Evaluation of TRMM PR Sampling Error Over a Subtropical Basin Using Bootstrap Technique

J. Indu and D. Nagesh Kumar

Abstract*—Quantitative use of satellite-derived rainfall products for various scientific applications often requires them to be accompanied with an error estimate. Rainfall estimates inferred from low earth orbiting satellites like the Tropical Rainfall Measuring Mission (TRMM) will be subjected to sampling errors of nonnegligible proportions owing to the narrow swath of satellite sensors coupled with a lack of continuous coverage due to infrequent satellite visits. The authors investigate sampling uncertainty of seasonal rainfall estimates from the active sensor of TRMM, namely, Precipitation Radar (PR), based on 11 years of PR 2A25 data product over the Indian subcontinent. In this paper, a statistical bootstrap technique is investigated to estimate the relative sampling errors using the PR data themselves. Results verify power law scaling characteristics of relative sampling errors with respect to space–time scale of measurement. Sampling uncertainty estimates for mean seasonal rainfall were found to exhibit seasonal variations. To give a practical example of the implications of the bootstrap technique, PR relative sampling errors over a subtropical river basin of Mahanadi, India, are examined. Results reveal that the bootstrap technique incurs relative sampling errors $< 33\%$ (for the 2° grid), $< 36\%$ (for the 1° grid), $< 45\%$ (for the 0.5° grid), and $< 57\%$ (for the 0.25° grid). With respect to rainfall type, overall sampling uncertainty was found to be dominated by sampling uncertainty due to stratiform rainfall over the basin. The study compares resulting error estimates to those obtained from latin hypercube sampling. Based on this study, the authors conclude that the bootstrap approach can be successfully used for ascertaining relative sampling errors offered by TRMM-like satellites over gauged or ungauged basins lacking *in situ* validation data. This technique has wider implications for decision making before incorporating microwave orbital data products in basin-scale hydrologic modeling.

***Index Terms*—Basin, bootstrap, sampling error, Tropical Rainfall Measuring Mission (TRMM).**

I. Introduction

SATELLITES offer gridded rainfall products at an extensive range of spatial (from a few kilometers to global) and temporal (from a few minutes to months) scales. These products, obtained in visible/infrared/microwave regions of the electromagnetic spectrum, can, in principle, be combined with one another or with the output of climate models to generate a realistic distribution of rainfall with better accuracy [1], [2]. Despite the advantages, these data products suffer from various sources of uncertainties, a major source of which is contributed by sampling errors resulting from infrequent satellite visits that offer difficulty in measuring the spatiotemporal variability of rainfall. Estimates of sampling errors are crucial to provide quantitative confidence on the satellite products before these can be applied for any scientific investigations or climate modeling studies. Valid error estimates depend on a number of factors like type of satellite, geographical location, season, precipitation type, etc. Depending on the satellite analyzed, sampling uncertainty studies can be broadly classified into two categories [3]. These are either using geostationary satellites which typically have a 1/2-h temporal resolution and a spatial resolution of a few kilometers or using low earth orbiting satellites with high spatial resolution and having a temporal resolution of a few passes per day [3].

For more than a decade, the low earth orbiting satellite of the Tropical Rainfall Measuring Mission (TRMM) has revolutionized the global view of precipitation by providing near-real-time data products. To improve the overall accuracy of global rainfall maps, TRMM carries several instruments onboard, including the passive sensor TRMM Microwave imager (TMI) and an active sensor Precipitation Radar (PR). The PR has a potential of providing 3-D vertical structure of precipitation with a very high spatial resolution. It provides the well-developed 2A25 rainfall retrieval algorithm [4] which is arguably one of the most reliable algorithms for overland precipitation determination at a spatial resolution of $\sim$5 km. TRMM, being in a low earth orbit at an inclination of 35°, measures precipitation infrequently at any single location, contributing to sampling errors of nonnegligible proportions [5]. Some of the prominent sampling-error-related studies relevant to TRMM rainfall products are discussed in the following.

During the prelaunch period of TRMM, studies related to temporal sampling errors using satellite-based rainfall estimates were undertaken by many researchers. Empirical studies evaluated sampling errors using ground data at periodic intervals, followed by a comparison with theoretical methods [6]–[8]. Laughlin [9] conducted studies using rainfall data over oceans (near the intertropical convergence zone) and showed that monthly averages of satellite-observed rainfall in the Global Atmospheric Research Program Atlantic Tropical Experiment (GATE) area will have sampling errors of the order of 10% of the mean. Several studies followed, which made a similar

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The authors are with the Department of Civil Engineering, Indian Institute of Science, Bangalore 560 012, India.

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conclusion but with a more realistic representation of rainfall and satellite sampling [5], [6], [10]. Statistically based parametric studies by Laughlin [9], Shin and North [11], North and Nakamoto [12], and Bell *et al.* [13], predicted sampling errors of 8%–12% per month relative to the mean rainfall. Using data from Patrick Air Force Base in Florida, Seed and Austin [14] estimated the sampling error with radar-derived rainfall estimates. They were the first to extend sampling error studies to data sets different from GATE. Soman *et al.* [15], [16] further enlarged the sites for sampling error studies by analyzing radar echoes collected in the vicinity of Darwin, Australia. Steiner [17] conducted related studies using an extensive network of tipping bucket rain gauges at Darwin, Australia, and Melbourne, Florida. Chang *et al.* [18] estimated the errors associated with monthly averages of rainfall obtained from the Special Sensor Microwave/Imager (SSM/I) on the Defence Meteorological Satellite Program satellites. Berg and Avery [19] analyzed the sampling errors in SSM/I rainfall averages using data from two SSM/I sensors. Their study resulted in an error budget summarizing errors from various sources including the effect of diurnal cycle of rainfall over oceans. Oki and Sumi [7] developed sampling errors of TRMM monthly rainfall over Japan using radar-AMeDAS (Automatic Meteorological Data Acquisition System) data. Their study, conducted at $5^\circ \times 5^\circ$ and $2.5^\circ \times 2.5^\circ$ areas, inferred that sampling errors were approximately 16% (with TRMM TMI) and 20% (with TRMM PR).

Sampling errors are complicated functions of the orbital geometry and statistical properties of measured fields [13], [20]. Lin *et al.* [21] showed that it is possible to combine the Colorado State University (CSU) Global Climate Models (GCM) with the TRMM orbital data to evaluate the sampling statistics of TRMM sensors. Their study concluded that, for a grid size of $2.25^\circ \times 2.25^\circ$, TRMM orbital geometry resulted in large systematic diurnal undersampling, especially for grid boxes located away from the equator which caused errors as large as 20% in tropics and 40% in subtropics for zonally averaged monthly mean rainfall products. Iida *et al.* [22] evaluated sampling errors due to five low earth orbiting satellites (Aqua, DMSP-F13, F14, F15, and TRMM) using radar-AMeDAS data of three years around Japan. Fisher [23] conducted error analysis using TRMM TMI and PR data products for a $2^\circ \times 2^\circ$ grid size over the TRMM ground validation site at Melbourne, Florida.

The TRMM Multisatellite Precipitation Analysis (TMPA) third level data product 3B42 is considered to be a more realistic representation of rainfall when compared with GCMs. TMPA is a merged microwave–infrared data product that provides fine-scale precipitation estimates at 3 hourly resolutions for $0.25^\circ \times 0.25^\circ$ grids over the tropical regions [24]. Nesbitt and Anders [25] estimated the relative sampling errors using the 3B42 data product of TMPA. Fisher *et al.* [26] estimated the sampling and retrieval errors for five different spaceborne sensors onboard nine orbiting satellites using an error decomposition methodology for 0.25° resolution grids over ground-based weather radars of Kwajalein, Marshall Islands, and Melbourne, Florida.

