regions are bounded, for Oklahoma, by 32.0^{o}N to 39.0^{o}N and –92.0^{o}W to –102.0^{o}W; and, for Florida, by 20.0^{o}N to 26.0^{o}N and –84.0^{o}W and –80.0^{o}W (Fig. 3).

Table 2 summarizes the missing data statistic at that native scale as part of QA/QC of calibration data. All data were then remapped to the consistent scale of 0.25^{o} and 3 hourly to allow inter-comparisons among products. Figure 4 demonstrates the POD_{NORAIN} for various products across the two regions and seasons. The nuances across products and seasons (particularly for CMORPH) are apparent in this figure. Figure 5 shows the POD_{RAIN} as a function of NEXRAD rain rate. As mentioned earlier in Section

Table 2 Missing data statistic for four global satellite rainfall products at native scale over the United States for 2004 (the two regions – Oklahoma and Florida are combined)

	Native scale		Percentage of missing data			
Products	Temporal (h)	Spatial (°)	Winter (JF)	Spring (AM)	Summer (JJA)	Fall (SON)
3B41RT	1	0.25	0.97	2.18	1.18	1.00
3B42RT	3	0.25	1.46	2.10	1.45	1.00
PERSIANN	1	0.04	2.30	1.43	1.22	1.10
CMORPH	3	0.25	0.00	0.00	0.00	0.00

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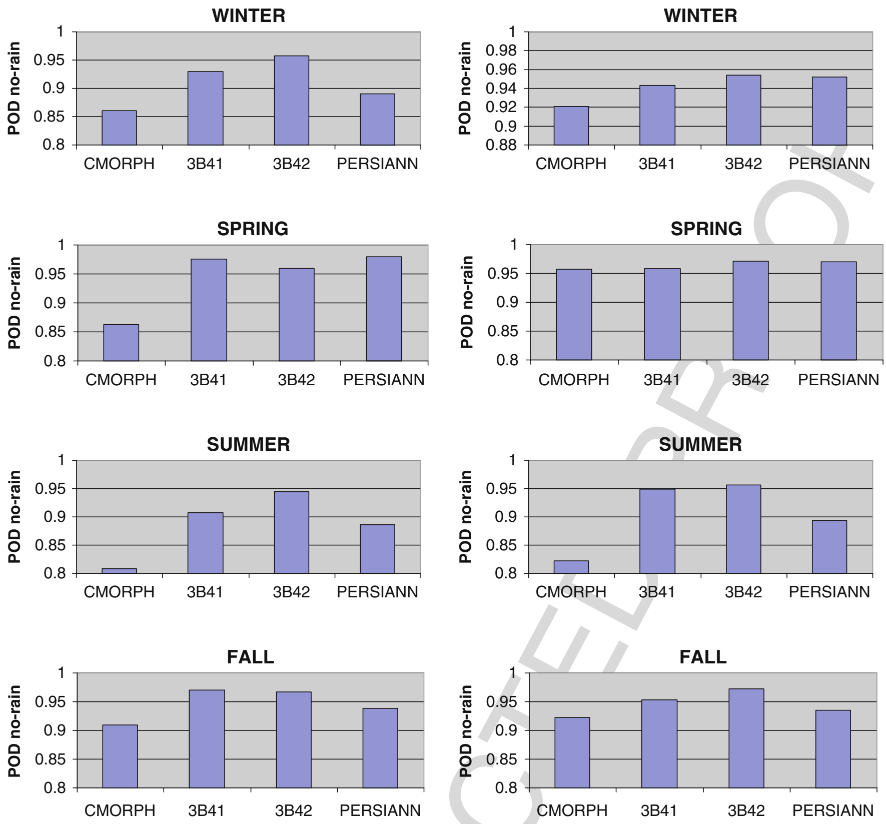

Fig. 4 POD_{NORAIN} for CMORPH, 3B41RT, 3B42RT and PERSIANN across four seasons in 2004. Left panels – Oklahoma; Right panels – Florida

Four, the functional form of POD_{RAIN} is almost invariably found to obey the logistic pattern. Users need to fit appropriate parameter values for A and B of Equation 3 to model the POD_{RAIN} as a function of NEXRAD rain rate. There are several non-linear optimization routines that can be used to robustly derive A and B values. However, we recommend that the user also applies some human judgment to check for the closeness of the idealized logistic curve with empirical one derived (Fig. 5) at low rain rates (∼1–5 mm/h).

