Oceanic Rainfall Estimation: Sampling Studies of the Fractional-Time-in-Rain Method

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ABSTRACT

The relationship between monthly mean area-averaged rainfall and monthly mean fractional rainfall occurrence is used to develop a new method of open ocean rainfall estimation. This method uses acoustic sensors attached to drifting buoys to sample rainfall occurrence in space and time. The fractional rainfall occurrences measured by the sensors are used in a linear relationship to estimate monthly rainfall averaged over large (i.e., 2.5° × 2.5°) areas. This estimation method is tested for different scenarios using a stochastic model. Results support the feasibility of this new rainfall estimation scheme. Simulations show that the existing density of drifting buoys is inadequate, but densities around 10 times the existing density will give correlation coefficients between estimated and true rainfall around 0.55. Estimates obtained with this method may be used to calibrate and/or validate the satellite-based methods of open ocean rainfall.

1. Introduction

A great deal of attention has been devoted to the problem of tropical rainfall estimation. Tropical convective precipitation is an important process to understand because the large amount of latent heat released in the process is a critical component of the general circulation of the atmosphere. Accurate estimates of rainfall amounts in the Tropics averaged over large spatial scales (i.e., 2.5° × 2.5°) and long timescales (i.e., one month) would be helpful to general circulation modeling efforts. Since much of the Tropics is covered by ocean, it is difficult to monitor tropical rainfall because rainfall cannot be measured over the ocean using conventional earthbound monitoring systems (Bell et al. 1990).

Oceanic rain gauge networks are limited primarily to atolls and islands. Unfortunately, orographic effects near many islands create rainfall amounts that differ from open ocean conditions. Optical rain gauges are mounted on six TOGA moorings along the equator in the western Pacific, but the cost of a network of these moorings dense enough to provide good area-averaged estimates over large areas would be significant (Morrissey et al. 1994). Satellite-based remote sensing is the only currently available method of obtaining estimates of large-scale convective precipitation over ocean on a regular long-term basis (Arkin and Meisner 1987).

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To increase the effectiveness of current satellite-based methods, new methods should be developed to calibrate the relationship between area-averaged rainfall rates and satellite data. The objective of this study is to formulate and test (by numerical simulation) a new rainfall estimation method, using in-situ sensors, that is more efficient and economical than existing methods. This method is based on sensors that monitor rainfall occurrence and uses the linear relationship between rainfall and fractional rainfall occurrence for large space and time scales. The accuracy of this linear method depends upon the length and frequency of rainfall occurrence sampling, and these sampling issues are investigated. This method could be used in the calibration and validation of open ocean rainfall estimation methods using satellite observations of cloud-top temperatures. The objective of this study is to test, via simulations, whether the linear method can produce relatively accurate monthly area-averaged rainfall estimates using realistic arrangements of sensors.

This paper will first describe the theoretical basis of the linear estimation methods. The stochastic rainfall model used in the study will then be explained. A detailed description of the estimation algorithm will be given, followed by the methodology used to test the algorithm. Results of the simulations will be presented, followed by a discussion and summary of the results.

2. The fractional-time-in-rain method

The relationship between the accumulated rainfall over a period of time and the fraction of the time rainfall occurs in the period (FTR) is a new concept. Krajewski

(1993) first investigated the relationship inspired by methods used in the spatial domain for radar and satellite rainfall estimation (Arkin 1979; Atlas et al. 1990; Rosenfeld et al. 1990; Krajewski et al. 1992). He found that high correlation exists between fractional time in rain over a month and mean monthly rainfall if the sampling of rainfall occurrence is sufficient. The sampling depends upon the temporal resolution and precision of the sensor. Morrissey et al. (1994) investigated the relationship using data from the TOGA buoys.

The derivation of the linear relationship in time by Morrissey et al. (1994) is given below. This derivation is similar to the derivation of the linear relationship between area-averaged rainfall and the fraction of the area with rain (Kedem et al. 1990).

Define R as the accumulated rainfall over a time T and $\langle [r(t) | r(t) > 0] \rangle$ as the temporal average over T of the instantaneous rain rate $r(t)$, conditional on rain occurrence at time t. Then,

$$R = \mathrm{FTR} \langle [r(t) | r(t) > 0] \rangle \, T. \tag{1}$$

The FTR is equal to the average of an indicator variable I over T, or

$$\mathrm{FTR} = \langle I[r(t) > 0] \rangle, \tag{2}$$

where I is defined by

$$I(r > 0) = \begin{cases} 1, & r > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Morrissey et al. (1994) point out that when rain gauge data are used, $I[r(t) > 0]$ is approximated by $I[r_s(t_i) > 0]$, where $r_s(t_i)$ is the rain rate averaged over the accumulation time t_a represented by a single measurement assigned to interval t_i and is defined by

$$r_s(t_i) = \frac{1}{t_a} \int^{t_a} r(t) \, dt. \tag{4}$$

Using $r_s(t_i)$, the FTR within accumulation period T (e.g., one month) is equal to