To date, studies related to TRMM sampling errors compare the rainfall rates from a surface-based dense network of rain gauges with that from TRMM. Availability of high-resolution surface-based rainfall data of high accuracy is limited to regions possessing surface-based equipment [6], [9]–[11], [13]–[15], [22], [27]–[31]. To circumvent this problem, attempts have been made to estimate sampling errors on a global scale using globally available satellite rainfall data products themselves [21], [25]. Recently, Iida *et al.* [32] have developed a method to evaluate relative sampling errors of PR-observed trimonthly rainfall, by employing a statistical bootstrap technique. Their study concluded that the bootstrap technique can successfully estimate relative sampling errors in TRMM PR rainfall products using PR orbital data products themselves, for 5° grid sizes globally over the tropical region. The technique by Iida *et al.* [32] located relative sampling error magnitudes of 15%–50% for the Indian subcontinent. Although this technique has successfully evaluated relative sampling errors globally for 5° grid sizes without relying on rainfall from a dense network of ground instruments, its potential in estimating sampling uncertainty for hydrologically relevant watersheds of small areal extent has not been examined so far. Sampling errors in remotely sensed rainfall products are known to potentially cause high uncertainties during simulation of runoff at the watershed scale [33]–[36]. Hossain *et al.* [37] have shown that the error components of satellite-based rainfall products interact nonlinearly with hydrologic modeling uncertainty, thereby hindering the accurate estimation of the resulting flood forecasts. The error characteristics derived using the bootstrap technique have tremendous potential to ascertain the applicability of TRMM PR orbital rainfall products for hydrological modeling over small catchments or ungauged basins.

For the present study, sampling uncertainty of TRMM PR 2A25 orbital data product is evaluated over the Indian subcontinent using the bootstrap technique. The sparse observations from the narrow swath of TRMM PR are subjected to large sampling errors which include the effects of diurnal cycle for monthly rainfall averages. Hence, the present study analyzes seasonal rainfall to minimize the bias offered by diurnal cycle. Furthermore, the applicability of the bootstrap technique to estimate relative sampling errors for a hydrologically relevant watershed of Mahanadi, India, is examined using different grid sizes of 2°, 1°, 0.5°, and 0.25°. The present study analyzes an 11-year data period of TRMM seasonal rainfall from June 2002 to September 2012. Post 2001 data products are considered for analysis owing to the TRMM orbital boost from 350 to 402.5 km in August 2001 which altered the data quality significantly. Section II provides an overview of evaluating relative sampling errors from PR-observed seasonal rainfall using the bootstrap approach. Section III provides scale dependence of the calculated relative sampling errors over India and over the Mahanadi basin. In addition to grid sizes, the relative sampling errors are also known to vary with respect to rainfall type (convective or stratiform). Hence, discussion regarding rainfall-type dependence on relative sampling errors over the study region is incorporated in Section III. Comparative analysis of relative sampling errors estimated using latin hypercube sampling (LHS) approach is also discussed here. Section IV gives the summary and conclusion.

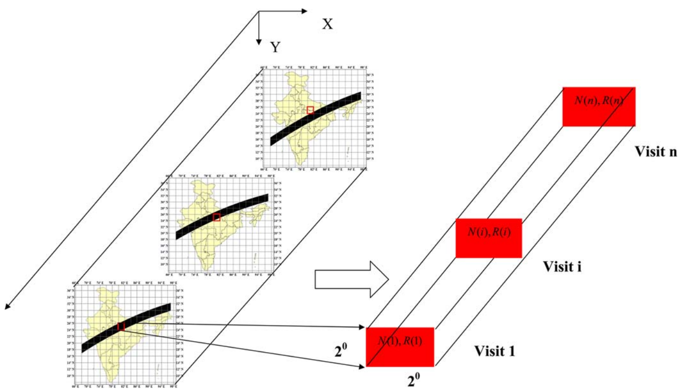


Fig. 1. Schematic showing collection of N and R over a $2^\circ \times 2^\circ$ grid box [in the aforementioned figure, $N(1) > N(2) > N(3)$].

II. Relative Sampling Error Evaluation Using the Bootstrap Approach

The sources of errors in TRMM rainfall estimates over any area can be examined by analyzing the individual overlapping coincident snapshots of rain events in the orbital passes. For an area, simple assumptions regarding the statistical behavior of rainfall can aid in deriving equations relating sampling error with rainfall statistics. Let us assume that, over a sufficiently large area A and over a long enough time period T, rainfall occurs as separate uncorrelated events having certain properties like intensity, duration, area covered, etc. Then, the rainfall amount falling within A during T can be determined from the observed rain events, provided that their number is sufficiently large. Each event may result in different intensities of rainfall (differing from the mean rainfall) which eventually tends to average out when considered over a long time period. The rainfall climatology for A represents a statistical characterization of what might happen in A during time period T when all of the environmental factors that affect rainfall statistics in A are specified (e.g., season, large-scale wind patterns, etc.). According to Bell and Kundu [29], "*A picture such as this underlies the area time integral (ATI) methods of estimating rainfall from the fraction of the area covered by rain*" [27], [38]–[40]. If $R(x, y, t)$ represents the true rainfall rate at a point in space during a time period, then, according to the ATI concept, the true area-time averaged rainfall amount (R_T) within a space–time domain can be expressed as

$$R_T = \int_0^T dt \int_A dx * dy * R(x, y, t). \tag{1}$$

Here, $\int_A$ denotes integration over a grid box area, A.

A schematic for the core idea of the bootstrap technique is given in Fig. 1. Pertaining to the Indian subcontinent, we consider that the true instantaneous area averaged (mean) rainfall rate in millimeters per hour falling over a $2^\circ \times 2^\circ$ grid box during a particular time period (season) cannot be observed with fine accuracy. Whenever the TRMM satellite visits a region/grid box of size A, the field of view (FOV) of TRMM sensors will not always cover the entire area of A; instead, it will sample a part/subregion of A. If the time during which any part of a satellite swath passing over a region (A) be termed as a visit, general practice to calculate satellite estimates of rainfall involves collecting all of the instrument footprints or FOVs that fall within A during T, converting the observations to rain-rate estimates and averaging them (by summing up and dividing by the total number of observations). From Fig. 1, let $i = 1, 2, 3, \ldots, n$ denote the number of times the satellite visits an area (grid size in our study), $R(1), R(2), R(3), \ldots, R(n)$ be the corresponding area averaged rain rates from all footprints that are in the box, and $N(1), N(2), N(3), \ldots, N(n)$ be the number of PR footprints associated with each visit. Then, the average seasonal rainfall (in millimeters) observed by PR within each grid (of area A) can be expressed as

$$R_S = \frac{\sum_{i=1}^{n} N(i) * R(i)}{\sum_{i=1}^{n} N(i)} * 24 * 122. \tag{2}$$

As the Indian summer monsoon spans over the months of June, July, August, and September (JJAS), in (2), 122 denotes the number of days in JJAS. R_S serves both as a measurement within the area of the box and as an unbiased estimate of the true rainfall amount R_T. Our interest lies in estimating the closeness of R_S with R_T

$$\sigma_E^2 = E\left[(R_S - R_T)^2\right]. \tag{3}$$

In (3), the expectation (E) denotes the average of an ensemble of rain scenarios representing the seasonal rain climatology within an area A. When σ_E^2 is obtained for every grid box (of area A), the result is a global "error climatology" for the satellite rain estimates. Many studies have attempted to estimate the variance σ_E^2. In the present study using the bootstrap technique, the PR data themselves are used to calculate PR relative sampling errors.