Figure 6 shows the probability distribution of false alarm rain rates of satellite products. The distribution appears exponential like. The mean (expected value) of this distribution comprises another SREM2D metric (1/λ). Care must be applied in the derivation of the false alarm distribution as it is sensitive to the choice of bin size. Users can apply more rigorous statistical tests and the maximum likelihood method to derivemore robust estimates of the false alarm metric. Figure 7 shows the spatial covariance structure of rain retrieval (conditional), rain detection and

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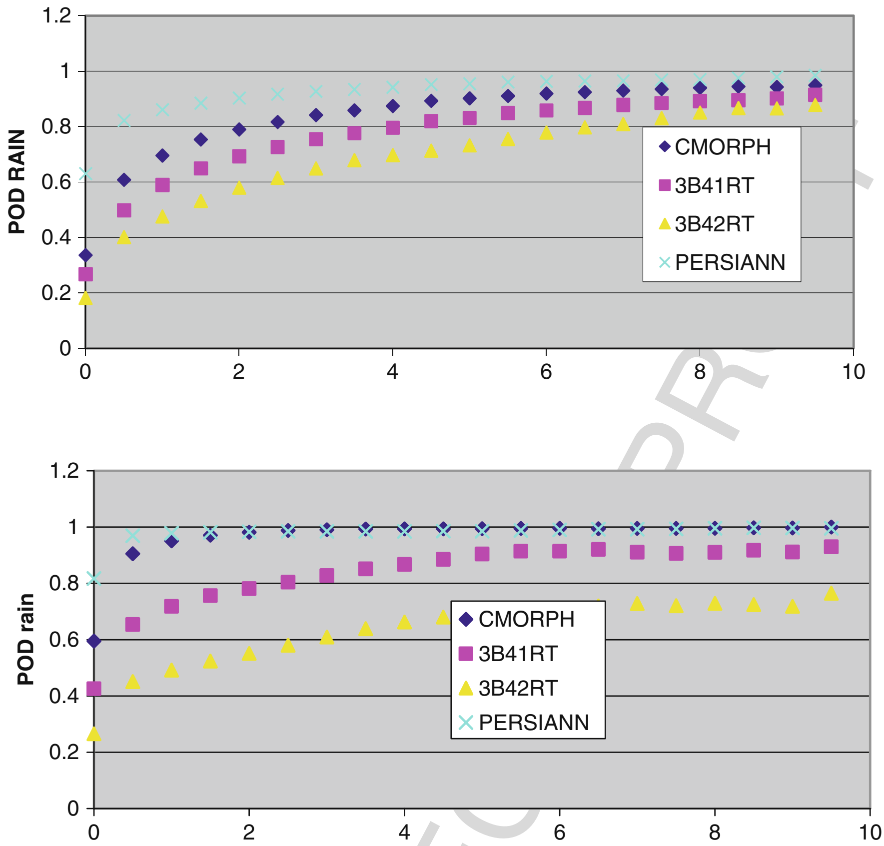

Fig. 5 POD_{RAIN} as a function of NEXRAD rain rate. *Upper panel* – Florida for Winter 2004; *Lower panel* – Oklahoma for Fall 2004. X-axis represents NEXRAD rain rates at 0.25° 3 hourly resolution

no-rain detection for Florida (Summer 2004). Assuming that an exponential correlation model is representative, the separation distances where the correlation drops to 1/e (=0.368) comprise the correlation length (CL) error metrics for SREM2D for generation of correlated random fields. Certain instances may result in the correlation never (at least over the domain of the study region) dropping to 1/e. For example, in arid and clear-sky climates, the correlation length CL_{NORAIN} for an Infra-red satellite rainfall product will probably be associated with large values. For such cases, we recommend that the user constrain the spatial structure by applying correlation length values compatible with the domain size of interest. A downside of large correlation lengths in error modeling, particularly for rain retrieval, is that the conditional error standard deviation may be under-simulated due to spatial similarity of the generated random values. This aspect is discussed in more detail in the next section.

