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Abstract	Abstract 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. In this chapter, we provide 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 (<i>IEEE Transactions on Remote Sensing and Geosciences</i> , 44(6), pp. 1511–1522, 2006). Our guide first provides an overview of the philosophy behind SREM2D and emphasizes the need to flexibly interpret the error model as a collection of modifiable concepts always under refinement rather than a final tool. Users are encouraged to verify that the complexity and assumptions of error modeling are compatible with the intended application. The current limitations on the use of the error model as well as the various data quality control issues that need to be addressed prior to error modeling are also highlighted. Our	

motivation behind the compilation of this practical guide is that readers will learn to apply SREM2D by recognizing the strengths and limitations simultaneously and thereby minimize any black-box or unrealistic applications for surface hydrology.

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

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and Efthymios I. Nikolopoulos

Abstract Abstract 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. In this chapter, we provide 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). Our guide first provides an overview of the philosophy behind SREM2D and emphasizes the need to flexibly interpret the error model as a collection of modifiable concepts always under refinement rather than a final tool. Users are encouraged to verify that the complexity and assumptions of error modeling are compatible with the intended application. The current limitations on the use of the error model as well as the various data quality control issues that need to be addressed prior to error modeling are also highlighted. Our motivation behind the compilation of this practical guide is that readers will learn to apply SREM2D by recognizing the strengths and limitations simultaneously and thereby minimize any black-box or unrealistic applications for surface hydrology.

Keywords Satellite rainfall · Infrared · Passive microwave · Uncertainty

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

51 Models that simulate the rainfall generation process are aplenty. Using various
 52 discrete pulse-type probability distributions and/or the physics of the atmospheric
 53 process, these models can simulate the evolution of rainfall in the space-time con-
 54 tinuum. The modeling of the rainfall process has been a much studied topic since
 55 the 1970s (see for example, Anagnostou and Krajewski, 1997; Rodriguez-Iturbe and
 56 Eagleson, 1987; Stewart et al., 1984; Bras and Rodriguez-Iturbe, 1976; Eagleson,
 57 1972). For a review of currently available rainfall models, the reader is referred to
 58 Waymire and Gupta (1981) and Fowler et al. (2005).

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

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

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

AQ1

AQ2

AQ3

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

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

111 112 113 **2 Why SREM2D?** 114

115 Although existing rainfall error metrics and error models have undoubtedly
 116 advanced the application in terrestrial hydrology (Huffman, 1997; Gebremichael
 117 and Krajewski, 2004; Steiner et al., 2003; Ebert, 2008), some issues continue to
 118 remain open. Firstly, most error models treat error as a uni-dimensional (i.e., a
 119 single quantity) measure without an explicit recognition that rainfall is an inter-
 120 mittent process that can also affect the measurement accuracy. These models use
 121 the power law type relationships for estimating this aggregate error as a function
 122 of spatial and temporal sampling parameters. Such models may be acceptable
 123 for estimating the average error over large areal and temporal domains (e.g 512 X
 124 512 km², monthly or daily accumulations). However, there is no clear indication
 125 at this stage about the implication of using such coarse-grained error models
 126 for hydrologic error propagation experiments where the space-time covariance
 127 structure of the estimation error may not be preserved. For example, a satellite
 128 rainfall product with an error standard deviation of X mm/h can be generated from
 129 a multiplicity of distinct space-time patterns of rainfall. Each pattern, however, will
 130 have a different response in surface hydrology at fine space-time scales (see for
 131 example, Lee and Anagnostou, 2004).

132 Thus, there is a need to transition current error models to a level that recognizes
 133 at a minimum the need for preservation of covariance structure of the measured
 134 rainfall and the associated measurement accuracy as a function of space and time.
 135 With this need comes the recognition for a change in paradigm that single aggregate

136 error metrics (such as error variance) are not sufficient metrics for error models that
137 aim to simulate the hydrologically-relevant features of satellite rainfall uncertainty.
138 SREM2D is one such error model developed for space-time generation of satellite
139 rainfall fields in response to the limitations of current error models that tend to
140 simplify the uncertainty.

143 3 General Modeling Structure Of SREM2D

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

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

- 162 1) Satellite successfully detects rain (successful rain detection, or “hit”).
- 163 2) Satellite fails to detect rain (unsuccessful rain detection, or “miss”).
- 164 3) Satellite successfully detects the no-rain case (successful no-rain detection).
- 165 4) Satellite fails to detect the no-rain case (unsuccessful no-rain detection, or
166 “false alarm”).

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

179 The successful rain or no-rain detection capability may exhibit a strong covari-
180 ance 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).

