The relationship between half-hourly rainfall occurrence and daily rainfall

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Abstract

Application of satellite rainfall estimation techniques often necessitates an indexing approach in which rain occurrence is accumulated and used as an indicator of total rainfall. This paper describes a simulation to assess the extent to which half-hourly rain occurrence can be used to estimate daily rainfall in a two-month period of the rainfall season in the South African summer rainfall region. The results of the simulation showed that indexing is a valid approach, and that most of the information on daily rainfall totals is contained in rainfall occurrence. At a sampling frequency exceeding 75% (i.e. more than 36 times per day), 90% of variation in daily rainfall could be accounted for by an accumulated rain occurrence index (AROI). At a sampling frequency of 8 samples, equal to the available frequency of Meteosat imagery, for the time period of this study, up to 79% of daily rainfall variation could be accounted for by AROI. It is also shown that estimation accuracy is highly sensitive to rain-rate.

Introduction

Information on the accumulation and distribution of daily rainfall is a primary concern in all agricultural areas of the world (Barrett and Martin, 1981; Atlas and Thiele, 1982). Rainfall estimates are also necessary for various hydrological applications, e.g. evaluation of flood potential, and flood forecasting (McGinnis et al., 1980; Scofield and Spayd, 1984; Bonifacio, 1991). Moreover, measurement of rainfall has major scientific advantages (Griffith et al., 1978, Atlas and Thiele, 1982). Tropical convective precipitation is a major forcing mechanism of the general circulation of the atmosphere, because of the significantly large quantities of latent heat released. Precipitation is thus an important and sensitive indicator of various convective parameters, such that careful monitoring of rainfall variation improves the capability for diagnosis of the behaviour of the global climate system (Martin and Scherer, 1973; Arkin and Meisner, 1987; Turpeinen et al., 1987; Turpeinen, 1989; Janowiak, 1991; Jobard and Desbois, 1992). However, rainfall is extremely variable in space and time, particularly at smaller temporal and spatial scales (Wilheit et al., 1977; Theon, 1988) and the inadequacy of rain gauges for providing estimates of areal rainfall has been well documented (Collier, 1985; Lee et al., 1985; Dugdale and Milford., 1986; Flitcroft et al., 1986; Scofield and Spayd, 1984; Turpeinen, 1989; Seed and Austin, 1990; Bonifacio, 1991; Xie and Arkin, 1995). The use of satellite-based rainfall estimation in addressing the shortcomings of gauge-derived rainfall has also been well documented (Martin and Scherer, 1973; McGinnis et al., 1980; Farnsworth et al., 1984; Scofield, 1987; O'Sullivan et al., 1990; Bonifacio, 1991; Adler et al., 1993; Sandham, 1993; Petty, 1995). Various approaches to satellite rainfall estimation have been developed, such as the life history, cloud indexing, thresholding and statistical pattern recognition groups of approaches. The latter two are indexing approaches, relying on the separation of raining from non-raining areas, e.g. the area time integral (ATI) method of estimating the volume rainfall of individual storms by measuring the area of the radar echo exceeding a certain threshold (i.e. a no-rain threshold) over the life of the storm (Atlas et al., 1990).

This paper reports on an investigation of the validity of an indexing approach for satellite-based estimation of daily rainfall in a part of the summer rainfall region of Southern Africa.

Harrison (1984) showed that monthly rainfall in 2° x 2° rectangular areas in the Eastern and Western Free State could be described by the frequency of rain days alone. Taljaard and Steyn (1988) report similar findings for the catchment of the Vaal River. Rain day frequency is determined in turn by the frequency of passage of relevant rain-producing systems. These findings represent an indexing approach on a monthly temporal scale. The same indexing principle needs to be tested for the determination of daily totals from half-hourly indices of rainfall occurrence. In order to achieve this goal the following objectives were set:

- To simulate a rain-measuring satellite, sampling half-hourly rain at a number of rainfall stations/locations, with the assumption that rain/no-rain occurrence is always correctly estimated, i.e. a perfect rain detector. The occurrence of rain at a location is incremented to produce a rain occurrence index (ROI).
- To accumulate ROI over 24 h (AROI) and convert to a rainfall duration index (RDI), assuming that rainfall occurrence represents the frequency of half-hourly rainfall duration proportional to the frequency of sampling.
- To correlate AROI and RDI to 24 h gauge totals for corresponding stations, in order to show how well sampling of the rain field in terms of rainfall occurrence approximates the 24 h gauge total.