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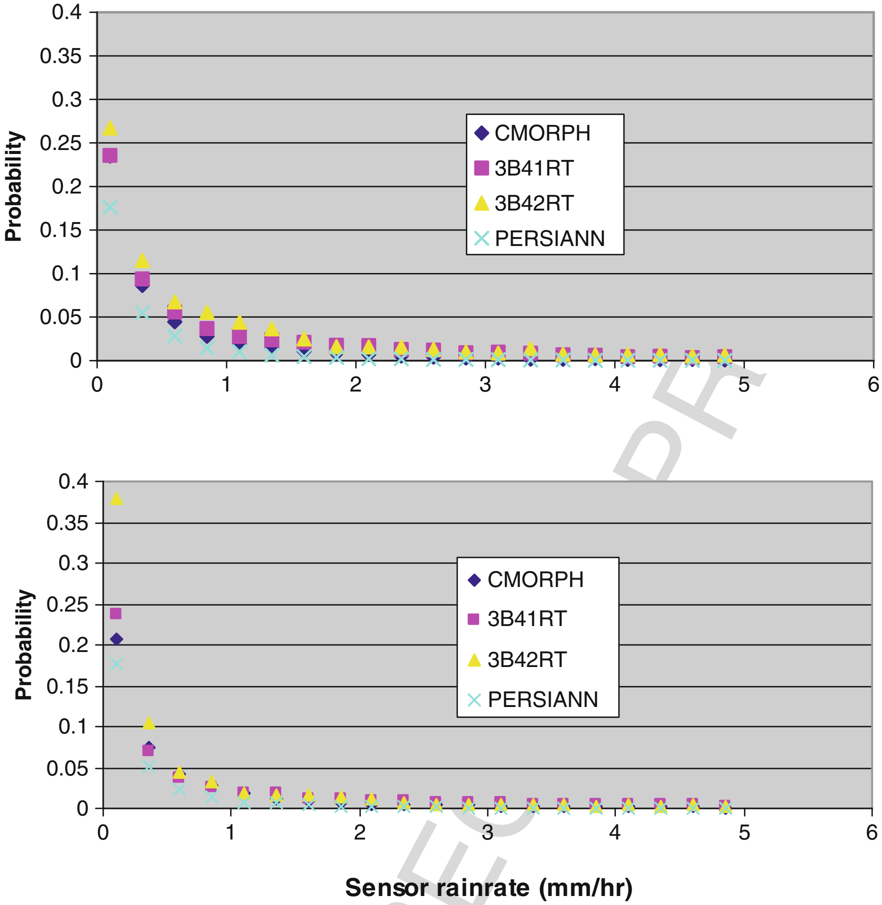

Fig. 6 False alarm rain rate distribution for satellite rainfall products. *Upper panel* – Florida-Summer; – Oklahoma-Spring. Sensor rainrate is the satellite rain estimate

6 SREM2D Simulation And Reproducibility Of Error Statistics

6.1 Simulation Issues

As model developers, we initially coded the first SREM2D error model using Fortran 77. However, we believe that the general modeling structure (Section 3) is tangible enough for any user to develop his/her own custom-built code. We therefore encourage users to rather understand the SREM2D philosophy first, assess if the complexity of the error modeling is compatible with the intended application and then apply/modify or simplify the error model accordingly using the preferred computing platform.