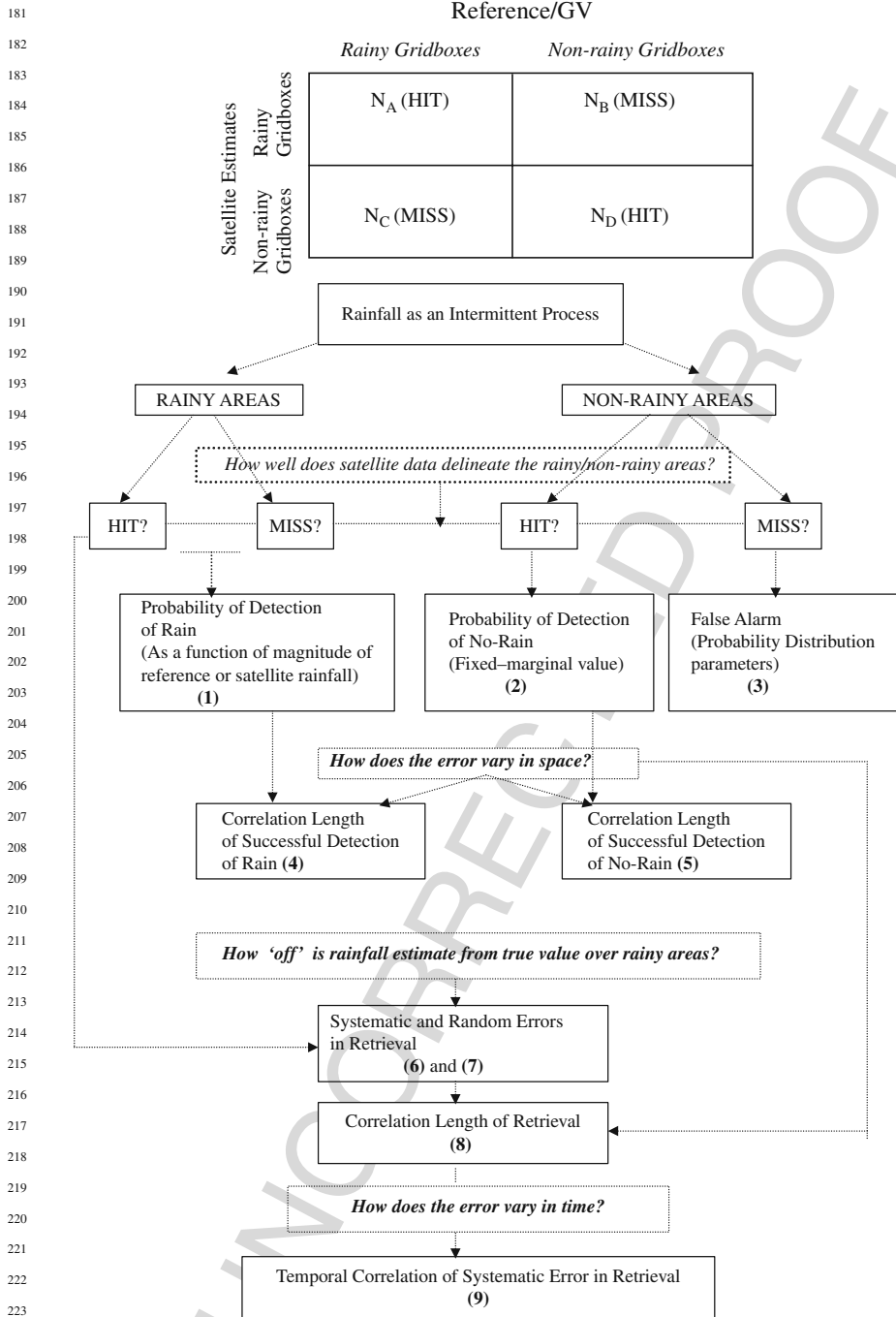


Fig. 1 Generalized framework for building error metrics and error models, (taken from – Hossain and Huffman(2008), “Investigating Error Metrics for Satellite Rainfall at Hydrologically Relevant Scales, Journal of Hydrometeorology vol. 9(3), pp. 563–575”)

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,

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

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

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

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271 models the dependency of the probability of rain detection in the form of a logistic
272 regression model as follows:

$$273 \text{PODRAIN (RREF)} = \frac{1}{274 A + \exp(-BR_{REF})} \quad (3)$$

275 Subscript “REF” refers to reference rainfall (A and B are logistic parameters).
276 The use of an idealized rain detection efficiency function may have its demerits
277 when the empirical detection property deviates significantly from the logistic form.
278 Users are therefore encouraged to verify the form and consider modeling POD_{RAIN}
279 from an empirical look-up table (discussed in detail in Section Five).
280

281 The $\text{POD}_{\text{NORAIN}}$, is the unitary probability that satellite retrieval is zero when
282 reference rainfall is zero, which is also determined on the basis of actual satellite
283 and reference rainfall data (Eq. 2).
284
285
286

287 4.2 False Alarm Rain Rate Distribution (Metric 3)

288 A probability density function (D_{false}) is defined to characterize the probability dis-
289 tribution of the satellite estimates when there are misses over non-rainy areas. This
290 function is also identified through calibration on the basis of actual sensor data.
291 Hossain and Anagnostou (2006) have reported that this D_{false} probability density
292 function typically tends to appear exponential. Hence, both the moments (first and
293 second) can be defined using only one parameter (a SREM2D metric) of the distribu-
294 tion, λ . This can be computed using the chi-squared or maximum likelihood method.
295 We must however stress that it is up to the user to verify the assumption of exponen-
296 tial distribution and use the appropriate probability distribution for sampling these
297 false alarm rain rates.
298
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300