$$\mathrm{FTR} = \frac{1}{N} \sum_{t_i=1}^{N} I[r_s(t_i) > 0] P[r(t) > 0 | r_s(t_i) > 0], \tag{5}$$

where $P[r(t) > 0 | r_s(t_i) > 0]$ is the average fraction of r_s that is raining when $r_s > 0$. In practice, when there are N measurement periods within T, FTR is estimated by

$$\mathrm{FTR} = \frac{1}{N} \sum_{t_i=1}^{N} I[r_s(t_i) > 0]. \tag{6}$$

Comparing the two equations, the actual FTR is equal to the estimated FTR multiplied by $P[r(t) > 0 | r_s(t_i) > 0]$. As t_a approaches 0 (i.e., $r_s = r$), $P(r > 0 | r_s > 0)$ approaches 1 and the estimated FTR approaches the actual FTR. As t_a is increased, $P(r > 0 | r_s > 0)$ decreases and the bias increases. The slope of the linear relationship between accumulated rainfall and FTR decreases because the estimated FTR increases for the same accumulated rainfall value. Morrissey et al. (1994) also supported the hypothesis that this bias causes a nonlinear relationship between accumulated rainfall and FTR.

The accuracy of the method therefore depends upon the two products in (1), FTR and $\langle [r(t) | r(t) > 0] \rangle$. Morrissey et al. (1994) showed that FTR becomes accurate as t_a approaches 0. This theoretical scenario requires a rainfall sensor with the ability to measure an infinitely small rainfall accumulation. It was also shown by the law of large numbers that $\langle (r | r > 0) \rangle$ becomes more stable as T increases. The period of $T = 1$ month was chosen as a sufficient period of time for the standard deviation of $\langle (r | r > 0) \rangle$ to stabilize (Morrissey et al. 1994).

One possible method of FTR estimation is the use of underwater acoustic rainfall sensor. An acoustic rainfall sensor measures the acoustic signal of bubbles resulting from raindrop impact on the ocean surface. The acoustic signal produced by rainfall can be distinguished from signals of other phenomena such as ocean spray (Nystuen 1986). An acoustic sensor can detect the impact of raindrops on the ocean surface, so it can record whether or not there is rainfall at a given time, recording a ‘‘yes’’ or ‘‘no’’ for that time. FTR could be estimated from the acoustic rainfall occurrence data.

Figure 1 shows examples of the linear relationship between the monthly mean rainfall rate and the fractional time in rain at a rain gauge located on the Kwajelein atoll in the equatorial western Pacific. Note that the correlation coefficient increases as the temporal resolution of the data increases. This points to the importance of estimating the fractional time in rain with high accuracy, that is, from high temporal resolution observations. This issue was studied using 15-min data by Lin (1993), who estimated that for data with resolution of about 1 min, the correlation coefficient of the linear relationship can be as high as 0.98.

The objective of this study is to extend the linear relationship from application at points in space to large spatial areas. To investigate the use of the linear relationship for rainfall averaged in space and time, the stochastic open ocean rainfall model created by Bell (1987) was used.

3. Bell’s stochastic oceanic precipitation model

One comprehensive data collection mission was the GATE [GARP (Global Atmospheric Research Program) Atlantic Tropical Experiment] experiment. During the GATE experiment, detailed measurements from rain gauges and radars were made over an area covering a 400-km-diameter hexagon centered on 8°30′N, 23°30′W off the west coast of Africa (Nakamoto et al. 1990). Bell (1987) used the data from the GATE experiment to create a model that produces random spatial rainfall patterns with spatial and temporal distributions similar to the GATE data. The model has been used in