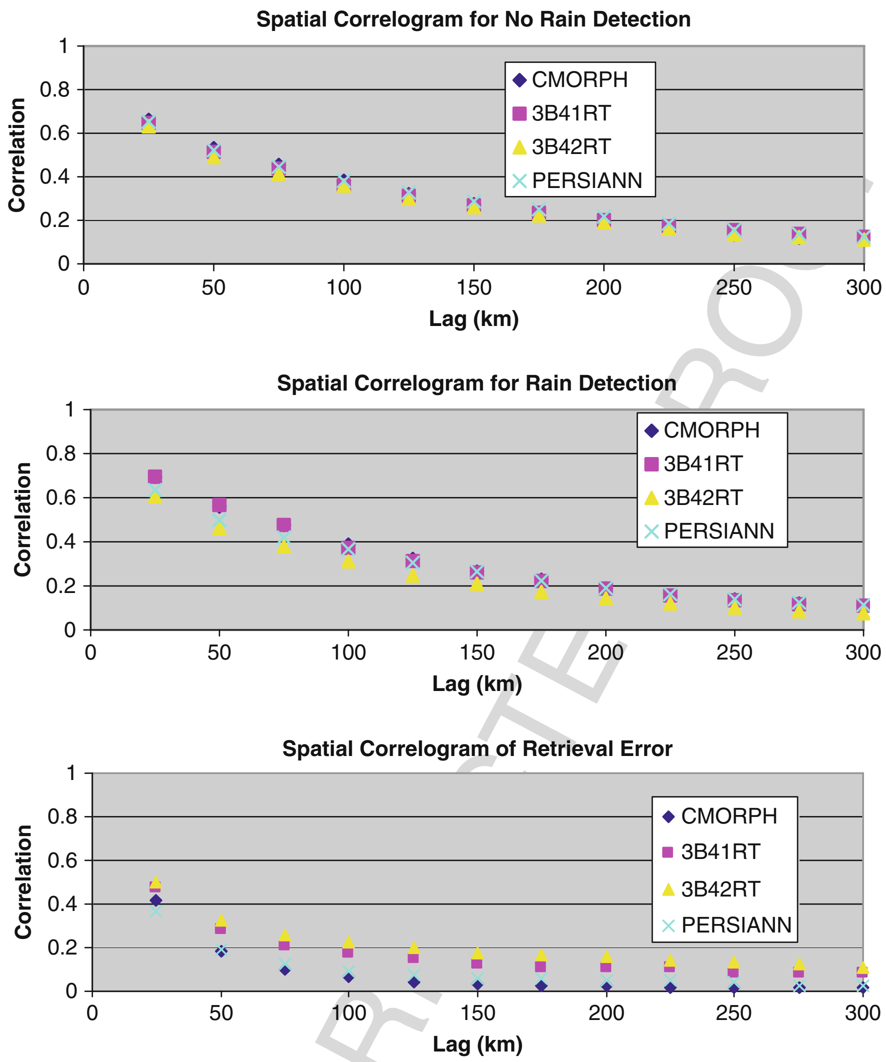

Fig. 7 Spatial covariance structure of rain retrieval, rain detection (*middle panel*) and no-rain detection (*upper panel*) for Summer 2004 in Florida

An aspect that adds to the computational burden of SREM2D is the need for generation of correlated Gaussian random fields. First, the spatial structure of rain and no-rain joint detection probabilities is modeled using Bernoulli trials of the uniform distribution with a correlated structure that is generated from Gaussian random fields. These two Gaussian random fields (one each for rain detection and no-rain detection) are transformed to the uniform distribution random variables via an error function transformation. Spatially correlated field of Gaussian N(0,1) random deviates is generated in 2-D space based on Turning Bands (Mantoglou and

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Wilson, 1982). The N(0,1) spatially correlated random field is then transformed to uniform U[0,1] field as follows:

$$x_j = \frac{1}{2} + \frac{1}{2} erf(\varepsilon_j/\sqrt{2}) \tag{7}$$

where x_j, is a U[0,1] random deviate for pixel j generated from the corresponding N(0,1) deviate, ε_j. The $erf(\varepsilon_j)$ is the error function defined by the following integral,

$$\mathrm{erf}(\varepsilon_j) = \frac{2}{\sqrt{\pi}} \int_0^x \mathrm{e}^{-\mathrm{w}^2} \mathrm{dw} \tag{8}$$

The uniform random fields are then scaled by its standard deviation to yield a unitary variance (this ensures the maximum covariance of 1.0 at lag 0). Numerical consistency checks have revealed that correlation length is altered significantly by this non-linearity only at lags (grid spaces) beyond 10 and should be accordingly accounted for modeling the join probability of detection if necessary. Execution of this procedure yields a spatially correlated uniform field of U [0,1] random deviates that are now amenable for Bernoulli trials for rain and no-rain detection with *a priori* spatial structures. A third Gaussian random field is generated next for the simulation of correlated retrieval error field pertaining to N (μ,σ).

Hossain and Anagnostou (2006) provide the simulation algorithm for SREM2D that outlines each simulation step for the error model in the form of a programming flow-chart. We recommend that users refer to that algorithm flow-chart to clarify the individual process calculations that SREM2D computes in space and time.

