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EVALUATION AND APPLICATION OF A REAL-TIME METHOD TO ESTIMATE MEAN AREAL PRECIPITATION FROM RAIN GAGE AND RADAR DATA

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ABSTRACT. Mean areal precipitation estimates are necessary for many hydrologic applications, especially in the field of hydrologic forecasting. Because of the large variability of precipitation in time and space and the typical wide spacing of operational rain-gage stations, it is important to consider other sources of rainfall information available from remote sensors such as weather radars and satellites. This paper establishes the criteria for and describes the framework of a multivariate precipitation analysis method which merges precipitation data from radar and rain gages to obtain "optimal" grid-point precipitation estimates. A numerical simulation experiment, to compare the relative accuracy of the individual univariate analysis to the multivariate analysis, is described. Error statistics for various size areas and for daily and hourly estimates are derived to provide a basis for evaluation and comparison of results. The results show that estimation errors generally decrease with increasing duration and averaging area and, for the smaller areas, rainfall estimates are improved with the addition of radar data, even for the higher gage densities. The multivariate analysis method is found to be stable and capable of satisfying the basic criteria desired for one major component of an operational system. The significance of the results and their relevance to various levels of technological capabilities for field implementation are discussed. Plans for additional refinements to the system and for its operational implementation are presented.

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1. Introduction

The process of quantitative hydrologic forecasting consists of acquiring information about the states of the hydrologic cycle, assembling this information in an intelligent form, and putting the information into models and procedures to predict the future states of a hydrologic (for example, river) system or subsystem. Often, the single most important hydrometeorological input to a streamflow prediction model is precipitation. Yet, because of its large variability in space and time, precipitation is difficult to measure accurately in real time without a very dense automated rain-gage network.

Land-based weather radar potentially is a very important remote sensor providing the capability to measure precipitation continually in time and space out to distances of approximately 200 km from the radar sites. Real-time processing of the radar data is possible if the radar is equipped with a computer and digital signal processing equipment, as will be the case for the Nation's network of Next Generation Weather Radars (NEXRAD Program Development Plan, 1980; Bonewitz, 1981). In the interim, until NEXRAD is implemented in the field in the late 1980's, the primary radar test bed which will be used for development and testing is the NWS Radar Data Processor II (RADAP II, formerly called D/RADEX) network (Greene et al., 1983) located in the south central and Appalachian regions of the country. The south central network, consisting of six NWS radars equipped with RADAP II equipment, will be especially appropriate for development and testing of procedures for a multivariate radar system covering a large geographic region of the country. This network covers almost all (about 90%) of the area of forecast responsibility for the Tulsa RFC (portions of seven states). This will enable a full system check, including compositing of precipitation estimates from multiple radars and derivation of mean areal precipitation estimates for input to the NWS River Forecast System for all of the watersheds in a large river system (i.e., the Arkansas River basin).

Using data from NEXRAD, combined with available rain-gage data, it should be possible to realize large improvements in the accuracy of estimating areal precipitation. These improvements should, in turn, lead to large economic benefits resulting from better hydrometeorological forecasts. Bussell et al. (1978) suggest that a radar network, supplemented by rain gages, is the most cost effective network design for England, where the radar network serves both the meteorological and hydrological communities. Such a network strategy also seems applicable in the United States where the existence of the network radars can be justified on the basis of meteorological applications alone; although, the potential benefits to be realized from the use of radar data for hydrologic forecasting are probably comparable in magnitude to those resulting from purely meteorological applications.

Benefits, in addition to those attributed just to the alleviation of flood losses, should be accrued from the application of improved precipitation measurements from radar to support a variety of water management and agricultural activities. However, full benefits, at least for hydrologic applications, can be realized only if the precipitation estimates from radar are consistently accurate and reliable, i.e., they must be quantitatively meaningful to a precision which is acceptable for a particular hydrologic application.

Because of the rather stringent requirements for quantitative accuracy for hydrologic applications, and because raw data from weather radars, as from most remote sensors, are characteristically in error due to equipment and/or meteorological variabilities, it is critical that the processing stream for quantitative radar data include adequate data processing, quality control, and analysis steps. One of the significant components of such a processing stream is a multivariate objective analysis system which includes "optimal" interpolation techniques to integrate radar and rain-gage data (Hudlow et al., 1983). Ideally, the multivariate analysis system should possess the following characteristics:

(1) Capability to provide "optimal" estimates of precipitation, from given information, improving or conserving accuracy of precipitation estimates as additional information from individual sensors is added.

(2) Numerical stability under all operational conditions.

(3) Robustness in handling any operational condition or network configuration.

(4) Uniform grid network analysis capability.

(5) Fully automated, fail-safe operation.

(6) Efficient usage of computer resources.

The next section of this paper describes an "optimal" interpolation method which shows good potential for satisfying the above six characteristics. In Section 3, a method is presented for testing and evaluating this or other interpolation procedures. Preliminary results from the tests are presented in Section 4. Experience from these tests indicates that further refinements will be necessary to fully meet the six characteristics. These refinements and future plans for operational implementation of the analysis method are discussed in Section 5.