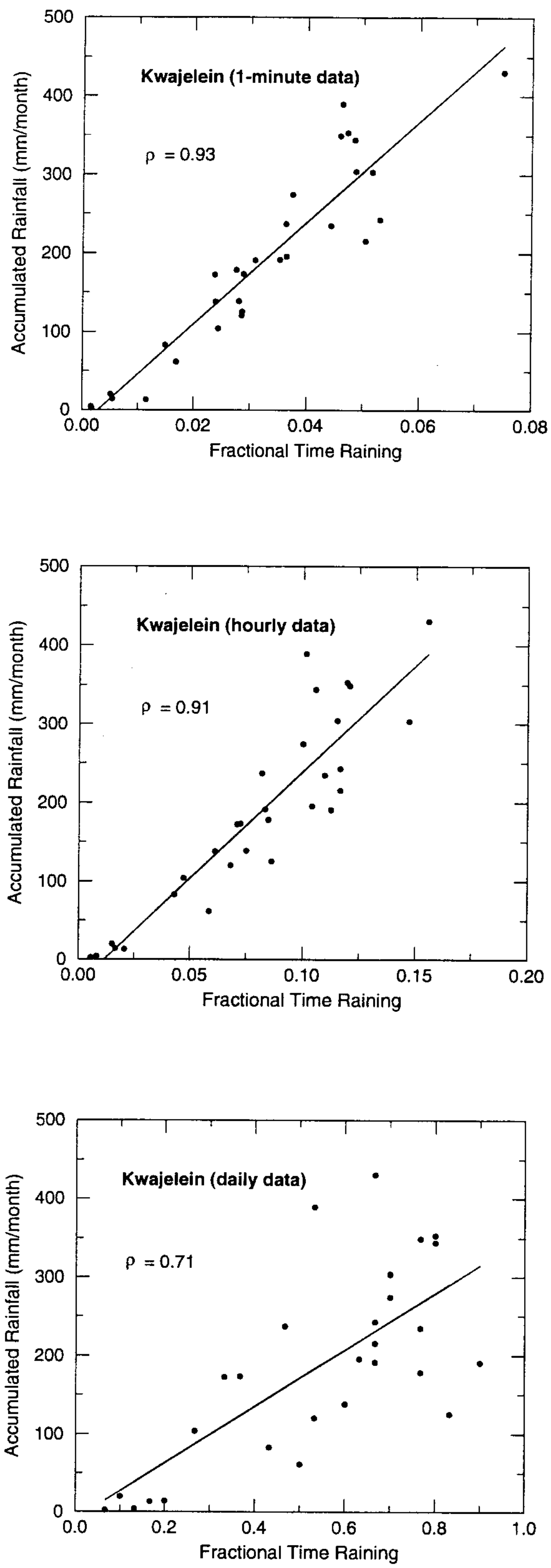

FIG. 1. A comparison of monthly rainfall accumulations with the fractional time raining as estimated using 1-min data (top), hourly data (middle), and daily data (bottom).

sampling studies of oceanic rainfall in support of the Tropical Rainfall Measuring Mission (TRMM) to be launched in 1997 (Simpson et al. 1988).

The model has the following characteristics. Rainfall rates are defined on a grid of 4 km × 4 km boxes such that the rainfall rate is constant over each box. On average, it rains at any one grid point a specified fraction f of the time. When it rains, the rain rate has a lognormal probability distribution with specified parameters. The rain fields are spatially homogeneous and isotropic, and the spatial correlation between any two grid boxes is prescribed. Area-averaged rainfall has time-lagged autocorrelations that depend on the size of the area, such that larger areas have longer correlation times. To summarize, rainfall is generated in the model from the portion of a correlated Gaussian random field that exceeds a threshold corresponding to the specified probability of rainfall. The portion of the field above the threshold is rescaled to have a lognormal probability distribution (Bell 1987).

The GATE data were analyzed by Bell et al. (1990) to determine more accurate parameters for the model. The fraction of time it rains at any point was determined from the data, as were the mean and standard deviation of the logarithm of nonzero rain rates. Figure 3 of Bell et al. (1990) shows correlation of rain rate versus separation distance of GATE rainfall. The correlation distance (the distance at which the correlation is $1/e$) from this plot is around 15 km and the correlation decreases to a value close to zero at 200 km. Figure 6 of Bell et al. (1990) displays the correlation times of GATE rainfall as a function of averaging area. This plot shows correlation times of around 1 h for an area 4 km on a side and about 7.7 h for the GATE area, 280 km on a side. These figures also show that the model fits the GATE data quite well.

4. The proposed rainfall estimation method

In this proposed method, monthly rainfall for the climatologically significant 2.5° × 2.5° grid is estimated from the average fractional time in rain. The estimate of fractional rainfall occurrence is made from acoustic sensors mounted on drifting buoys. The study proposes the use of sparsely spaced moored rain gauges to determine the slope of the linear relationship between monthly area-averaged rainfall rate and average fractional time in rain detected by the rainfall sensors. This slope would be indicative of the average conditional rainfall intensity of the area around the moored buoy.

An important requirement is that the time resolution of the rain gauge be matched to the resolution of the acoustic sensor data collection scheme. For example, moored optical rain gauges can operate over a wide range of resolutions. This would be beneficial because very high time resolution (1 min) data were shown to result in correlation coefficients as high as 0.99 for the linear relationship (Morrissey et al. 1994). The rainfall sensors proposed in this method also would have high temporal resolution.

A rainfall sensor will result in an accurate estimate of the mean rainfall rate at the sensor's location if the average conditional rainfall intensity at the sensor remains the same as the value at the moored rain gauge at which the slope was determined. If this average conditional rainfall intensity is found to change over a certain distance another moored rain gauge would be installed to provide values of the slope for drifting buoys in the vicinity of the moored rain gauge. The variability in average conditional rainfall intensity over oceans is known to be much less than that over land (Morrissey et al. 1994; Petty 1995). This means that a single moored rain gauge could provide the slope for the drifting rainfall sensors over a large area of constant mean conditional rainfall intensity surrounding the moored rain gauge.

It was shown in Morrissey et al. (1994) that the rainfall frequency at a point can give a very good estimate of the accumulated rainfall at the point. The accuracy of the space–time rainfall estimate, which is the goal of this estimation method, depends upon the spatial and temporal sampling by the sensors. It is unknown whether the estimate of space–time rainfall frequency provided by a network of sensors is sufficient to be used in a linear relationship to produce rainfall estimates for a domain (such as $2.5° \times 2.5°$) much larger than the small areas for which the sensors can determine rainfall occurrence. The accuracy will depend upon the correlation distance of the oceanic rainfall. If it is large enough, an isolated sensor could provide much more spatial information than rainfall occurrence only at the sensor's location.