6.2 Reproducibility of SREM2D Error Statistics

Before the assessment of satellite rainfall products for decision-making can begin, users must verify that the ensembles of satellite rainfall data simulated by SREM2D are adequately realistic. In other words, the reproducibility of error statistics (metrics) by SREM2D needs to be verified. Like any other mathematical model, SREM2D does not perfectly mimic the uncertainty as expected from the calibrated metrics. Nevertheless, the user must set some minimum standards on reproducibility based on the intended application. We recommend two particular ways by which SREM2D can be verified of this “reproducibility” property. These are as follows:

1) Checking the consistency of ensemble of cumulative rainfall hyeotograph against actual satellite rainfall data.
2) Checking the accuracy of error metrics computed from simulated satellite rainfall data against actual reference rainfall data.

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The first method checks if the actual cumulative rainfall hyeotograph is enveloped reasonably realistically by the ensemble of SREM2D generated synthetic satellite hyetographs. Because actual satellite rainfall data is not used in the generation of SREM2D synthetic data, this test can considered an independent check. Users are recommended to perform this test over the whole domain and a few random smaller sub-domains within the study region. An additional aspect to check is to verify if the simulated hyetographs exhibit a pattern of jumps and plateaus similar to the actual data. The second method computes the nine SREM2D error metrics from synthetic satellite data against actual reference rainfall data to check the closeness of the values with calibrated measures. This check may be done on individual realizations or over a set of ensembles. The latter is likely to yield more accurate results due to the larger space-time sample size that minimizes the randomization effects per each realization.

In the following, we provide an example of the two error reproducibility tests over an alpine basin in Northern Italy.

6.2.1 Checking the Consistency of Ensemble of Cumulative Hyetograph Against Actual Satellite Rainfall Data

Figure 8 shows the alpine region of Northern Italy over which SREM2D error metrics were calibrated for three satellite rainfall products. The three shaded grid boxes represent the location of actual satellite pixels at 0.25^{o} scale for three satellite products

3B41RT, 3B42V6 and KIDD. Herein, KIDD represents a high resolution (0.04°) Infrared (IR)-based satellite rainfall product produced by Kidd et al. (2003). Six months of satellite data spanning June–November 2002 were used for calibration of SREM2D metrics. Reference data comprised gage rainfall from a dense network represented by the black circles shown in the figure. Table 3 shows the SREM2D metrics calibrated for the satellite products at the 0.25^{o} 3 hourly scale. A threshold of 0.1 mm/h was assigned to separate the rainy events from non-rainy events. Figure 9 demonstrates the cumulative hyetographs generated from 100 SREM2D realizations (mean and $\pm\sigma$) and actual satellite rainfall data for 3B41RT and 3B42V6. We observe that 3B41RT is relatively more accurately enveloped than 3B42V6. Overall, the simulation of both products appear reasonably realistic for the domain of interest in Northern Italy.

6.2.2 Checking Reproducibility of Error Metrics

In Table 4, the reproducibility of the mean and standard deviation of log-error for retrieval is demonstrated for a few random SREM2D realizations against the calibrated values (that served as input to the error model) for the KIDD satellite product. While the POD_{NORAIN} and bias of log-error is reasonably well reproduced for each selected realization, the standard deviation of log-error is found to be consistently underestimated by margins of 10–15%. A recently-identified limitation of the SREM2D model is that the generation of correlated random fields with long