A schematic explaining the bootstrap approach [41] by Iida *et al.* [32] is summarized using Fig. 2. The present study collects the samples of N and R accumulated within each grid box over a time period T and estimates the empirical distribution of N and R, provided that the sample sizes are large enough. Using random sampling based on the bootstrap technique, two bootstrap samples (of N and R) can be drawn from the empirical distributions. This procedure can be repeated n number of times with replacement. The calculation of relative sampling error using the bootstrap approach assumes that the probability distribution functions of seasonally averaged and simulated rainfall (R_S) within each grid box are independent of each other in the individual simulations. The value of relative sampling error σ can be calculated using 1000 bootstrap samples of R_S. In the bootstrap technique by Iida *et al.* [32], standard deviation is regarded as a measure of sampling error, and the value of the relative standard deviation is considered as a measure of relative sampling error.

The bootstrap technique assumes that each element of the random sample, i.e., N and R, is independent. Theoretically, PR data are spatially and temporally correlated with each other. In the present work, the temporal correlation between the

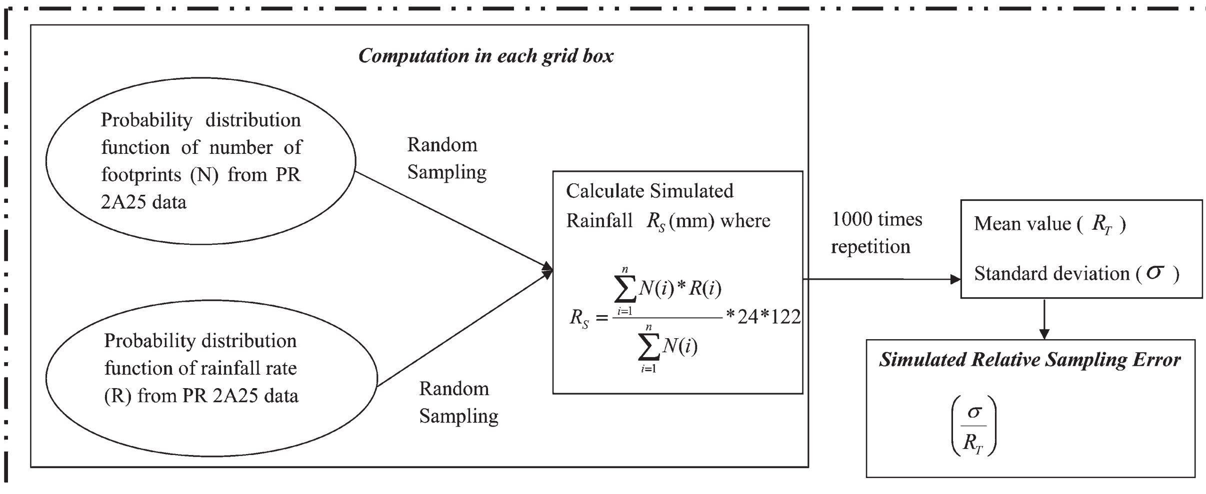


Fig. 2. Conceptual diagram of sampling error estimation using the bootstrap technique over a grid box.

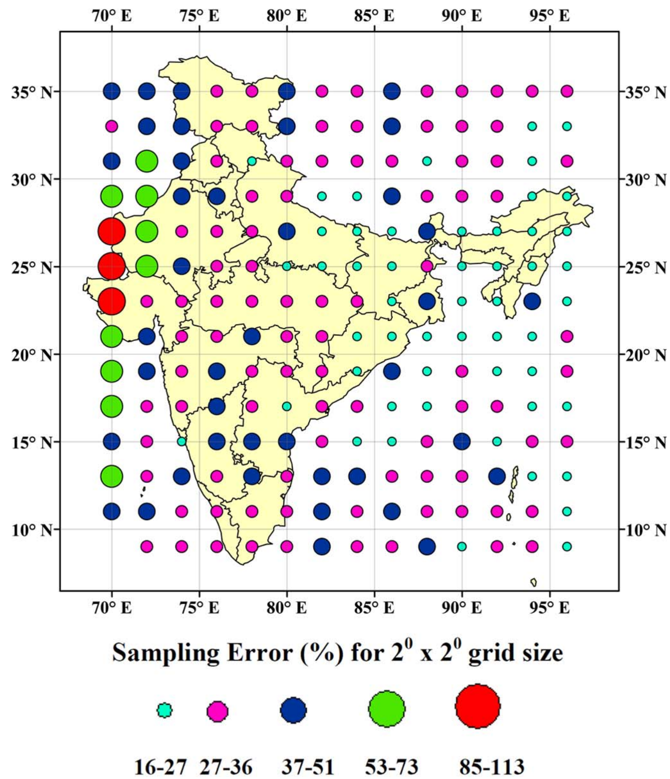
successive visits of PR is ignored because the time interval between the PR successive visits is much longer than the temporal rainfall correlation time at almost all latitudes, except for the midlatitudes around 34° N and S. Also, as the PR footprint size is ~5 km, estimation of spatial correlation among rainfall rates at individual footprints of a single visit becomes difficult. Therefore, rainfall averages from the individual PR visits taken over a grid size are used such that these can be considered independent in the bootstrap samples. Furthermore, spatial averaging also considers the spatial rainfall correlation in the PR fractional coverage on the space domain. Hence, this study averages rainfall (from PR data) over each grid box, thereby considering them independent in the bootstrap samples [41]–[43].

III. Results

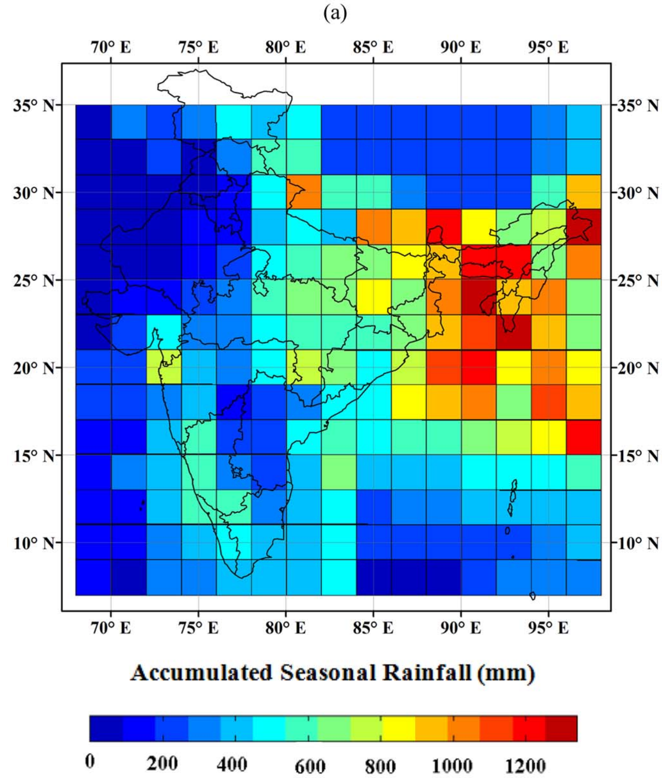
A. *Relative Sampling Errors Over India in the $2^\circ \times 2^\circ$ Boxes*