Note that the above concept requires that the sensor used for the fractional time in rain determination only detects rain and does not measure its intensity or accumulation. An underwater acoustic noise detector is an example of such a sensor (Nystuen 1986). Underwater acoustic rainfall sensors are not as costly as conventional rain gauges due to the less complicated technology of the sensors. Satellite-tracked buoys carrying the measurement devices could be allowed to drift throughout the ocean (Sombardier 1994), an arrangement that costs less than moored buoys and increases the extent of spatial sampling. An objective of this study is to test if these money-saving strategies can be used in an accurate estimation scheme. If the space–time estimates produced by these sensors are accurate, they could provide a useful tool for 1) calibration of satellite-based rainfall estimation procedures over oceans, and 2) validation of satellite estimates.

5. Methodology

An analysis of the linear relationship was performed with the results of Bell's (1987) stochastic open ocean rainfall model. The model output consists of instantaneous rainfall rates at 15-min intervals for a 256×256 grid. Thirty consecutive months of oceanic precipitation were simulated for different scenarios. To verify whether the model reproduces the linear relationship at a point, grid squares were randomly chosen, and for each one the rainfall rate during each simulated 15-min interval was recorded. The number of observations exceeding different thresholds was divided by the total number of observations in a month (2880 observations) to obtain the monthly fractional time in rain for the grid point. The 2880 rainfall rates were averaged to obtain the monthly average rainfall rate for the grid point. The monthly average rainfall rate was plotted against the monthly fractional time in rain and the linear correlation coefficient was calculated. The results (not shown) show similar statistics for the different randomly chosen grid squares, which was expected due to the spatial homogeneity of Bell's model. These preliminary simulations also verified the linear relationship for isolated grid squares.

After testing the linear relationship for isolated grid points, the linear relationship between spatially and temporally averaged simulated rainfall and fractional time in rain detected by simulated stationary sensors in the area was tested. Specified numbers of sensors were randomly placed at points throughout the simulated grid of specified size (subareas of the simulated 1024 km $\times$ 1024 km grid were used for the smaller areas). For each simulated month, the fractional times of rain for all the sensors were averaged and the average rainfall rate for the entire grid was recorded. Thirty months of simulation resulted in 30 points for the analysis of monthly mean area-averaged precipitation versus fractional time in rain averaged in space and time. The linear correlation coefficients were calculated from the data.

The random effect of sensor location was reduced by simulating 30 randomly chosen groups of sensors. For each group, the relation between rainfall and fractional rainfall occurrence was calculated for subgroups containing 1–50 sensors. The average correlation coefficient from the 30 groups was calculated for each number of sensors to determine the relationship between number of sensors and correlation coefficient for areas of different sizes.

The method was extended to simulate sensors mounted on buoys drifting across the grid. At each simulated 15-min interval, the occurrence of rain was checked for the grid squares containing the sensors. The number of sensors on the grid was kept constant for each time interval, which resulted in the same number of measurements each interval. When one sensor left the grid, another was randomly placed on the grid border with a random inward direction. The correlation coefficient of the linear relationship between rainfall and fractional rainfall occurrence was determined for different groups of simulated sensors. Similarly to the plot using stationary sensor data, the relationship between the mean linear correlation coefficient from 30 groups and the

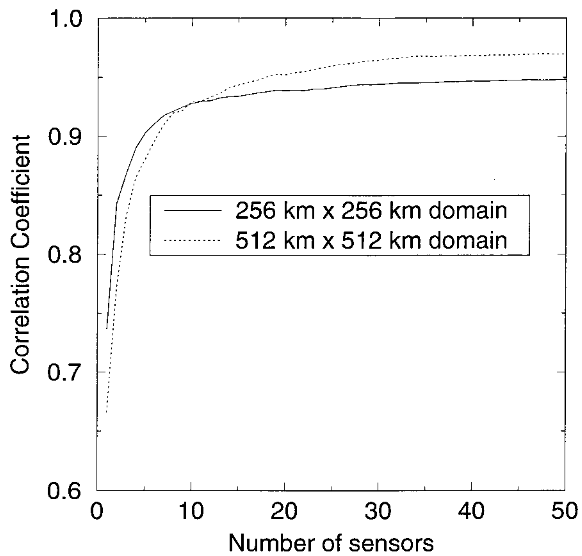

FIG. 2. Variation of mean correlation coefficient for stationary sensors.