The results are then used to test the assumption that RDI values can adequately describe the depth of the 24h rainfall field. If successful, it lends credence to the use of satellite-derived

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rainfall occurrence and duration indices for the determination of rainfall fields. At maximum temporal resolution, i.e. all available half-hourly data, it will indicate how well Meteosat infrared imagery at a rate of 48 infrared images in 24 h can be expected to perform at best. At poorer temporal resolution, it provides an indication of the upper limit of accuracy to be expected from a satellite-based scheme in which the satellite temporal sampling frequency is low.

Materials and methods

All available half-hourly precipitation data for January and February 1989 were obtained from the South African Weather Bureau (SAWB). These data are mainly from the relatively dense network of approximately 170 automatic rain-gauges and weather stations (AWS) established in the area around Bethlehem in the Orange Free State for the needs of the National Precipitation Research Programme (NPRP). No Meteosat data were used since the conversion of half-hourly rainfall data to rainfall occurrence simulated satellite-derived occurrence indices.

The dates in Table 1 were selected for use in this study because of the occurrence of several relatively widespread rain events.

TABLE 1
DATES SELECTED FOR ANALYSIS

Calendar date*	Julian date
Jan 4 - 9	4 - 9
Jan 20 - 25	20 - 25
Jan 27 - 30	27 - 30
Feb 1 - 6	32 - 37
Feb 9 - 16	40 - 47
Feb 21 - 24	52 - 55
All wet spell days	
Jan 1 - Feb 28	1 - 59

(* Short periods represent wet spells)

Methodology of rainfall occurrence simulation

The simulation was applied to the total data set of all half-hourly measurements of rainfall for January and February 1989. All cases were used, i.e. maximal sampling with no exclusions. A variety of rainfall thresholds were used according to which all rainfall values below a particular threshold were regarded as no rain, and all other values as rain, i.e. a station scores 0 for no-rain and 1 for rain. This index is called the rain occurrence index (ROI). ROI was incremented per station for every rainfall accurrence for every day and named AROI (accumulated rain occurrence index). However, AROI reflects the actual number of occurrences per day (which vary between 0 and 48) and does not take into account the maximum possible number of observations (maximum 48/d). To normalise for the number of actual observations, AROI was multiplied by the quotient of 24 h to the number of observations. The result is referred to as RDI (rain duration index), because these values reflect the duration of rainfall in terms of both the actual rain occurrence and the number of observations. Thus:

$$RDI = \frac{24}{N} \times AROI$$

where

N = number of observations per day.

Simultaneously, rainfall totals were accumulated (TRAIN) for corresponding days and stations. Accumulated rainfall was then correlated to RDI, AROI and N.

The application of the simulation is ordered by the grouping of the data. The first group of data includes maximum temporal resolution of sampling, and the second group a reduced sampling frequency matching that of the Meteosat data, i.e. 8 images in 24 h. Both groups are subdivided into one group containing all 59 d of the dataset, and another group containing only the wet spell days.

The general research hypothesis, i.e. that rainfall occurrence in terms of indices is positively related to 24-h gauge totals was tested by means of the following hypothesis:

- H_0: There is no relation between AROI or RDI and TRAIN.
- H_1: There is a significant relation between AROI or RDI and TRAIN.