The motivation for this study comes from the need to fully characterize the relative sampling error of TRMM PR at high resolutions so that it can be linked to a hydrological model for future studies. Using the bootstrap technique, we estimated seasonal relative sampling errors for $2^\circ \times 2^\circ$ boxes over the Indian subcontinent during the JJAS months of 2002. For each of the 2° grid boxes, the total counts of PR footprints (N) and the PR near surface rainfall rate (R) falling within each box were estimated. For each of the 418 orbits passing over the Indian subcontinent, a total of 306 samples of N and R were considered over India. The overall range of values considered for JJAS seasonal months of 2002 was from 0 to 2280 for N and 0 to 22 mm/h for R. A total of 1000 seasonal rainfall amounts were then simulated for each grid box using (2). The mean and standard deviation pertaining to the value of R_S were calculated according to the schematic shown in Fig. 2. The spatial distribution of relative sampling errors obtained for 2° grid boxes over the Indian subcontinent for the 2002 monsoon season (JJAS) is shown in Fig. 3(a). The mean accumulated rainfall R_T in millimeter for JJAS of 2002 is also shown in Fig. 3(b). Theoretically, the relative sampling error depends upon the rainfall variability and the space–time correlation length of rainfall, in addition to the mean rainfall amounts and the sampling frequency [13], [30]. Fig. 3(a) shows that the relative sampling errors are relatively larger over the western regions of India over states of Gujarat, Haryana, and Rajasthan. A comparison of accumulated rainfall shows that these regions receive the least amount of rainfall during JJAS months. This spread of relative sampling error is consistent with the theoretical prediction by Bell and Kundu [29] that regions of high (low) rainfall will possess relative sampling errors to be generally small (high). Studies by Steiner *et al.* [31] had found relatively lower sampling uncertainty over oceans when compared to land owing to larger variability and shorter correlation time of rainfall over land than over oceans. However, some regions over Sikkim and Calcutta were observed with larger relative sampling errors in spite of the large seasonal rainfall amounts over these regions. Similarly, some regions over Bay of Bengal depicted low value of relative sampling error even though these regions received small seasonal rainfall amounts. From the studies of Bell and Kundu [29], these discrepancies can be attributed to the difference in the rainfall variability and space–time correlation length of point rainfall in these regions. However, this issue needs a deeper investigation before any conclusion can be drawn. From Fig. 3(a), it can be observed that a large number of boxes over oceans possess low relative sampling error between the range of 16%–27%. With the exception of the eastern coastline of the Indian subcontinent, all of the other land regions seemed to depict a higher range of relative sampling errors (> 35%).

To study the dependence of sampling uncertainty on rain rates, the present study computed the mean intensity of rainfall (in millimeters per hour) for all of the $2^\circ \times 2^\circ$ grid boxes over the Indian subcontinent during the monsoonal months of 2002. These were then sorted into bins of size 0.05 mm/h in the order of increasing values of rain rates. It should be noted that the process of binning destroys information regarding the geographical location of a particular box and the observation month because samples containing similar monthly averaged rain rates are lumped together regardless of their location or



(a)



(b)

Fig. 3. (a) Spatial distribution of sampling error using the bootstrap technique over the $2^\circ \times 2^\circ$ box during monsoon season of 2002. (b) Spatial distribution of accumulated rainfall (in millimeters) over the $2^\circ \times 2^\circ$ grid box for 2002 seasonal rainfall.

time of observation [29]. Results are plotted for each bin as shown in Fig. 4. The figure brings out two striking characteristics of PR relative sampling error estimates: 1) The estimated

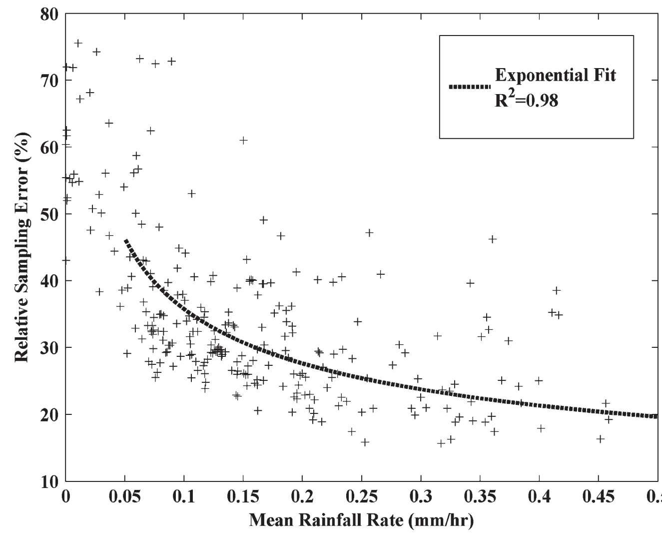


Fig. 4. Power law fit of mean rainfall rate with respect to relative sampling errors during JJAS 2002 for the $2^\circ \times 2^\circ$ grid box over the Indian subcontinent (the relationship of relative sampling error and mean rainfall rate is given by the expression $\sigma/R = 15.16 * R^{-0.37}$).

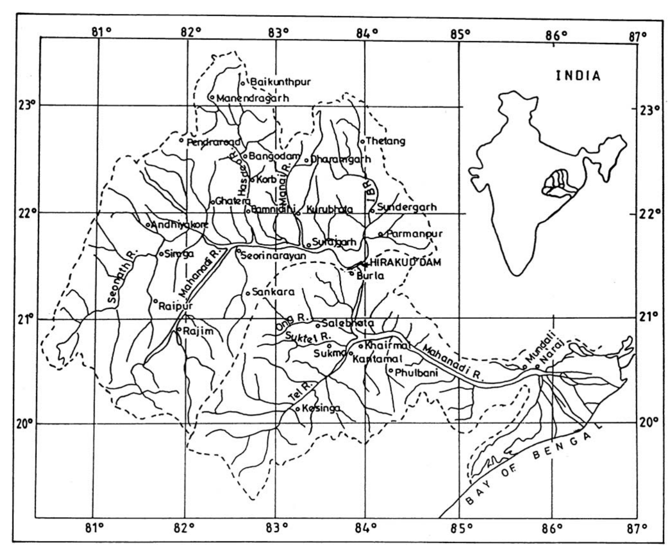


Fig. 5. Location of Mahanadi basin, India.

relative sampling errors in PR averages are 17%–42% for various seasonal mean rainfall rates (> 0.05 mm/h) and 2) The relationship of relative sampling errors with mean rainfall rates can be expressed using a power law relationship of $\sigma/R = 15.16 * R^{-0.37}$. This result is in agreement with earlier studies on sampling uncertainty which have reported the existence of compact expressions relating sampling error with large-scale observables like mean rain rate.

The current method enables a near global evaluation of relative sampling errors using TRMM PR. To give one practical example of the implications of the bootstrap technique, we examine the TRMM relative sampling errors for a hydrologically relevant basin of Mahanadi (Fig. 5). The basin, situated toward the eastern coast of India, was subjected to the lowest range of relative sampling errors in 16%–27%, when calculated for 2° grid boxes. Hence, PR relative sampling error studies over

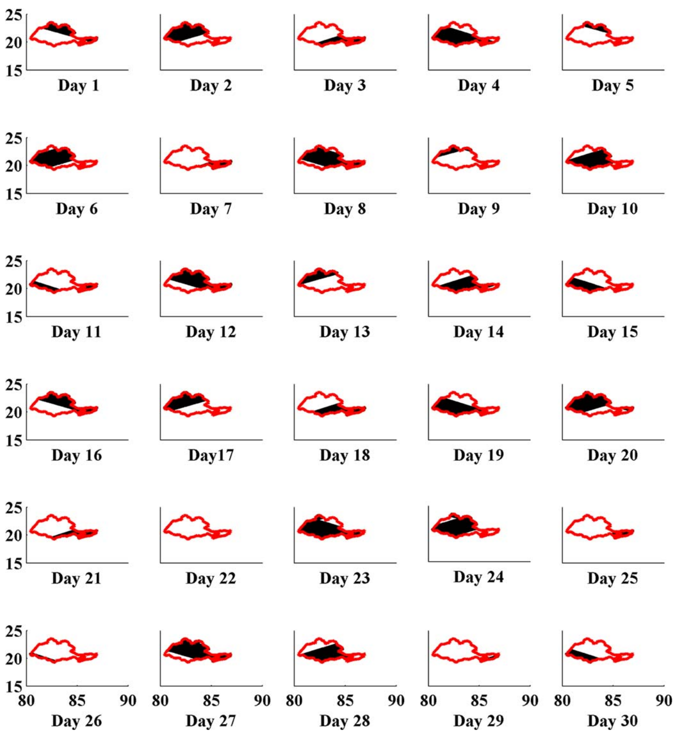


Fig. 6. Sampling by TRMM PR over the Mahanadi basin during June 2002. Each day's orbits are clipped within the boundary of the Mahanadi basin, with the x- and y-axes representing longitude and latitudes, respectively.