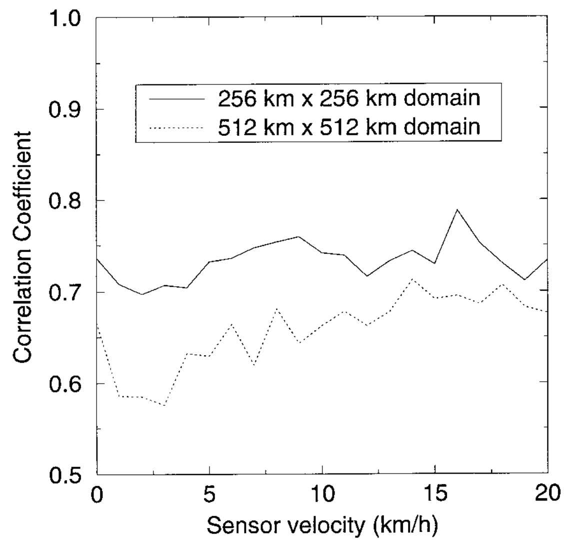

FIG. 3. Variation of mean correlation coefficient with velocity for one sensor.

number of sensors in a given area was determined. Different velocities were simulated to investigate the effect of the buoy velocity on the correlation coefficient.

After testing the linear method for different hypothetical situations, more realistic situations were simulated using buoy densities determined from buoy position data of the tropical Pacific. A major difference from the previous simulations is that using realistic scenarios, it is possible to have times with no sensors in a domain. Thus, domains could have measurements for only part of the month or even no measurements for the entire month. Buoy densities relative to the existing buoy densities were also tested.

Figures 2 and 3 show the results of the proposed linear relationship in the space–time domain. The figures show the mean correlation coefficient from 30 plots of monthly mean area-averaged rain rate versus fractional rainfall occurrence over a threshold averaged in space and time for a given grid size, number of sensors, and sensor velocity. The fractional time in rain data is from simulated sensors randomly placed throughout the grid. A "yes" reading in the determination of fractional rainfall occurrence is given if the instantaneous rainfall rate (observed every 15 min) for the grid box containing the sensor exceeds a threshold rate specified at 0.1 mm h^{-1}. This threshold was chosen as a conservatively low estimate of the rate above which an acoustic rainfall sensor could distinguish rainfall from other phenomena, such as ocean spray, producing acoustic signals. For each grid size, number of sensors, and sensor velocity, the mean correlation coefficient from 30 different sets of randomly placed sensors was calculated. The averages of 30 different sets were used in an attempt to eliminate the random effect of sensor location within the grid.

The effects of three variables upon the correlation coefficient were tested. One variable was the size of the domain over which the mean rainfall and rainfall occurrence were averaged. This variable was tested to give an idea of the size of the area for which the estimation method is effective. This size should depend upon the number of sensors in the area. The accuracy of this method should increase with the number of sensors, because more sensors should give a better estimate of the fractional rain area above a threshold. Finally, the sensor velocity was investigated to determine whether higher velocities result in higher correlation coefficient due to the greater extent of spatial sampling achieved by sensors with higher velocities. Based on the empirical spatial (temporal) decorrelation lengths (times) used in the model, it was difficult to predict whether moving buoys would give significantly better sampling and a higher correlation coefficient.

6. Results of preliminary simulations

Figure 2 is from data produced by stationary simulated sensors randomly placed throughout domains of different sizes. In Fig. 2, the correlation coefficient becomes insensitive to the addition of more sensors when the number of sensors is high enough. This implies the area is sufficiently sampled. For just one stationary sensor, the highest correlations are from the smallest grid size, an intuitively reasonable concept. When many sensors are used, the highest correlations result from the largest grids. The reason for this is not as intuitive.

For large numbers of sensors, the correlation coefficients for the large grids were highest because of a fundamental concept behind using a linear relationship to estimate rainfall. The relationship between area-averaged rainfall and fractional rain area becomes more linear (the correlation coefficient increases) as the sample size used to create the two averages increases. For the larger grids, the correlation coefficients are higher because there are more independent rainfall samples given the same number of sensors. The inherent linear relationship between average rain and the probability of its occurrence can be determined empirically if rainfall variability is well sampled. For a mathematical explanation, see Kedem et al. (1990).

Figure 3 shows data from one simulated sensor in grids of different sizes. For the smallest grid, the correlation coefficient is not influenced by an increase in sensor velocity. This suggests that one sensor with negligible velocity could sample the area as well as if it were moving through the area. For the larger grid it appears that a higher sensor velocity may lead to an increase in ρ. For the larger area, the increased velocity might provide for better sampling and a higher correlation coefficient. However, the sensor velocity effect is not very strong for the larger grid, so it is assumed that the time–space sampling issue can be reduced to the question of number of sensors within given domains.

The preliminary results were encouraging because the correlation coefficient is greater than 0.55 for all scenarios investigated and increases quickly to around 0.95 as sensors are added. The correlation coefficient may be systematically lower in reality due to approximations in using the model. However, when compared to results of the rainfall estimation algorithm study reported in Arkin and Xie (1994), the results show that the correlation coefficient obtained using feasible (small numbers of sensors with small velocities) scenarios is high enough to be beneficial to oceanic rainfall studies.