Results

Simulation at maximum sampling frequency

For these analyses all available data were used. It was observed that, with minimal exceptions, TRAIN correlated more strongly to AROI than to RDI. This was unexpected, and seems to indicate that the assumption governing the conversion of rainfall occurrence to rainfall duration is perhaps invalid. However, this does not affect the question under investigation, i.e. “Can rainfall total be adequately estimated by an indexing approach?” Consequently, all tables in this paper show ***r*** as the coefficient of correlation between TRAIN and AROI. The coefficient of determination (r^2) in all tables represents the fraction of variation in TRAIN explained by AROI.

Simulation using all available days

Simulation was performed using various rain-rate thresholds. Thresholds represent an inclusive upper limit of no-rain, e.g. 4.0 mm implies that all rain-rates lower than and including 4.0 mm are regarded as no-rain. Applying various rain-rates varied the number of 30 min intervals in which rain was measured. All references to rain-rates are to 30 min totals varying from 0 mm to 5 mm, and results are shown in Table 2.

These results show that relatively high rain-rates account for a large part of the daily rainfall, with best correlation coefficients at rain-rates of 2.0 mm. This implies that even when all cases of half-hourly totals of less than 3.0 mm are regarded as no-rain, the use of an index of rain occurrence can still explain almost 60% of variation in daily rainfall. This appears to be in general agreement with the finding of Weiss and Smith (1987), from CCOPE data (Co-operative Convective Precipitation Experiment), that whereas heavier rain events (rain-rate 10 mm/h) might constitute only 25% of cases, they contribute the majority (75%) of the total volumetric rainfall of a storm. The results are also confirmed for South Africa by the findings of Mittermaier and Terblanche (1997) and Mather et al. (1997) from National Precipitation Research Programme (NPRP) data where 25 to 40% of the total volume of rainfall is contributed by rain-rates up to and including 4 mm/h.

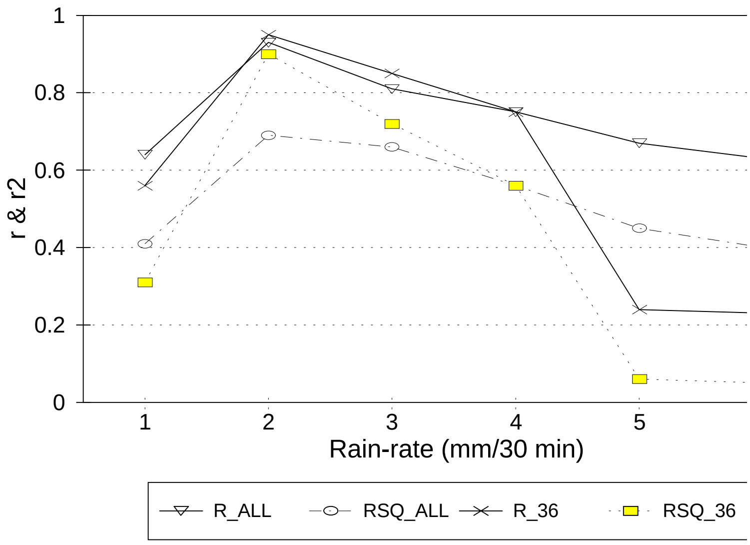
TABLE 2 TRAIN VS AROI, ALL AVAILABLE DAYS AT MAXIMUM SAMPLING FREQUENCY							
	Rain-rate threshold (<=mm/30min)						
Coefficients	**N**	**0.0**	**1.0**	**2.0**	**3.0**	**4.0**	**5.0**
r r^2	2352	0.64 0.41	0.66 0.44	0.82 0.67	0.77 0.59	0.70 0.49	0.66 0.44
N = sample size							

Simulation using wet spell days only

For this analysis only days on which significant rain had been measured were selected and subjected to analysis at a variety of thresholds. Figure 1 presents the results for the data set made up of the wet spell days.

The results for the wet spell days without a sampling frequency threshold are in general agreement with results for all days (Table 2).