301 4.3 Correlation Lengths (Metrics 4, 5 and 8)

302 To identify the correlation lengths of error (i.e., *how does the error vary in space*)
303 a simple exponential type auto-covariance function is assumed in SREM2D (users
304 may opt for more sophisticated approaches if necessary). The correlation length (the
305 separation distance at which correlation $= \frac{1}{e} = 0.3678$) is thus determined on the
306 basis of calibration with actual data over a large domain. For identifying the spatial
307 correlation length of rain detection, CL_{RAIN} (or, no-rain detection – CL_{NORAIN}) from
308 data, all successfully detected rainy (non-rainy) pixels are assigned a value of 1.0
309 while the rest has a value of 0.0. The empirical semi-variogram is then computed as
310 follows:
311
312

$$313 \gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} (z(x_i) - z(x_i + h))^2 \quad (4)$$

316 where $z(x_i)$ and $z(x_i + h)$ are the binary pixel values (0 or 1) at distance x_i and
 317 $x_i + h$, respectively and h is the lag in km. n represents the number of data points at a
 318 separation distance of h . The term $\gamma(h)$ is the semi-variance at separation distance h .
 319 Assuming that the empirical variogram is best represented by an exponential model,
 320 the functional parameters describing the spatial variability can be fitted as follows,

$$321 \quad \gamma(h) = c_0 + c(1 - e^{-h/CL}) \quad (5)$$

322 where c_0 represents the nugget variance, c is the sill variance and CL is the dis-
 323 tance parameter known as ‘‘correlation length’’ (a SREM2D metric). Conversely, the
 324 correlation function is modeled as, $C = \text{EXP}(-h/CL)$, where C is the correlation.
 325

326 For identifying the correlation length for retrieval error (i.e., when both satellite
 327 and reference rainfall simultaneously register HITs), CL_{RET} , a similar set of steps
 328 are adopted as above for rain/no rain detection, with the exception that the binary
 329 values (0–1) are no longer pertinent. Instead, one computes the correlation length in
 330 terms of retrieval error defined as the logarithmic difference between reference and
 331 satellite estimate.
 332

333 334 **4.4 Conditional Rain Rate Distribution (Metrics 6 and 7)**

335 The conditional (i.e., reference rainfall > threshold unit) non-zero satellite rain rates,
 336 R_{SAT} , are statistically related in SREM2D to corresponding conditional reference
 337 rain rates, R_{REF} , as,
 338

$$339 \quad R_{SAT} = R_{REF} \cdot \epsilon_s \quad (6)$$

340 where the satellite retrieval error parameter, ϵ_s , is assumed to be log-normally
 341 distributed. This assumption has its pros and cons. The advantage of such an
 342 assumption is that a log transformation [$\log(R_{SAT}) - \log(R_{REF})$] of Eq. 6 allows the
 343 ϵ_s to be mapped to a Gaussian $N(\mu, \sigma)$ deviate, ϵ (hereafter referred to as ‘‘log-
 344 error’’), where μ and σ are the mean and standard deviation, respectively. On
 345 the other hand, the assumption of log-normality implies that data on log-error is
 346 homoscedastic (i.e., the variance remains the same regardless of the magnitude
 347 of the log-error). Hence, it is the user’s responsibility to verify the assumption
 348 of log-normality and homoscedasticity and assess if log-normality is sufficient to
 349 model the skewness expected from non-zero and positive rainfall rates. Skewness
 350 of rainfall is known to diminish at longer space-time accumulations (from hourly
 351 to monthly). Thus, for a particular application, such as optimizing satellite rainfall-
 352 based irrigation schedule at weekly timescales, there may not be any need to account
 353 for skewness in the satellite rainfall. Vice-versa, skewness will be important for
 354 assessing the use of half-hourly real-time satellite rainfall data for flash-floods
 355 forecasting.
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357 Another aspect to highlight is the definition of the threshold rainfall rate to
 358 distinguish rainy events from non-rainy (dry) events. This is particularly
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 360