7. Results of simulations using realistic parameters

The results of the previous section provide insight into the effects of domain size, number of sensors in the domain, and sensor velocity upon the correlation coefficient between space–time rainfall and space–time fractional rainfall frequency. Considering the results, it is important to test the method with realistic parameters determined from drifting buoy data. Drifting buoy data from 1 June 1993 through 30 April 1994 for the tropical Pacific Ocean (Sombardier 1994) were obtained from the Marine Environmental Data Service (MEDS) of Canada, and the statistics of the buoys around the TOGA array were determined from this dataset.

Spatial domains of two different sizes, similar to those in the previous section, were analyzed: 2.5° × 2.5° and 5° × 5°. Figure 4 shows the area of study divided into 2.5° × 2.5° domains. The locations of five TOGA moored rain gauges are indicated in the figure. The locations of the buoys in the area for the month of June are shown in Fig. 4.

The most important characteristic of the buoy data needed for the simulations is the density of buoys within a domain of specified size. The simulation in the previous section always had at least one buoy in the domain

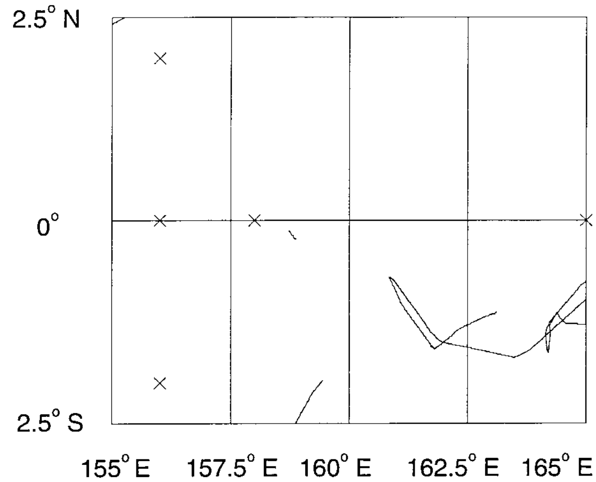

FIG. 4. Buoy paths from 1 to 30 June 1993.

for each time step. In reality, there are months and domains without any buoys, and even more often there is only partial coverage of a month. The buoy data were analyzed to obtain statistics that could be used in simulations to gain understanding into the number of buoys (relative to the current number) needed to make this rainfall estimation method effective.

The probability of a buoy entering a domain of specified size in any month and the distribution of the length of time a buoy spends in the domain were two statistics taken from the buoy data. These statistics were found for each 2.5° × 2.5° grid box in the area of study and the statistics were combined to determine the statistics used in the simulations. The velocity distribution was examined and 1 km h^{-1} was chosen as a reasonable speed for the simulated buoys. The results of the previous section showed that for realistic drifter velocities (0–2 km h^{-1}) the sensor velocity does not affect the computed correlations. It was assumed that the issue of sensor velocity could be neglected and that one representative speed would be adequate.

For simplicity, the simulated buoys moved in straight-line paths, as in the simulations of the previous section. This approximation follows from the assumption that the effect of the position of the buoy within the domain is small compared to the importance of whether or not the buoy is in the domain. Thus, an actual buoy may move in a curved path, resulting in a longer residence time in one grid box (Fig. 4). The straight-line path eliminates this event in simulations, but the total duration in the grid box is the same, as explained in the following paragraph.

As in the previous section, buoys were placed onto the grid with a random, inward direction. This simplification was made due to the assumption regarding the position of the buoy within the domain. The arrival of buoys on the grid border was modeled as a Poisson process in time with mean time between arrivals equal to the time determined from the buoy data for each domain size. The residence time of the arriving buoy within the domain was taken from a distribution determined from the buoy data for each domain size. If the buoy left the domain before the end of its residence time, another buoy was immediately placed on the border. The buoy was immediately removed from the domain when its residence time ended. The probability of a buoy in the domain at the start of the simulation was taken from the buoy data, and the positions of initial buoys were randomly chosen. To lessen the dependence of the results on the random buoy placements, 30 random sets of simulated buoys were used on the same simulated rainfall grid.

Moving the drifter to a new location will change the statistics of rainfall collected by that drifter from those collected by a drifter following a curved path. However, this is a simplistic model used to simulate the most important feature of drifting buoys for this application: the number within the domain at any given time. It is assumed that the model simplifications have a negligible effect on the computed correlations.

For a $2.5° \times 2.5°$ domain, the average fraction of months with no buoys in the domain at any time was 0.71. This result shows the proposed linear estimation method could not be applied in this situation, because monthly estimates can only be made when there is a buoy in the domain at least part of the month. The linear estimation method uses the fractional rainfall occurrence measured from all the sensors in a grid box for a particular month. If there are no buoys in a grid box for an entire month, an estimate cannot be made for that month. The analysis of the buoy data shows more buoys are needed, because estimates would be unavailable 71% of the time with the density found from the MEDS dataset.

The simulations were run for a total duration of 60 months using the statistics obtained from the buoy data. The statistics from the 30 scenarios were averaged to summarize the results. The average fraction of months without a buoy in the domain was 0.54, and the average correlation coefficient from the plot of mean monthly rainfall rate versus mean monthly fractional rainfall occurrence was 0.29. In addition to the low correlation coefficient, an estimation could only be made 46% of the time, a number obviously too small for practical application of the method.