The data were also tested for the effect of the number of observations by analysing only days having 36 or more observations, i.e. f $\geq$ 75%. The strength of the relationship is considerably improved, indicating the importance of a higher sampling frequency, with percentage variation explained increasing from 69% to 90%, but at a lower rain-rate. This indicates that higher rainfall totals are produced when rain occurs more frequently i.e. over prolonged periods, rather than more intensively.



r-ALL and r^2-ALL are values for all wet spell days
r-36 and r^2-36 are values for days with at least 36 observations

Figure 1
Simulation at maximum sampling frequency for wet spell days

Simulation at reduced temporal frequency

Simulation using all available days

Two data sets simulating a reduced sampling frequency were randomly generated, and are typical of the times and frequency of available Meteosat imagery for this study period. Times appear in Table 3. The data set was then reduced further by selecting only those days on which a certain minimum number of observations were made, i.e. observation frequency thresholds of 4, 6 and 8 observations per day. The reason for this reduction is because the available satellite data-set frequently provided fewer than 8 images per day, and with the exception of one day, never more than 8 images.

TABLE 3 SIMULATED OBSERVATION TIMES	
Data set A	**Data set B**
(GMT)	(GMT)
01:00	02:00
04:00	05:00
07:00	06:00
10:00	12:00
13:00	14:00
16:00	17:00
19:00	20:00
22:00	22:30

The observation frequency threshold values were selected because 4 observations necessitate the assumption that every index value must be extrapolated to represent a mean rain duration of 6 h, which is regarded as a poor frequency for effective temporal sampling of a quantity such as daily rainfall which is highly variable in both space and time. A frequency of 6 represents 4 h per index value, and also 75% of the maximum available data frequency. A value of 8 represents 3 h per index value, which was shown by O'Sullivan et al. (1990) to be a reasonable lower frequency limit for effective estimates. In addition, analysis using only 8 observations will indicate the best possible results to be expected from a satellite indexing scheme operating at 8 images per day, which was also the average

TABLE 4 TRAIN VS AROI AT REDUCED SAMPLING FREQUENCY FOR ALL AVAILABLE DATA									
			Rain-rate threshold (<=mm/30min)						
Data set	**MS**	**N**	**Coeff**	**0.0**	**1.0**	**2.0**	**3.0**	**4.0**	**5.0**
A	4	309	$\mathbf{r^2}$	0.28*	0.46*	0.37*	0.25*	0.11*	0.10*
	6	111	$\mathbf{r^2}$	0.10*	0.46*	0.42*	0.28*	0.10*	0.10*
	8	20	$\mathbf{r^2}$	0.13	0.79*	0.62*	0.40**	0.00	0.00
B	4	291	$\mathbf{r^2}$	0.28*	0.42*	0.18*	0.06*	0.02**	0.02**
	6	113	$\mathbf{r^2}$	0.16*	0.52*	0.22*	0.03	0.00	0.00
	8	20	$\mathbf{r^2}$	0.05	0.67*	0.30**	0.00	0.00	0.00

MS = minimum samples/d out of a possible maximum of 8
N = number of cases
Significance of r corresponding to $\mathbf{r^2}$
* significance level = 0.001 (0.1%)
** significance level = 0.01 (1%)

TABLE 5 TRAIN VS AROI AT REDUCED SAMPLING FREQUENCY FOR WET DAYS ONLY									
			Rain-rate threshold (<= mm/30min)						
Data set	**MS**	**N**	**Coeff**	**0.0**	**1.0**	**2.0**	**3.0**	**4.0**	**5.0**
A	4	276	r^2	0.28*	0.48*	0.37*	0.25*	0.11*	0.10*
	6	107	r^2	0.16*	0.52*	0.44*	0.29*	0.09**	0.09**
	8	20	r^2	0.13	0.79*	0.62*	0.40**	0.00	0.00
B	4	258	r^2	0.26*	0.42*	0.18*	0.06*	0.02*	0.02**
	6	106	r^2	0.20*	0.55*	0.24*	0.03	0.00	0.00
	8	18	r^2	0.12	0.79*	0.38**	0.00	0.02	0.00

MS = minimum samples/day, out of a possible maximum of 8
N = number of cases
Significance of r corresponding to r^2
* significance level = 0.001 (0.1%)
** significance level = 0.01 (1%)

frequency of imagery of the SAWB Meteosat archive covering the time period of this research. Values in Table 4 show the results for all days in both data sets as reduced in terms of the thresholds.