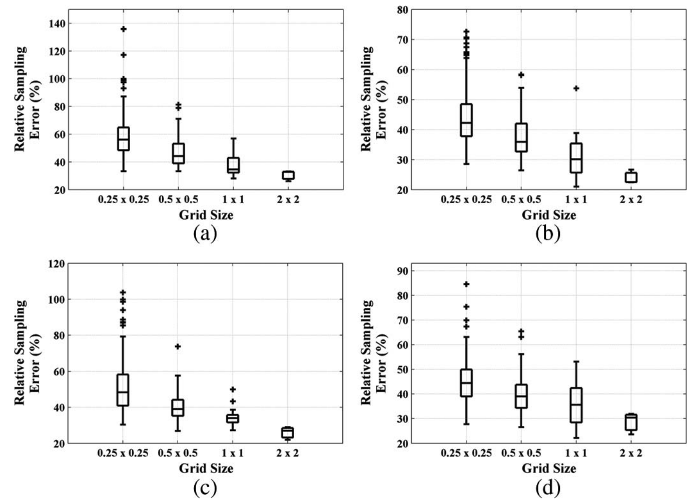


Fig. 7. Scale dependence of relative sampling errors estimated using the bootstrap approach over the Mahanadi basin for (a) 2002, (b) 2003, (c) 2004, and (d) 2005 (In these plots, the values of the 25th and 75th quartiles form the ends of the box, the line inside the box represents the median value, and the whiskers end at the 5th and 95th quartiles. The data points which exist far away from the 95th quartiles indicate outliers, i.e., points which lie far removed from the majority of data points).

the basin can be further extended to higher resolution grid sizes and used as a deciding factor before incorporating PR data products for basin-scale hydrological modeling studies. The hydrological importance of the basin lies in the fact that it receives heavy to very heavy rainfall when monsoon depressions from the Bay of Bengal move north-westward slightly south of their normal track. The Mahanadi basin is notorious for being subjected to frequent flooding every year. Nearly 91% of annual precipitation (600 to over 1600 mm) for the basin occurs from June to September (JJAS), known as the summer monsoon months which are responsible for influencing the agricultural output from the basin. Even a small variation of this seasonal rainfall can have an adverse impact on the economy. The reliability of PR data for hydrological modeling over the basin commands a proper understanding of the associated errors offered by the infrequent PR sampling.

The apparent inhomogeneity owing to the narrow swath width of PR is highlighted by Fig. 6, which shows the daily sampling pattern of the PR orbital data product of 2A25 over the Mahanadi basin for the month of June 2002. This includes periods of low coverage as well as periods of higher coverage. It can be seen that several regions of the basin receive very little to no coverage during certain days. TRMM takes around 46 days to revisit an area at approximately the same local time, which implies a requirement of 46 days to cover the diurnal cycle. Hence, if a monthly time period be considered to estimate the true averaged rainfall, the varying sample sizes (of N and R) observed during different times of the day will contribute to a bias in the calculated average rainfall rate. To minimize the resulting bias, this study considers seasonal averages. Earlier studies on sampling uncertainty have indicated that, for a given increase in sampling size, greater reduction in sampling uncertainty can be achieved if the extra samples were spread over time [44]. Thus, examining seasonal averages are considered more effective in reducing sampling uncertainty than monthly averages. Hence, the present study examines sampling uncertainty for seasonal rainfall observations over the basin. To date, studies related to sampling uncertainty of global rainfall products using the bootstrap approach have been conducted solely for a grid size of $5^\circ \times 5^\circ$ [32]. Adequate information is not available to test the suitability of this technique for higher resolution grid sizes. The ensuing results of scale dependence with respect to relative sampling error estimates are discussed in the next section.

B. Effect of Grid Size on Relative Sampling Error

The relative sampling error values depend on the grid size as well as their integration time. For the present study, the integration time was fixed as 122 days (spanning over the JJAS monsoonal months). The relative sampling errors estimated using the bootstrap approach over the Mahanadi basin for various grid sizes of 0.25°, 0.5°, 1°, and 2° are plotted in Fig. 7 for 2002, 2003, 2004, and 2005. In these plots, the values of the 25th and 75th quartiles form the ends of the box, the line inside the box represents the median value, and the whiskers end at the 5th and 95th quartiles. The data points which exist far away from the 95th quartiles indicate outliers, i.e., points which lie far removed from the majority of data points. From Fig. 7 and Table I, the median of sampling uncertainty at seasonal scale for various grid sizes was observed to be $< 33\%$ (for the 2° grid), $< 36\%$ (for the 1° grid), $< 45\%$ (for the 0.5° grid) and $< 57\%$ (for the 0.25° grid). Theoretically, the total sampling errors are known to be inversely proportional to space scales [9], [11], [13], [17], [29]. This tendency can be observed from Fig. 7 that, as the

TABLE I
RELATIVE SAMPLING ERROR (IN PERCENT) FOR VARIOUS QUARTILES OBTAINED DURING 2002, 2003, 2004, AND 2005

YEAR	Quartiles for $0.25^0 \times 0.25^0$				Quartiles for $0.5^0 \times 0.5^0$				Quartiles for $1^0 \times 1^0$				Quartiles for $1^0 \times 1^0$			
	25th	50th	75th	95th	25th	50th	75th	95th	25th	50th	75th	95th	25th	50th	75th	95th
2002	48.40	56.09	64.95	84.80	38.96	44.24	53.14	70.95	**32.34**	**34.62**	**42.96**	**55.52**	27.74	32.84	33.01	33.07
2003	37.77	42.25	48.46	63.21	32.70	35.89	42.00	53.52	**25.68**	**30.07**	**35.36**	**50.76**	22.48	22.50	25.64	26.68
2004	40.93	48.31	58.26	85.83	35.19	39.00	44.17	55.86	**31.60**	**33.95**	**35.73**	**48.54**	23.18	27.01	28.52	29.12
2005	39.00	44.42	49.91	61.74	34.40	39.98	43.82	55.85	**28.46**	**35.68**	**42.44**	**51.94**	25.34	30.40	31.60	32.00

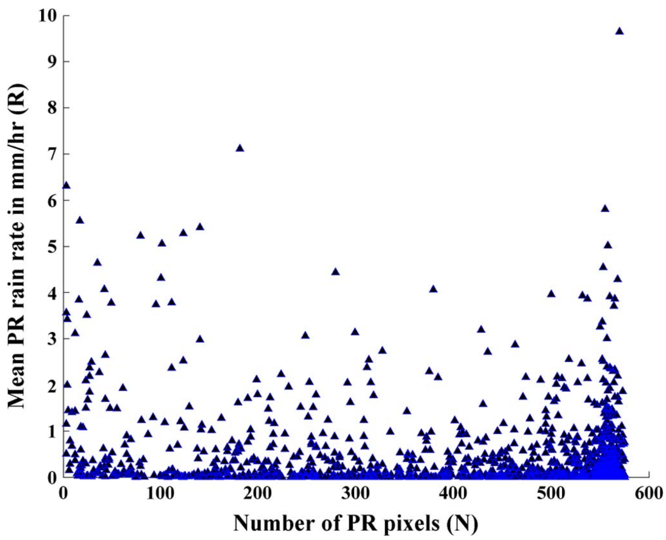


Fig. 8. Scatter plot of N versus R for ten grid boxes using JJAS 2002 rainfall over the Mahanadi basin.