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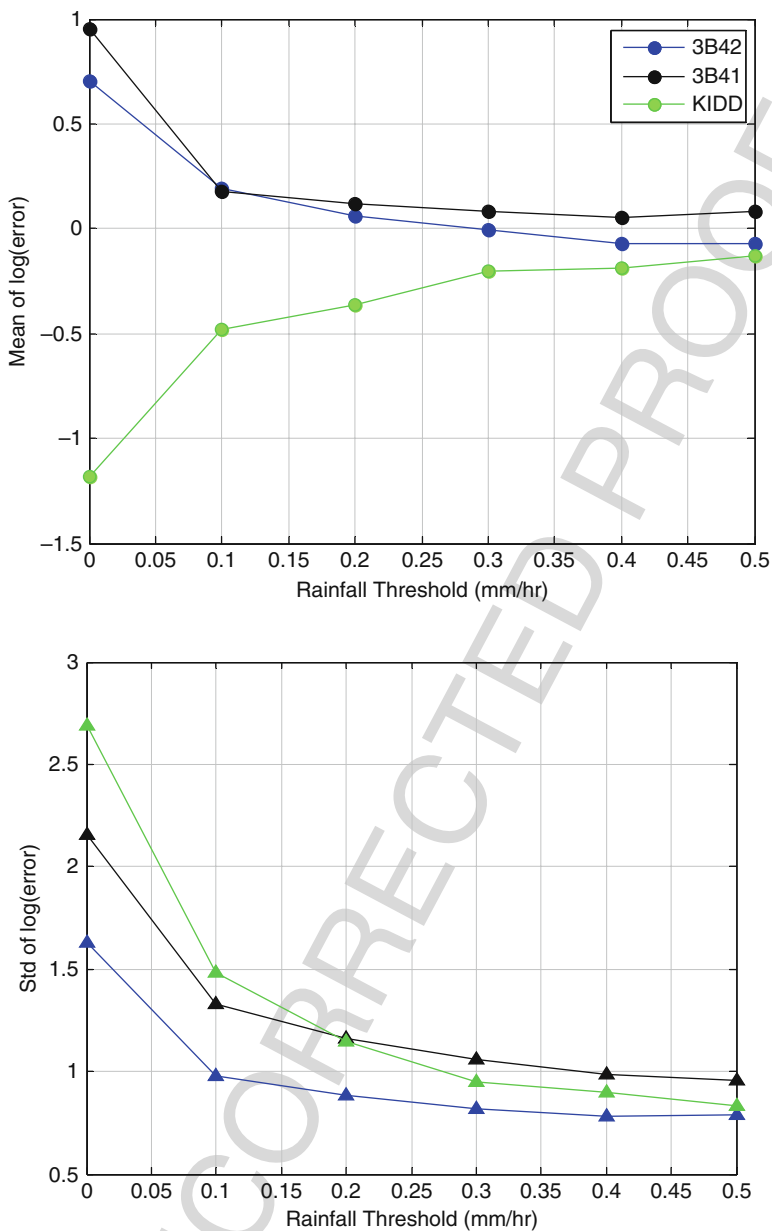


Fig. 2 Impact of reference rainfall threshold on the derivation of the mean and standard deviation of log-error for SREM2D for three high resolution satellite rainfall products (3B41RT, 3B42V6 and KIDD) over Northern Italy. Here, KIDD is a IR-based satellite rainfall product by Kidd et al. (2003)

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 $\langle \iota \rangle \mu \langle \iota \rangle$ 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 $\langle \iota \rangle \mu \langle \iota \rangle$ (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 ($\sim 5\text{--}15\%$), 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° 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*)

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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°N to 39.0°N and -92.0°W to -102.0°W; and, for Florida, by 20.0°N to 26.0°N and -84.0°W and -80.0°W (Fig. 3).

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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° 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

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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)

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Products	Native scale		Percentage of missing data			
	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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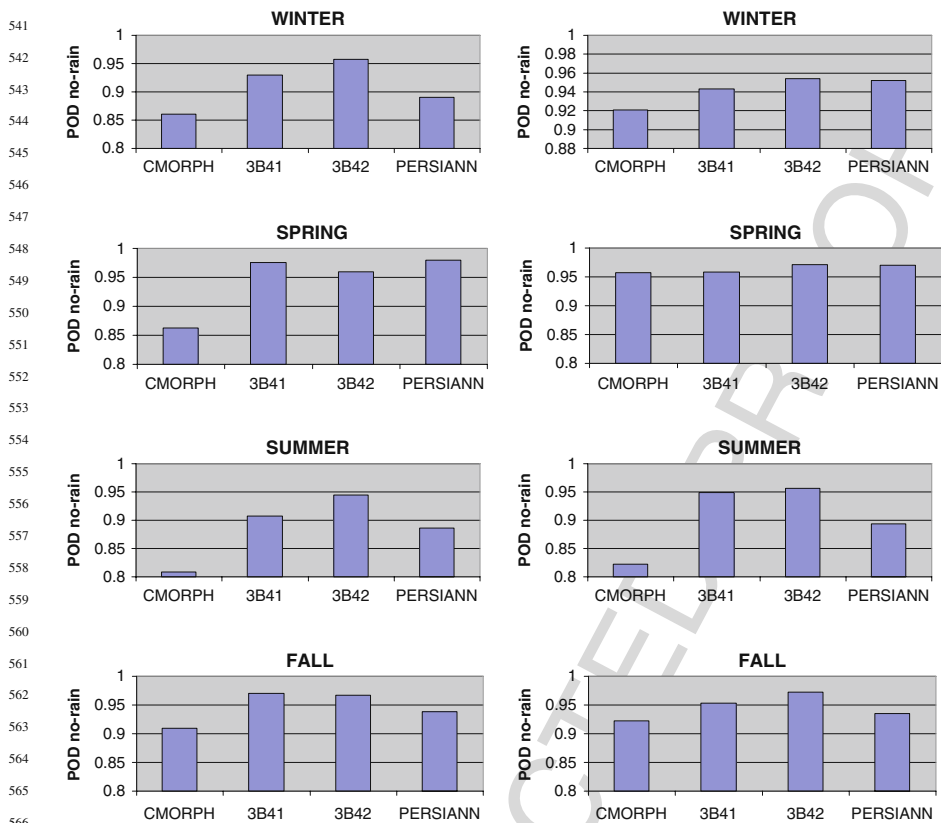