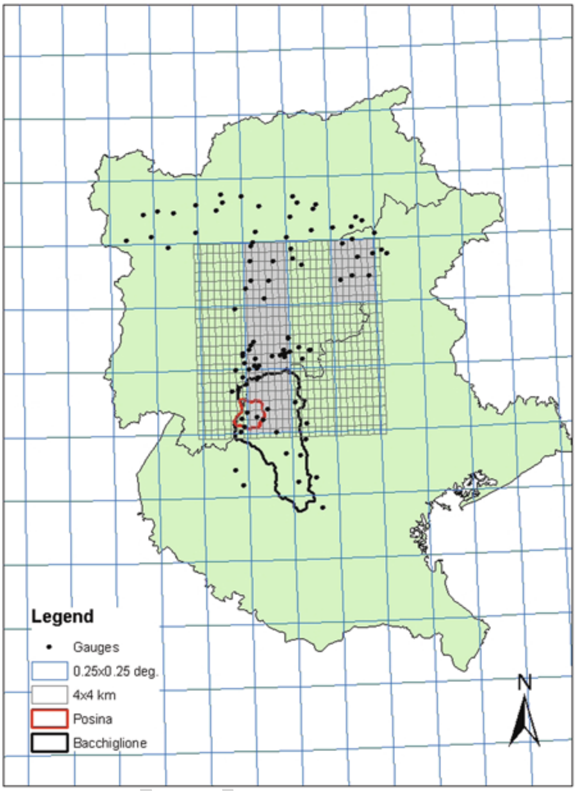

Fig. 8 Alpine region of Northern Italy. Shaded grey boxes represent the actual location of the 0.25° satellite pixels for 3B41RT and 3B41V6 data used in the calibration of SREM2D error metrics. Black circles represent the location of tipping bucket gages that comprised reference rainfall data

Table 3 SREM2D error metrics calibrated for 3B41 and 3B42 for the region of Northern Italy

Metrics	3B41	3B42	KIDD
A	1.05	1.1	1.1
B	1.85	1.08	1.2
Mean (mu-Gaussian of log-error)	0.026	−0.1102	−0.226
Sigma (std.dev Gaussian of log-error	0.942	0.764	0.733
False Alarm mean rain rate (mm/hr)	0.433	0.760	0.680
Lag-one correlation	0.41	0.13	0.41
POD no-rain	0.81	0.97	0.99
*CL_{ret} km	50	50	50
*$CL_{rain\ det}$ km	0	0	0
*$CL_{no\ rain\ det}$ km	75	75	75

correlation lengths for retrieval error tend to conflict with the standard deviation of retrieval error and result in under-simulation (i.e. underestimation). This underestimation appears to magnify as the domain size increases. We do not know yet how