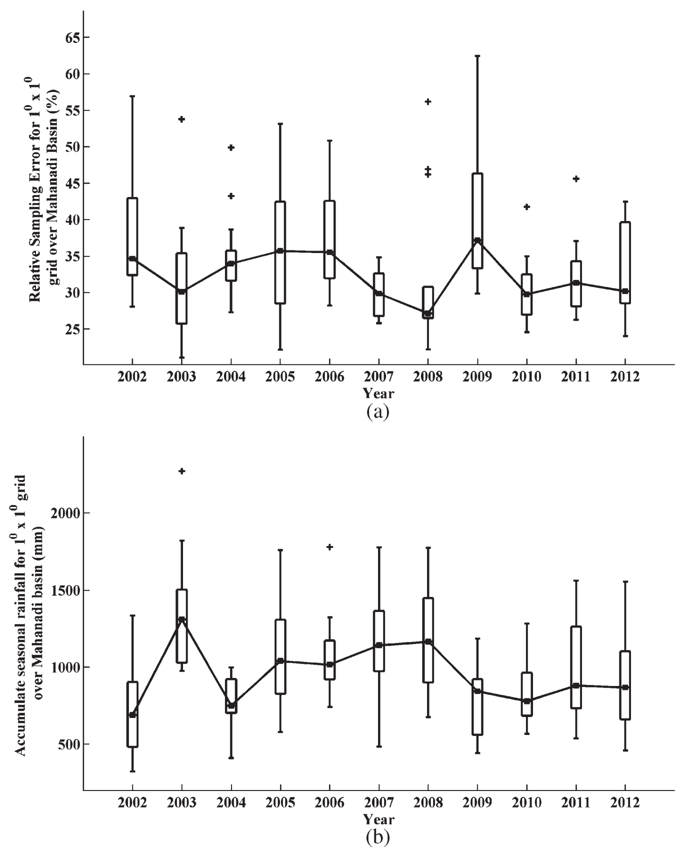


Fig. 9. Time series over the Mahanadi basin for the $1^\circ \times 1^\circ$ grid size for the 11-year data period showing (a) relative sampling errors (in percent) and (b) accumulated seasonal rainfall (in millimeters).

space scale becomes smaller than the $2^\circ \times 2^\circ$ grid size, the dependence of total relative sampling error on space scale becomes larger. This dependence results as a manifestation of the central limit theorem, wherein the average of n identically distributed random variables with finite mean and difference is known to differ from the true mean with a root-mean-square difference proportional to $n^{-1/2}$.

Selection of an appropriate grid size for our study area warrants a compromise between two major competing factors. First, the grid box is required to be large enough so that the assumption of statistically uncorrelated rain rates in neighboring boxes remains valid. This assumption treats rainfall averages over each grid box to be statistically independent samples enabling the use of statistical measures to estimate confidence intervals for these averages. Second, the grid sizes should be as small as possible to give a realistic representation of local rain rate with as little error as possible. This allows the rain rates within each grid box to be treated as approximately homogeneous. With these factors in mind, we have chosen a grid box of $1^\circ \times 1^\circ$ for further analysis of seasonal rainfall over the Mahanadi basin. A prime condition which must be satisfied for bootstrap technique is the independence between N and R. Theoretically, N is not a random number as its value can be easily predicted using orbital calculations pertaining to the TRMM satellite. Hence, a scatter plot relating the two variables N and R for 2002 is shown in Fig. 8. It can be observed that the actual PR data do not show any structure between N and R. Hence, for a 1° grid size over the basin, we conclude that N and R can be assumed as independent random variables.

To check consistency of performance of the bootstrap technique, we present in Fig. 9 the relative sampling errors (in percent) and accumulated seasonal rainfall (in millimeters) calculated for 1° grid boxes over the basin based on the bootstrap technique for seasonal rainfall during the data period of 11 years (2002–2012). It can be concluded that the year-to-year differences in relative sampling errors over the Mahanadi basin [from Fig. 9(a)] result mainly due to the year-to-year difference in rainfall amounts during the JJAS season [from Fig. 9(b)]. This is in accordance with the studies by Bell and Kundu [29]. Apart from accumulated seasonal rainfall, relative sampling error values might also be affected by other factors like precipitation type, inherent retrieval errors of the PR 2A25 rainfall algorithm, type of resampling used, etc. These are investigated in the next sections.

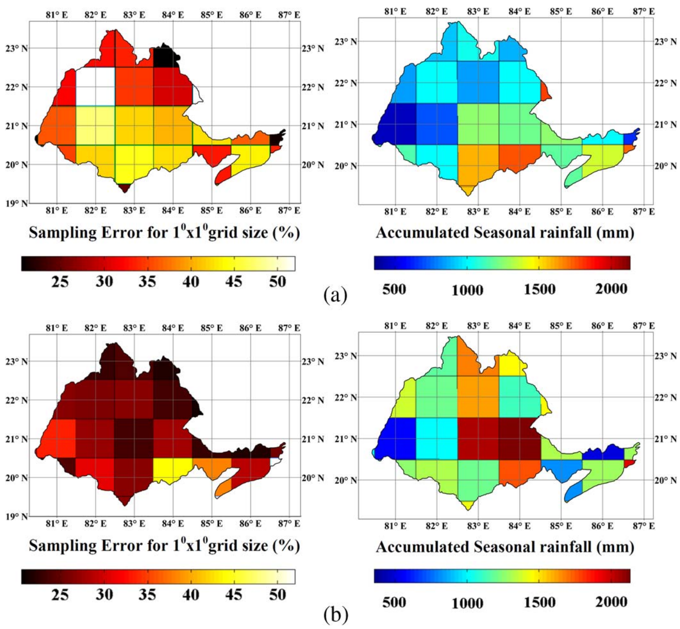


Fig. 10. Spatial distribution of overall relative sampling error and accumulated rainfall over the Mahanadi basin during the monsoonal season of (a) 2006 and (b) 2007.

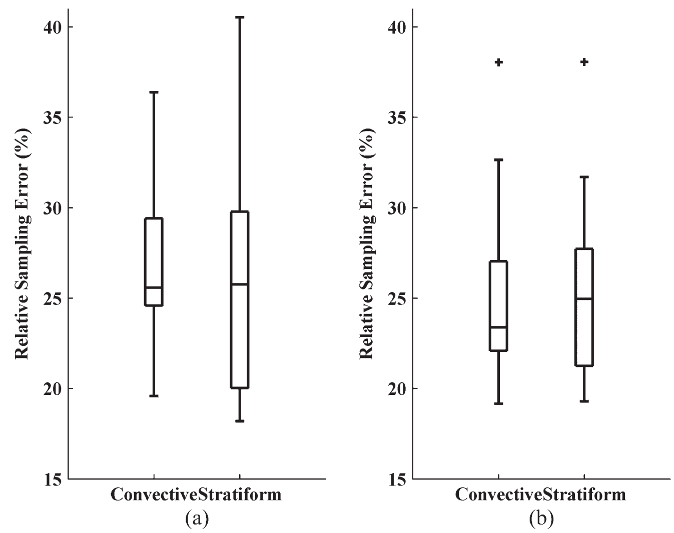


Fig. 11. Box plots showing the relative sampling errors estimated over the 1° grid size of the Mahanadi basin for convective and stratiform rain types during the monsoonal season of (a) 2006 and (b) 2007.