Fig. 4 POD_{NORAIN} for CMORPH, 3B41RT, 3B42RT and PERSIANN across four seasons in 2004. Left panels – Oklahoma; Right panels – Florida

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 ($\sim 1-5$ 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 ($1/\lambda$). 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 derive more robust estimates of the false alarm metric. Figure 7 shows the spatial covariance structure of rain retrieval (conditional), rain detection and

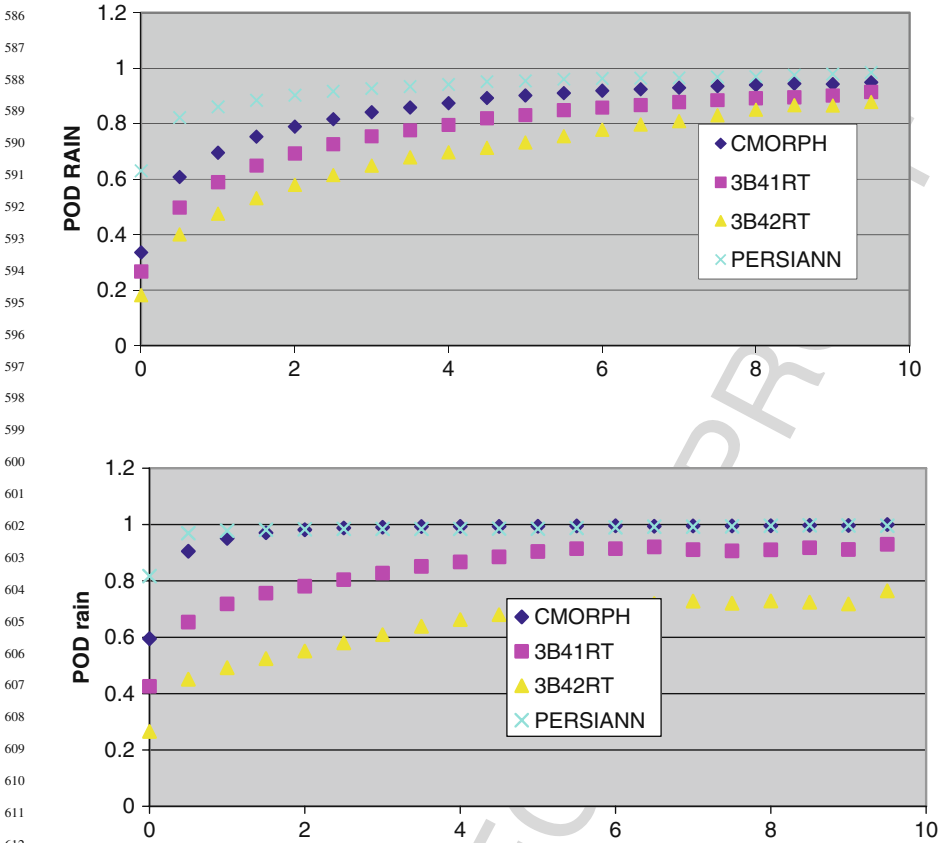


Fig. 5 POD_{RAIN} as a function of NEXRAD rain rate. *Upper panel* – Florida for Winter 2004; *Lower panel* – Oklahoma for Fall 2004. X-axis represents NEXRAD rain rates at 0.25° 3 hourly resolution

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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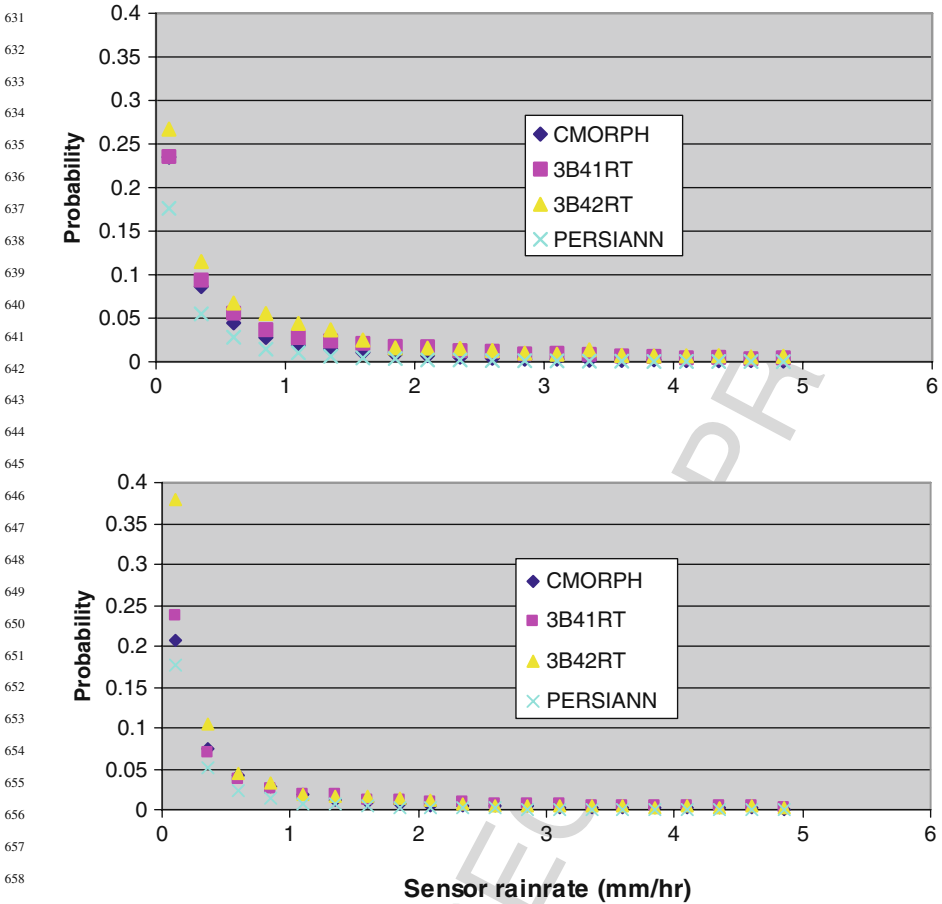