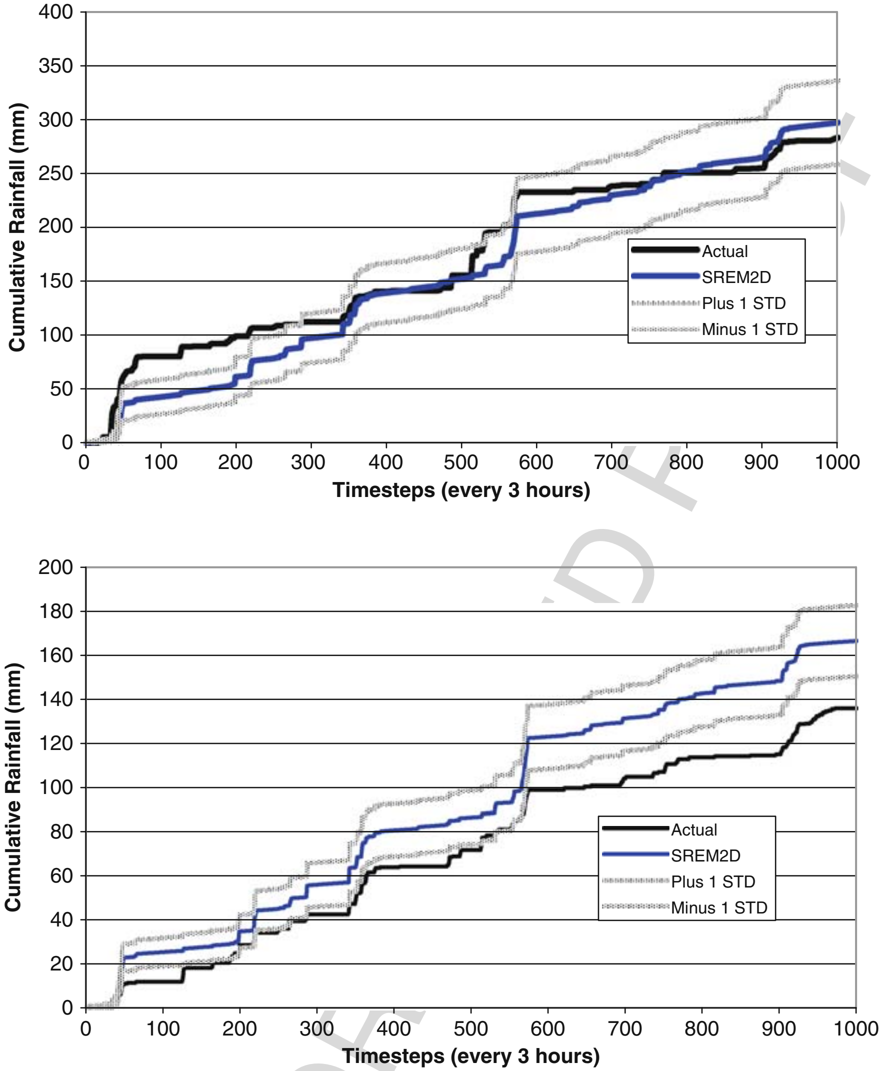

Fig. 9 Cumulative rainfall hyetographs over Northern Italy. Blue line represents the mean of 100 SREM2D realizations. Solid black line represents the actual satellite hyeotograph. Upper panel – 3B41RT; Lower panel – 3B42V6

to address this problem at this stage, but it is certainly an aspect that users should be cognizant of and strive for rectification in future improvements of the SREM2D model. Users should also perform similar consistency checks for all other SREM2D metrics and not just of conditional bias and standard deviation.

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Table 4 Reproducibility of some SREM2D error metrics for a few random realizations over Northern Italy for KIDD (KIDD is the IR-based satellite rainfall product by Kidd et al. 2003)

	POD $_{NORAIN}$	Bias (log-error)	Std Dev (log error)
Empirical	0.986	0.727	1.19
Realization 1	0.983	0.672	0.98
Realization 2	0.983	0.496	1.04
Realization 3	0.990	0.545	1.05
Realization 4	0.990	0.747	1.01

7 Conclusions

For continual refinement of error models and their promotion in prototyping satellite-based hydrologic monitoring systems, a practical user guide that readers can refer to is useful for potential users of HRPPs. In this chapter, we have provided our readers with one such practical guide on a space-time stochastic error model called SREM2D (A Two Dimensional Satellite Rainfall Error Model) developed by Hossain and Anagnostou (*IEEE Transactions on Remote Sensing and Geosciences*, 44(6), pp. 1511–1522, 2006). This practical guide overviewed the philosophy behind SREM2D and emphasized the need to flexibly interpret the error model as a collection of modifiable concepts always under refinement. We stressed at various stages of the guide the importance of verifying that the complexity and assumptions of error modeling were compatible with the intended application. Our motivation behind the compilation of this practical guide was that readers should learn to apply SREM2D recognizing the strengths and limitations simultaneously and thereby minimize any black-box or unrealistic applications for surface hydrology. We also hope that developers of other error models will produce similar "guides" to make the pros and cons of the error modeling philosophy open for the user.

Like any other model, SREM2D is not without limitations. The requirement of continuous data (reference and satellite) in space and time may be considered a short coming for calibration of SREM2D error metrics. For advancing the application of satellite HRPPs, the associated uncertainty information is critical for users to understand the realistic limits to which these HRPPs can be applied over an ungauged region. However, this represents a paradox. Satellite rainfall uncertainty estimation requires reference (ground validation-GV) data. On the other hand, satellite data will be most useful over ungauged regions in the developing world that are lacking in GV data. Consequently, we need to ask ourselves several questions for SREM2D. *Can the model parameters/metrics be transferred from one region to another? Can they be regionalized?* At this stage, there is no clear answer, although there is work on-going by the authors to resolve this paradox and understand how reliable is the "transfer" of error from a gauged location to an ungauged one.

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On the computational side, the need to generate three independent and correlated random fields increases simulation runtime for SREM2D. The need to convert Gaussian random fields to uniform random fields by the non-linear error transformation also results in an unknown change of spatial structure that is not yet completely constrained at large space lags (> 10). The spatial correlation also has the effect of imparting negative bias to the standard deviation of retrieval error.

Despite these limitations, SREM2D represents a unique hydrological transition from current error models because it explicitly recognizes the need for preservation of covariance structure of rainfall and the associated measurement accuracy as a function of space and time. It also provides greater versatility in error modeling by moving away from the single aggregate error metric models to a multi-dimensional one comprising nine metrics. We believe that subject of space-time error modeling of high resolution satellite rainfall products can reach closure with the systematic evolution of the philosophy and concepts embedded in the SREM2D model.

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Chapter 9

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