C. Effect of Rainfall Type on Relative Sampling Error

In general, tropical precipitation can be classified into two major classes, namely, convective and stratiform precipitations [45]. Convective precipitation regions are generally identified with intermittently strong vertical velocities ($> |\pm 1$ m/s$|$), high rain rates (> 5 mm/h), and small (∼1–10-km horizontal dimension) but intense horizontally inhomogeneous radar echo. Stratiform precipitation areas are characterized by statistically small vertical velocities ($< |\pm 1$ m/s$|$), low rain rates (< 5 mm/h), and widespread (∼100-km horizontal dimension) horizontally homogeneous radar echo [46].

This study demarcates PR data points into convective and stratiform categories using the rain classifications embedded within version 7 of TRMM 2A23 data product [47]. This algorithm classifies PR data into two categories using both vertical profiles of radar reflectivity (from which the brightband, echo top height, and maximum reflectivity in the vertical profile are identified) and the horizontal variability of echo. The algorithm also assigns certain radar echoes into "other" category which represents either noise or zero precipitation near the surface. For analysis, the present study examines only those data points which were flagged as "convective certain" and "stratiform certain." The data samples belonging to convective and stratiform classes were individually subjected to the bootstrap technique to retrieve the associated sampling uncertainty. The results are discussed for two chosen years (2006 and 2007), which showed typically higher and lower distributions of relative sampling errors [from Fig. 9(a)].

Fig. 10 shows the spatial distribution of accumulated rainfall and overall relative sampling errors obtained for 2006 and 2007. Fig. 11 shows the distribution of sampling uncertainty calculated for convective and stratiform rain types for each of these two years. For 2006, even though the median for both rainfall types was the same, significant differences were observed between their distributions. The prominent characteristics observed from the box plots in Fig. 11 are summarized in the following.

1) For 2006, the central 50% of relative sampling errors (region between the 25th and 75th quartiles) are located between 25% and 28% for convective rainfall and 20% and 30% for stratiform rainfall. However, for 2007, the central 50% of sampling uncertainty was observed to be nearly the same for both rainfall types (within 23%–27% for convective and 22%–28% for stratiform rainfall).
2) For 2006, from the location of the median (50th quartile), a greater number of convective data points are observed near to 25% (25th quartile). Whereas for the stratiform rain type, the median is slightly toward the 75th quartile, indicating that majority of the relative sampling errors will be found near to 30% (75th quartile). This tendency can also be observed for 2007, wherein the median is biased toward the 25th quartile for convective and 75th quartile for the stratiform rainfall type.
3) The range of sampling uncertainty (i.e., minimum and maximum values indicated by the whiskers of the box plot) was found to be greater for the stratiform rainfall type during 2006. However, for 2007, the ranges of errors were observed to be nearly the same for both rainfall types.

Based on the aforementioned observations, it can be concluded that the relative sampling error of stratiform rainfall has a wider distribution, with a higher value for the 95th percentile when compared with the relative sampling error of convective rainfall. Overall, a compact (tight) distribution of relative sampling errors toward a lower range [for example years 2007, 2008, 2010, and 2011 from Fig. 9(a)] suggests that there is no significant difference in relative sampling errors offered by both rainfall types. Whereas a larger range of overall relative sampling error (as observed in Fig. 9(a) for 2006) indicates that overall sampling uncertainty will be dominated by the sampling uncertainty resulting due to stratiform rainfall. Among the total number of data points chosen for analysis, approximately 65% belonged to stratiform rainfall type, and the rest represented convective type. Even though stratiform rainfall is known to have low intensity and low variability in space, for the study region of the Mahanadi basin, the relative sampling errors of stratiform rainfall show a wider distribution in comparison with convective rainfall. This behavior is in agreement with the power law relationship which quantitatively explains the dependence of relative sampling error with respect to mean rainfall rate [18]. The power law relationship indicates that an increase in relative sampling error with decreasing average rainfall rate is plausible. This relationship has interesting implications, which suggests that some geographical locations have more rainfall than others mainly because rain events occur more frequently in those areas and not necessarily because the intensity or coverage of individual events are greater [29]. However, further conclusions based on this behavior can only be provided after thorough examination which will be undertaken as part of future studies. The averages of satellite-retrieved rainfall rates are known to be subjected to bias dependent on the type of rain or some characteristic that changes slowly in space/time (e.g., the relative amount of area covered by convective and stratiform rainfall). Based on the aforementioned discussions, it can be concluded that the intensity of rainfall is not the sole factor controlling relative sampling error estimates. Rainfall type, sample number corresponding to each rainfall type, area covered by each rainfall type, etc., all play crucial roles in estimating sampling uncertainty.

D. Effect of LHS on Relative Sampling Error

A broader assessment of PR sampling uncertainty warrants the investigation of computationally more efficient sampling schemes having potentially greater flexibility in simulating satellite relative sampling errors. LHS, also known as stratified Monte Carlo sampling method, is a technique that offers promise in reducing the computational burden using fewer runs [48], [49]. LHS has found application in a wide variety of uncertainty assessment problems pertaining to hydrological and environmental modeling. For further details about the LHS technique, the reader is referred to McKay *et al.* [48], Iman and Shortencarier [50], Stein [51], and Isukapalli and Georgoopulos [52]. The specific question that the present study seeks to answer is the following: *Is it possible to infer similar sampling uncertainty in PR rainfall using LHS scheme as those derived with bootstrap sampling but with fewer simulations*? Using LHS, we try to explore the parameter space completely by stratification and with as few samples as possible. Let N and R be two variables representing PR counts and mean rainfall rate falling within each grid box over the study region. Then, LHS involves dividing the cumulative distribution of each variable into a number of equally probable nonoverlapping intervals (bins), as shown in Fig. 12. A value is selected at random from each interval. In LHS, the values obtained for each variable are paired randomly with the other variable.

From Fig. 13, it can be seen that relative sampling errors estimated using the LHS sampling technique are similar to those

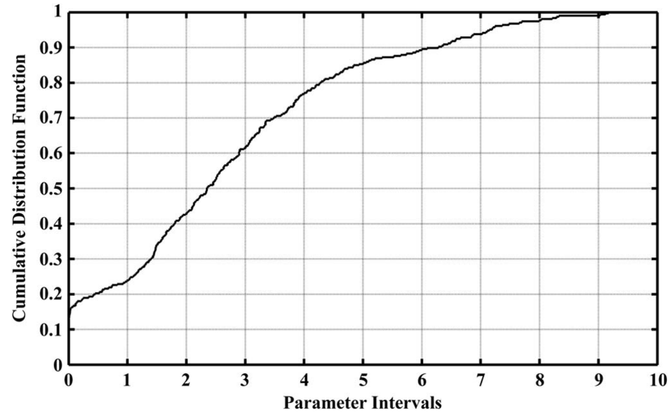


Fig. 12. Intervals used for LHS sampling showing division of a hypothetical cumulative distribution function for a nonuniform random variable (N or R) into 10 intervals [the value of the parameter within each interval changes according to the variable considered (N or R)].

from bootstrap sampling. The correlation between bootstrap and LHS results are high, indicating that a linear relationship between both methods explains more than 65% of the variance of the uncertainty estimates. Also, results from LHS were obtained in comparatively lower number of simulation runs (20 simulation runs) as compared with the bootstrap resampling technique which used 1000 simulations. Further examination reveals that the LHS sampling technique tends to slightly overestimate the relative sampling error values. This tendency might be owing to the difficulty in correctly estimating the optimum number of samples required for convergence of distribution on the mean of the cumulative density function generated. However, the slight overestimation in relative sampling errors by LHS needs to be assessed pertaining to PR orbital data products before any clear conclusion can be drawn of its significance. At this stage, it is appropriate to highlight that, even though LHS is more efficient computationally, there exist circumstances when a good performance may not be obtained, which may result in overestimation of errors. Whether this tendency arises due to the limitation of the LHS technique or type of PR data samples encountered or due to the low number of simulations or a combination of any/all of them remains an open-ended question. An answer to this question in future research endeavors will have a wider implication to the usefulness of the LHS technique for studies pertaining to sampling uncertainty.