Fig. 6 False alarm rain rate distribution for satellite rainfall products. *Upper panel* – Florida-Summer; – Oklahoma-Spring. Sensor rainrate is the satellite rain estimate

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.

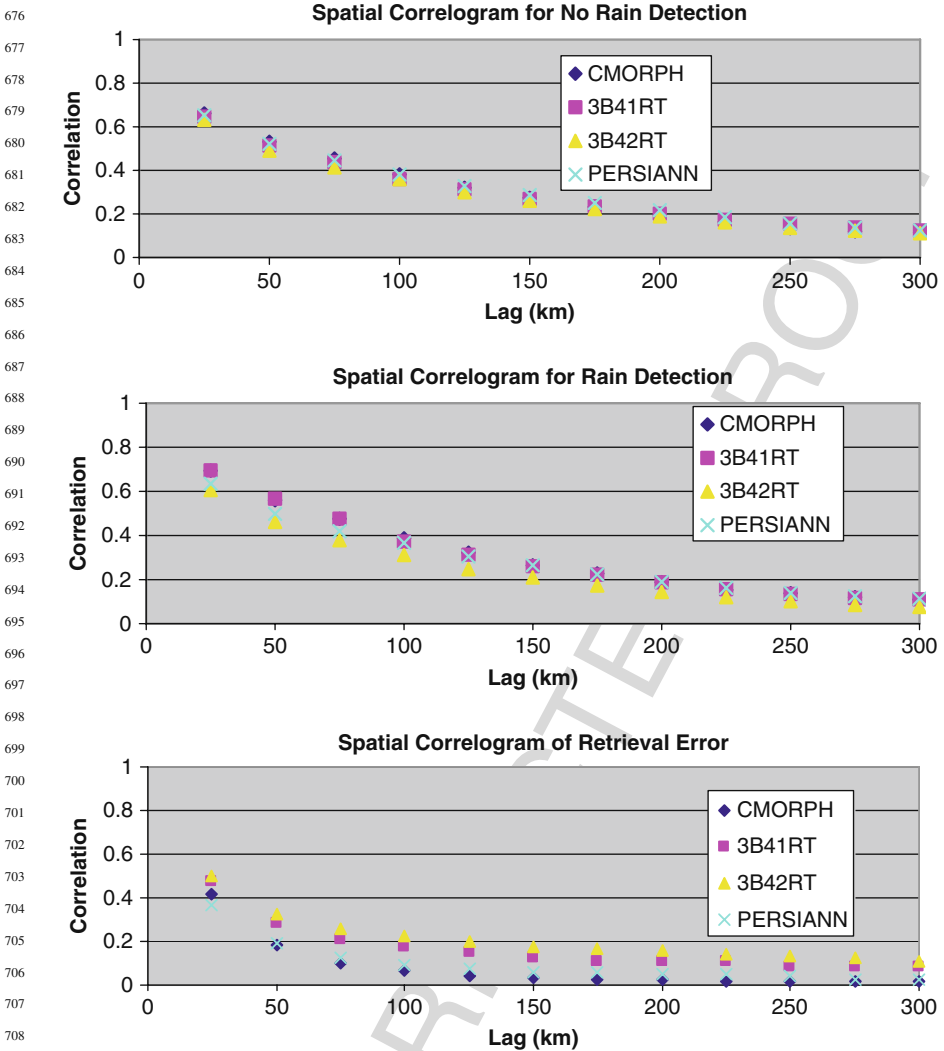


Fig. 7 Spatial covariance structure of rain retrieval, rain detection (middle panel) and no-rain detection (upper panel) for Summer 2004 in Florida

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

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

$$723 \quad 724 \quad 725 \quad x_j = \frac{1}{2} + \frac{1}{2} \operatorname{erf}(\varepsilon_j / \sqrt{2}) \quad (7)$$