Clearly the lower sampling frequency provides a far poorer picture of the rainfall total, with a lower rain-rate threshold peak than was the case with full temporal data resolution. The reduction in terms of increasing observation frequency caused an improvement in the correlation coefficients as well as in the percentage variation explained. It is encouraging to note that over 50% of variation in rainfall can be accounted for by the rain occurrence index, even at reduced sampling frequency. However, the number of observations plays a critical role, as is evident from the improvement in $\boldsymbol{r}$ and $\boldsymbol{r^2}$ as N increases. The values for the two independent groups of data (data sets A and B), generated at nominal 3 h frequency are in general agreement.

The lower rain-rate at which the correlations peak can be ascribed to the fact that at a lower sampling frequency, smaller amounts of rain make a bigger impact on the accumulated index so that the probability of a "hit" on the higher half-hourly totals is reduced, with the result that if the high rain-rates are never hit, good correlations cannot obtain for higher thresholds. Lower thresholds however, ensure a better "hit rate" by the index, because there is a greater number of low rain-rate cases, and therefore AROI will be larger at lower rain-rate thresholds, with consequently better coefficients of correlation and determination. Whereas with a higher sampling frequency as in Tables 2 and 3, when higher rainfall totals are "hit" by the index, those higher totals contribute so much to the daily total that a regular frequency of hits enables the index to estimate the daily total to a greater degree of accuracy.

Simulation using wet spell days only

The analysis was applied to data sets A and B using wet spell days only, and the results are shown in Table 5.

The results are in general agreement with those in Table 4. Percentage variation explained peaks at a rain-rate of 1.0 mm while sampling frequencies of 6 and 8 are adequate to account for more than 50% of variation in daily rainfall. It is encouraging to note that up to 79% of variation in rainfall can be explained by variation in AROI. The results in Tables 4 and 5 appear to support the view that daily rainfall amount at a point is determined principally by the occurrence or absence of rainfall (Lovejoy and Austin, 1979; Richards and Arkin, 1981; Seed, 1992).

Discussion

Significance of correlation coefficients is meaningful only when testing the extent to which a sample represents a larger population. Therefore significances were not calculated for the simulations without frequency limits. However, the results in Table 2 show that the coefficients of correlation and determination at all rain-rates are sufficiently high for H_0 to be rejected and H_1 to be accepted, i.e. that there is a significant relation between AROI and TRAIN.

The simulation at reduced sampling frequency required the generation of two "random" samples, for which tests of significance were calculated (Du Toit, 1975), and are shown in Tables 4 and 5. All correlations at rain-rates of 1 mm were significant at a level exceeding 0.1%, warranting the rejection of H_0 and acceptance of H_1 at the 0.1% level of confidence. For other sampling and rain-rate thresholds, H_0 and H_1 respectively can be rejected and accepted at various levels of confidence in terms of calculated correlation coefficients and critical values.

Conclusion

The results of the simulation show that:

- The indexing approach is an effective method of estimating daily rainfall.
- Random sampling of the half-hourly rainfall data set at nominal 3 h intervals is likely to provide an adequate representation of the daily totals, and vindicates the use of attempts to estimate daily rainfall in South Africa by satellite-derived rain/no-rain indices.
- Dramatic improvements are experienced as the sampling frequency increases, and this bodes well for the effective use of Meteosat data at better temporal resolution.
- The efficacy of estimation of daily rainfall total is directly related to sampling frequency, and is sensitive to the rain-rate threshold as well as to the temporal distribution of half-hourly sampling.
- Non-raining days do not significantly alter the relationship of daily rainfall to rainfall occurrence.

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