IV. Summary and Conclusion

Issues related to sampling uncertainty are of major importance for establishing error characterization and for the improvement of satellite rainfall retrieval algorithms. In this paper, the authors have implemented a statistical bootstrap technique [32] to estimate relative sampling errors of TRMM PR over the Indian subcontinent. This approach calculates relative sampling errors using the PR data themselves instead of relying on *in situ* validation data. Results were shown for the seasonal rainfall over an 11-year (2002–2012) data period. Characteristics of relative sampling errors within 2° grid boxes over the Indian subcontinent reveal comparatively greater

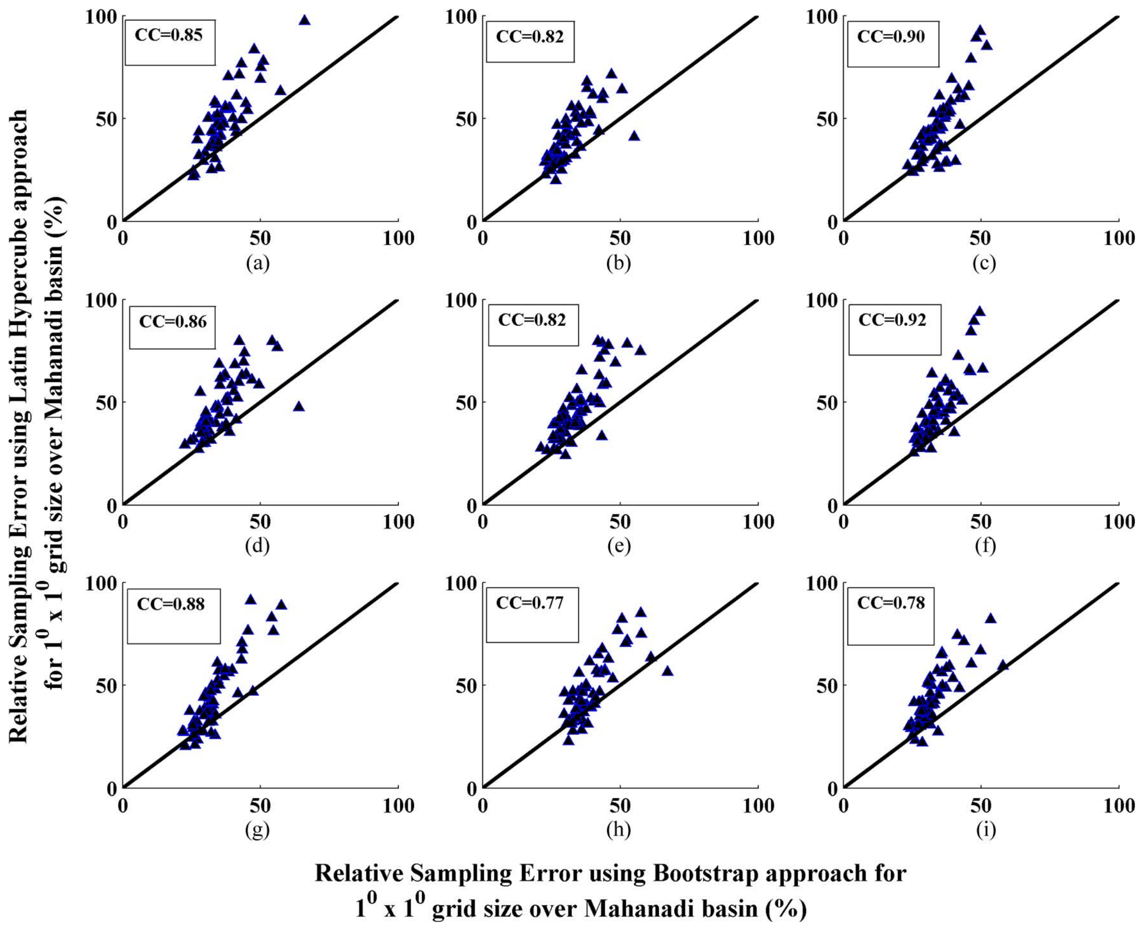


Fig. 13. Scatter plots showing the sampling errors estimated using the bootstrap approach versus that estimated using the LHS technique for (a) 2002, (b) 2003, (c) 2004, (d) 2005, (e) 2006, (f) 2007, (g) 2008, (h) 2009, and (i) 2010 [in the aforementioned figure, CC denotes correlation coefficient, and the continuous line (——) denotes one-to-one line].

relative sampling errors for land regions than for the adjoining oceanic regions. In addition, the value of sampling uncertainty was found to be smaller for areas with larger seasonal rainfall amounts and vice versa. This tendency was in agreement with the predictions by Bell and Kundu [29]. However, some regions showed discrepancies between the estimated relative sampling errors and the predictions by Bell and Kundu [29]. This discrepancy might be attributed to the difference in rainfall variability and space–time correlation length of point rainfall over these regions [29]. Furthermore, results obtained for the Indian subcontinent verified the power law scaling characteristics of sampling uncertainty with respect to seasonal rainfall averages within 2° grid boxes. The approach also revealed comparatively lower relative sampling errors over the eastern coast of India. This suggests that the bootstrap technique can be extended for higher resolution grid sizes over the eastern parts of India.

The present study examined the applicability of the bootstrap technique over a hydrological catchment of the Mahanadi basin situated along the eastern coast of India. Scale dependence studies for 4 grid sizes using a seasonal time scale yielded 1° grid size to be suitable for further studies over the basin, as it resulted in comparatively lower relative sampling errors. Authors conducted comparative evaluation of sampling uncertainty owing to difference in rainfall types. Results indicate that an increase in overall relative sampling error can be attributed to the increased occurrence of stratiform rainfall type over the study region. Retrieval of sampling uncertainty using LHS was shown to have implications for wide-scale assessment of satellite rainfall retrievals for hydrological model applications. It can be concluded that the bootstrap technique can be successfully implemented to map PR sampling uncertainty for 1° grid sizes over the study region. The bootstrap technique has great potential in decision making before incorporating PR orbital data products for hydrologic modeling over regions. The present work can also be adopted for studies employing similar microwave sensors like GPM, Megha Tropiques, etc.

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J. Indu received the B.Tech. degree in civil engineering from Mar Athanasius College of Engineering, Kerala, India, in 2004 with university third rank and the M.Tech. degree in geoinformatics from the Indian Institute of Technology Kanpur (I.I.T Kanpur), Uttar Pradesh, India, in 2008. She is currently working toward the Ph.D. degree in the Department of Civil Engineering, Indian Institute of Science, Bangalore, India.

Her current research interests include microwave remote sensing, uncertainty modeling, and nowcasting of precipitation.

D. Nagesh Kumar received the Ph.D. degree from the Department of Civil Engineering, Indian Institute of Science, Bangalore, India, in 1992.

He was a Boyscast Fellow with the Utah Water Research Laboratory, Utah State University, Logan, UT, USA, in 1999. He has been a Professor with the Department of Civil Engineering, Indian Institute of Science, since May 2002. Earlier, he was with the Indian Institute of Technology, Kharagpur, India, and National Remote Sensing Centre, Hyderabad, India. He is the coauthor of two text books entitled *Multicriterion Analysis in Engineering and Management* (New Delhi: PHI) and *Floods in a Changing Climate: Hydrologic Modeling* (U.K.: Cambridge University Press). His research interests include climate hydrology, climate change, water resource systems, ANN, evolutionary algorithms, fuzzy logic, MCDM, and remote sensing and GIS applications in water resource engineering.