726 where x_j , is a $U[0,1]$ random deviate for pixel j generated from the corresponding
727 $N(0,1)$ deviate, ε_j . The $\operatorname{erf}(\varepsilon_j)$ is the error function defined by the following integral,
728

$$729 \quad 730 \quad 731 \quad \operatorname{erf}(\varepsilon_j) = \frac{2}{\sqrt{\pi}} \int_0^{\varepsilon_j} e^{-w^2} dw \quad (8)$$

732 The uniform random fields are then scaled by its standard deviation to yield a
733 unitary variance (this ensures the maximum covariance of 1.0 at lag 0). Numerical
734 consistency checks have revealed that correlation length is altered significantly by
735 this non-linearity only at lags (grid spaces) beyond 10 and should be accordingly
736 accounted for modeling the joint probability of detection if necessary. Execution of
737 this procedure yields a spatially correlated uniform field of $U[0,1]$ random deviates
738 that are now amenable for Bernoulli trials for rain and no-rain detection with *a priori*
739 spatial structures. A third Gaussian random field is generated next for the simulation
740 of correlated retrieval error field pertaining to $N(\mu, \sigma)$.
741

742 Hossain and Anagnostou (2006) provide the simulation algorithm for SREM2D
743 that outlines each simulation step for the error model in the form of a programming
744 flow-chart. We recommend that users refer to that algorithm flow-chart to clarify the
745 individual process calculations that SREM2D computes in space and time.
746

747 748 749 750 **6.2 Reproducibility of SREM2D Error Statistics**

751 Before the assessment of satellite rainfall products for decision-making can begin,
752 users must verify that the ensembles of satellite rainfall data simulated by SREM2D
753 are adequately realistic. In other words, the reproducibility of error statistics (met-
754 rics) by SREM2D needs to be verified. Like any other mathematical model,
755 SREM2D does not perfectly mimic the uncertainty as expected from the calibrated
756 metrics. Nevertheless, the user must set some minimum standards on reproducibil-
757 ity based on the intended application. We recommend two particular ways by which
758 SREM2D can be verified of this “reproducibility” property. These are as follows:
759

- 760 761 762 1) Checking the consistency of ensemble of cumulative rainfall hyeotograph
763 against actual satellite rainfall data.
- 764 765 2) Checking the accuracy of error metrics computed from simulated satellite
rainfall data against actual reference rainfall data.

766 The first method checks if the actual cumulative rainfall hyetograph is
 767 enveloped reasonably realistically by the ensemble of SREM2D generated synthetic
 768 satellite hyetographs. Because actual satellite rainfall data is not used in the gener-
 769 ation of SREM2D synthetic data, this test can be considered an independent check.
 770 Users are recommended to perform this test over the whole domain and a few ran-
 771 dom smaller sub-domains within the study region. An additional aspect to check is
 772 to verify if the simulated hyetographs exhibit a pattern of jumps and plateaus simi-
 773 lar to the actual data. The second method computes the nine SREM2D error metrics
 774 from synthetic satellite data against actual reference rainfall data to check the close-
 775 ness of the values with calibrated measures. This check may be done on individual
 776 realizations or over a set of ensembles. The latter is likely to yield more accurate
 777 results due to the larger space-time sample size that minimizes the randomization
 778 effects per each realization.

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

781

782

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

783

784

785 Figure 8 shows the alpine region of Northern Italy over which SREM2D error
 786 metrics were calibrated for three satellite rainfall products. The three shaded grid
 787 boxes represent the location of actual satellite pixels at 0.25° scale for three satellite
 788 products

789 3B41RT, 3B42V6 and KIDD. Herein, KIDD represents a high resolution (0.04°)
 790 Infrared (IR)-based satellite rainfall product produced by Kidd et al. (2003). Six
 791 months of satellite data spanning June–November 2002 were used for calibration
 792 of SREM2D metrics. Reference data comprised gage rainfall from a dense network
 793 represented by the black circles shown in the figure. Table 3 shows the SREM2D
 794 metrics calibrated for the satellite products at the 0.25° 3 hourly scale. A threshold of
 795 0.1 mm/h was assigned to separate the rainy events from non-rainy events. Figure 9
 796 demonstrates the cumulative hyetographs generated from 100 SREM2D realiza-
 797 tions (mean and $\pm\sigma$) and actual satellite rainfall data for 3B41RT and 3B42V6. We
 798 observe that 3B41RT is relatively more accurately enveloped than 3B42V6. Overall,
 799 the simulation of both products appear reasonably realistic for the domain of interest
 800 in Northern Italy.