The simulations for the larger domains were also run for a duration of 60 months. From the buoy data using a $5° \times 5°$ domain, the mean fraction of months with no buoys in the domain was 0.43. This buoy density would also not be sufficient for estimation purposes. The mean fraction of months without buoys for the simulated data was 0.49 and the average correlation coefficient was 0.29.

Due to the small fraction of months producing rainfall estimates using the densities from the buoy data, a new scenario was simulated. The mean length of time between buoy arrivals and initial probabilities of the case of no buoys in the area were divided by 10, creating a scenario with 10 times the current number of buoys. This means that instead of eight buoys within the area of analysis during the 11-month period, in effect it was simulated that there were 80.

This considerably more dense buoy scenario led to better results. An average of 99% of the 60 simulated months for the $2.5° \times 2.5°$ domain had at least one sensor in the domain. The average correlation coefficient of the 30 groups for this domain was 0.56.

A similar simulation was performed to simulate 10 times the number of buoys for the $5° \times 5°$ domains. The average fraction of months without estimates was near 0 for the $5° \times 5°$ domain. Finally, the average correlation coefficient was 0.55. The results of these simulations suggest that if rainfall sensors were mounted on drifting buoys with a density 10 times the current number, much better estimates of monthly rainfall averaged over large areas could be made. These correlations of around 0.55 are less than those of the preliminary simulations due to the more realistic scenarios, but correlations in this range would still be useful for global climate modeling efforts.

8. Discussion

The objective of the simulations was to determine the effects of rainfall occurrence sampling upon the accuracy of monthly rainfall estimation using fractional time in rain. Bell's (1987) stochastic model was used to simulate open ocean rainfall. The correlation coefficient of the relationship between monthly mean area-averaged rainfall and average fractional time in rain was found for various sampling schemes over the simulated grid (Figs. 2 and 3).

The concept of a space–time linear relationship is a combination of the basic spatial and temporal relationships. The average rainfall over a large area for a period of time becomes a function of the fractional rainfall occurrence averaged in time and space. The stability of the conditional intensity is an important source of estimation error in this linear estimation method. Bell's model is calibrated with GATE data, so the simulated rainfall will be stationary in time with the rainfall regime found from the GATE data. A single rainfall regime has a characteristic conditional rainfall intensity, which is important for the accuracy of the linear estimation methods. Oceanic precipitation is also subject to seasonal effects, so this approximation of constant simulated rainfall regime should be taken into consideration.

In this open ocean rainfall estimation method, the areas of interest ($2.5° \times 2.5°$, $5° \times 5°$) are too large for isolated sensors to determine the occurrence of rain over the entire region, so the rain area is approximated by the data from the available sensors. The detection and sampling errors from the limited number of sensors are another estimation error source. Increasing the number of sensors increases the accuracy of the estimate of the fractional area. The fractional time in rain for the month becomes an average in time and space. The law of large numbers shows that the accuracy of this method should increase as the number of averaged observations is increased. The estimated time in rain for the entire region over a month approaches its expected value as the time interval between observations decreases and as the number of sensors increases. The results show that a limited number of sensors with measurements taken every 15 min may give relatively accurate estimates of the fractional time in rain averaged over space and time. This is due to the sufficiently long correlation distance of the simulated data. One practical conclusion from this study is that good estimates of monthly rainfall can be obtained from the TOGA array for the climatologically important grid of 2.5° × 2.5°.

Due to the stochastic nature of the model, the results of the simulations should be analyzed for their general trends, realizing that the correlation coefficient depends upon the approximations resulting from the use of this model. Four approximations used in the stochastic model should affect the computed correlation coefficient. One approximation, the assumed time resolution, should cause the value of ρ obtained from the simulated data to be lower than the ρ obtained from physical data. The time resolution of the simulated observations is 15 min, which should result in lower values of ρ than the 15-s resolution possible with actual acoustic sensors. This approximation was made to 1) save computational time and 2) to overcome the problem of the model inadequacy in simulation of small-scale variability of rainfall.

There are three model approximations that may result in an increased value of ρ. Bell's model produces rainfall values averaged over 4 km × 4 km grid squares. This approximation could improve the estimate of fractional rain area because the simulated sensor can detect rainfall with 100% accuracy for the entire 4 km × 4 km area, an unrealistic assumption. The sensor will detect rainfall over an area of ocean that depends on the depth of the sensor. Nystuen et al. (1993) found that 95% of the sound arriving at the hydrophone comes from an area roughly equal to πh^2 directly above the hydrophone, where h is the hydrophone depth. In this proposed method, the slope of the linear relationship is determined by moored rain gauges, which essentially detect rainfall occurrence at a point. So while the acoustic sensors have the ability to detect rainfall occurrence for large areas, the sensors for this study would be placed at relatively shallow depths so the area of rainfall occurrence would not be large and give a significantly positive bias to the fractional rainfall occurrence measurement. The area of detection is assumed to be small enough that the rain rate is constant over the area.