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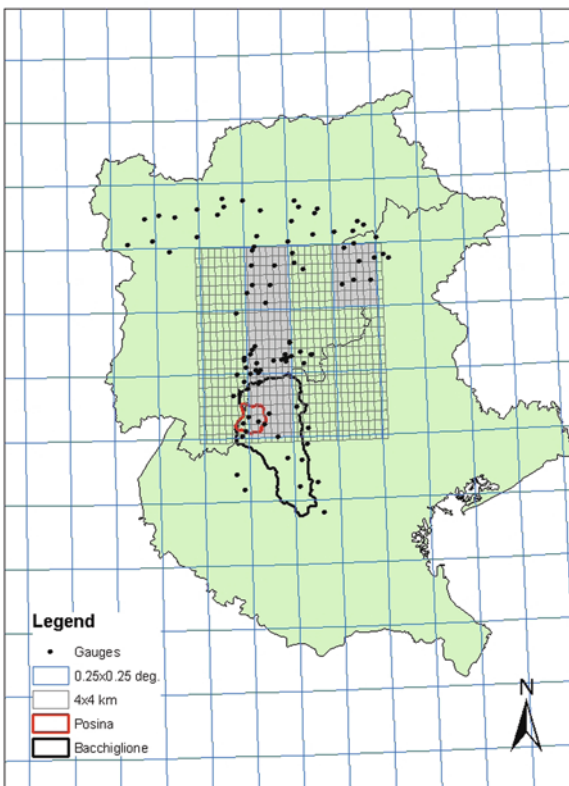
6.2.2 Checking Reproducibility of Error Metrics

803

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

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811 **Fig. 8** Alpine region of
 812 Northern Italy. Shaded grey
 813 boxes represent the actual
 814 location of the 0.25° satellite
 815 pixels for 3B41RT and
 816 3B41V6 data used in the
 817 calibration of SREM2D error
 818 metrics. Black circles
 819 represent the location of
 820 tipping bucket gages that
 821 comprised reference rainfall
 822 data



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

840 Metrics	841 3B41	842 3B42	843 KIDD
844 A	845 1.05	846 1.1	847 1.1
848 B	849 1.85	850 1.08	851 1.2
852 Mean (μ -Gaussian of log-error)	853 0.026	854 -0.1102	855 -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

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

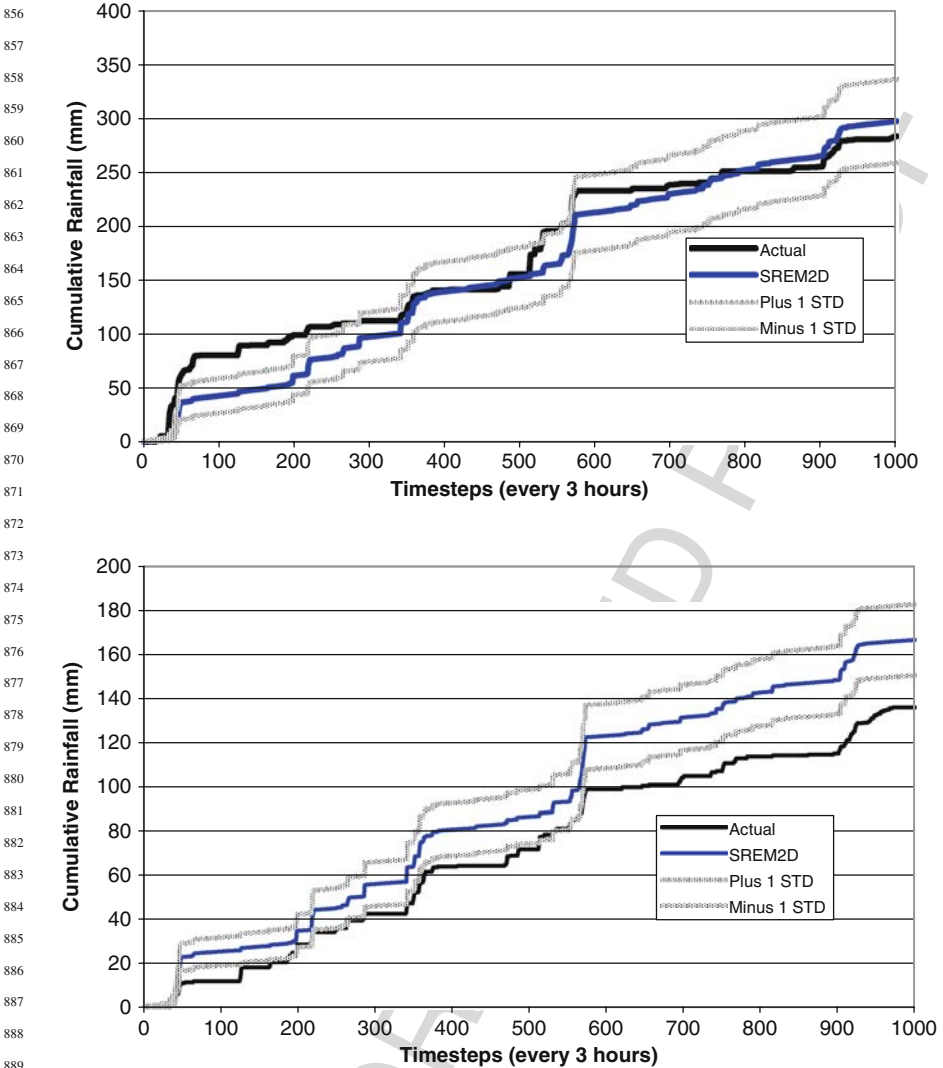


Fig. 9 Cumulative rainfall hietographs over Northern Italy. Blue line represents the mean of 100 SREM2D realizations. Solid black line represents the actual satellite hieotograph. Upper panel – 3B41RT; Lower panel – 3B42V6

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.

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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