Another approximation is that the simulated rainfall fields are homogeneous and isotropic, characteristics that would improve linear estimation methods. Physical oceanic rainfall over the large areas considered in this study may not have these characteristics. If not, the linear methods may not be as accurate as in the simulations, because the accuracy of the linear methods depends on the stability of conditional rainfall intensity in space and time.

Possibly the most important approximation concerns the spatial correlation function of the simulated data. This function is important because the ability of an isolated sensor to produce estimates of the fractional rain area over large areas depends upon a large correlation distance. An empirical equation (7) was fit to the GATE data and used in the model (Bell et al. 1990). The largest area of GATE data used to fit the equation was 280 km × 280 km. The model was used to simulate events over areas as large as 512 km × 512 km, so extrapolations to this larger scale were made. Bell (1987) found that it was reasonable to extrapolate the empirical spatial correlation function to areas around 500 km on a side, but it was not ruled out that the actual spatial correlation could be smaller than that predicted by the equation for a separation this large. Thus, in the ocean, one sensor might not lead to the high correlations for larger areas found in the results of the simulations. For this reason, the results for larger scales should be interpreted with greater caution.

Another practical conclusion from this study is that the current density of the open ocean buoys, both moored and drifting, is not adequate for climatological rainfall estimation. Since installation of the moored buoys is very expensive, and the number of the drifting buoys required to improve rainfall simulation is perhaps too high, too, another solution is needed. We propose to design an inexpensive powered buoy equipped with a Global Positioning Indicator system that would remain in a given vicinity of the moored buoys. A relatively small number of such buoys equipped with an acoustic sensor for monitoring rainfall occurrence would be sufficient to provide much improved area-averaged monthly rainfall estimates. These sensors could drift for extended periods of time, only occasionally correcting their positions to remain in a given region. The moored buoys would serve to provide the parameters of the linear relationship between time in rain and monthly rainfall.

Thus, this study proposes two alternatives for using the fractional-time-in-rain method: 1) increasing the existing buoy density substantially, and 2) increasing the buoy density slightly but using the proposed motorized system to ensure that there are always a specified number of buoys in the area. Figures 2 and 3 show the potential for high correlations when the number of buoys in a domain is kept constant (alternative 2). A cost–benefit analysis is beyond the scope of this paper. However, this study shows the benefits of each of these two alternatives.

The approach would be used only over homogeneous regions in terms of rainfall regime. Such regions could be found from the satellite data, not necessarily the satellite-based estimates, but climatologically averaged brightness temperatures or other cloud ensemble characteristics.

9. Summary

A method was developed to use the linear relationship between rainfall accumulation and fractional rainfall occurrence for estimation of monthly open ocean rainfall averaged over large domains. In this method, the fractional rainfall occurrence data used to make the rainfall estimations is obtained by acoustic rainfall sensors mounted on drifting buoys. This method uses the average fractional time in rain detected by the sensors in an area during a month to estimate the mean area-averaged rainfall rate for the month. These estimates could then be used for calibration of satellite methods and later for validation of the satellite estimates.

A stochastic oceanic precipitation model previously calibrated to GATE data by Bell et al. (1990) was used to investigate this method of open ocean rainfall estimation. Different arrangements of buoys throughout a large ocean area were simulated. It was shown that there were physically realistic scenarios that showed high linear correlations between space–time rainfall and space–time rainfall frequency, supporting the possibility of open ocean rainfall estimation from acoustic sensor data.

Drifting buoy data from the tropical Pacific were analyzed to determine the present density of drifting buoys in an area of ocean surrounding the TOGA moored optical rain gauge array. Results of this study indicate that for monthly rainfall estimation, a network of drifting buoys mounted with acoustic rainfall sensors should be deployed with a density at least one order of magnitude greater than the current density of drifting buoys. The simulated results indicate that with a density of drifting buoys equal to the current density multiplied by 10, estimates of mean monthly area-averaged rainfall rate over $2.5° \times 2.5°$ domains could be made an average of 99% of the months. The computed correlation coefficient between the mean monthly area-averaged rainfall rate and fractional rainfall occurrence detected by the acoustic sensors in the area is around 0.55.

Approximations were necessary in using the model to simulate rainfall estimation by acoustic sensors mounted on drifting buoys in the ocean. Additional work could be done to analyze the effect of these approximations. The sensitivity of the results to the assumed spatial correlation function could be investigated. A point process model could be calibrated to oceanic precipitation to eliminate the approximation of uniform rainfall over a 4 km $\times$ 4 km domain. Another improvement to this scheme may be to take advantage of the information provided by acoustic sensors concerning rainfall intensity. The scheme of this study uses the acoustic sensors only for the determination of rainfall occurrence, so additional information about the rainfall intensity may improve the accuracy of this method.

There is a great deal of future work to be done in the validation of the calibration method described in this paper. This work was done as an initial proof that the proposed method may be used in practice. Based upon the results of this study, it would be beneficial to continue work in this area with the goal of developing improved open ocean rainfall estimation methods.

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