2. Method Description

A short description of a statistical method for merging rain-gage and radar data is given in this section. The method is a linear estimation type of procedure with modeled covariance structure. Covariance modeling is done for each storm field separately, which can be accomplished using radar and rain-gage data collected in real time. Analysis is performed on a grid that makes the results easily comparable and usable for various applications, including the derivation of mean areal precipitation values for input to hydrologic models.

The method is based on the following assumptions:

(1) Radar data are given in digitized form, in precipitation units, on a rectangular grid.

(2) Rain-gage data and radar data are given for the same integration period.

(3) Radar data have systematic bias removed (mean bias over the entire field).

(4) Rainfall field is second-order stationary and ergodic.

(5) Radar errors are random and correlated.

Given these assumptions, the final estimator of rainfall at each grid location can be found as a linear combination:

$$Z^*_{k\ell} = \sum_{i=1}^{NR} \lambda_i Z^R_i + \sum_{j=i}^{NG} \lambda_j Z^G_j , \qquad (1)$$

where:

$Z^*_{k\ell}$ is the final rainfall estimator at the grid point (k,ℓ),

Z^R_i are radar estimators of rainfall from the surrounding bins,

Z^G_i are rain-gage estimators of rainfall from the surrounding gages,

λ_i, λ_j are the appropriate coefficients,

NR is the number of radar data bins used to estimate $Z^*_{k\ell}$, and

NG is the number of gage data values used to estimate $Z^*_{k\ell}$.

The coefficients λ_i and λ_j can be found by minimizing the variance:

$$\mathrm{Var}(Z_{k\ell} - Z^*_{k\ell}) = E[(Z_{k\ell} - Z^*_{k\ell})^2] , \qquad (2)$$

where $Z_{k\ell}$ is the true value of rainfall at the grid point (k,ℓ) and E is the expectation operator. This leads to the system:

$$\sum_{i=1}^{NR} \lambda_i C(i,n) + \sum_{j=1}^{NG} \lambda_j C(j,n) + \mu = C_{k\ell}(n)$$

$$\text{for } n = 1,\ldots,NR,\ldots,NR + NG \qquad (3)$$

and

$$\sum_{i=1}^{NR} \lambda_i + \sum_{j=1}^{NG} \lambda_j = 1 \qquad (4)$$

where:

$C(i,n)$ for $i=1,\ldots,NR$ and $n=1,\ldots,NR$ are auto-covariances between the radar points,

$C(j,n)$ for $j=1,\ldots,NG$ and $n = NR + 1,\ldots,NR + NG$ are auto-covariances between the rain gages,

$C(i,n)$ for $i=1,\ldots,NR$ and $n = NR + 1,\ldots,NR + NG$,

and

$C(j,n)$ for $j=1,\ldots,NG$ and $n = 1,\ldots,NR$ are cross-covariances between the radar and rain-gage points,

$C_{k,\ell}(n)$ for $n = 1,\ldots,NR$ are covariances between the point (k,ℓ) and radar points,

$C_{k,\ell}(n)$ for $n = NR + 1,\ldots,NR+NG$ are covariances between the point (k,ℓ) and rain-gage points,

μ is a Lagrange multiplier.

Condition (4), imposed on the weights, does not ensure unbiasedness of the rainfall estimator (Journel and Huijbregts, 1978) but allows us to deal with non-homogeneity of the mean. Note that the covariances, $C_{k,\ell}(n)$, for $n=1,\ldots,NR+NG$ are unknown and have to be obtained from a model: $C_{k,\ell}(n)$ for $n=NR+1,\ldots,NR+NG$ from a model of auto-covariance of the gages and $C_{k,\ell}(n)$ for $n=1,\ldots,NR$ from a model of cross-covariance between the gages and the radar. These models also are used to compute the $C(i,n)$ and $C(j,n)$ terms. The only exception is $C(i,n)$ for $n=1,\ldots,NR$, which can be obtained directly from the raw covariance matrix. Both models are derived from functions (5) and (6) which follow:

$$f(x,y) = \exp\left[-(h_1^2 x^2 + h_2^2 y^2)^{1/2}\right] , \tag{5}$$

where h_1 and h_2 are parameters to be estimated and $f(x,y)$ is for unit variance fields. In order to fully account for anisotropy of the covariance structure, one more parameter has to be estimated and that is the angle of rotation (Φ) of the coordinates so that

$$\begin{aligned} x &= x' \cos \Phi + y' \sin \Phi , \text{ and} \\ y &= y' \cos \Phi - x' \sin \Phi , \end{aligned} \tag{6}$$

where x', y' are coordinates of the original system. All the parameters can be estimated by fitting Eqs. (5) and (6) to the empirical (raw) covariance matrices using the least squares method. The raw covariance matrices can be obtained in the manner described by Crawford (1979), for irregularly spaced data (as is normally the case for rain gages) and by Ripley (1981) for gridded data. (Actually, the raw cross-covariances can be computed this way if the rain gages are "moved" to the closest grid point, since this generally will not affect the cross-covariance pattern significantly.) Thus, given the covariance models, we are able to apply the method.

In practice, the system of equations [Eqs. (3) and (4)] has to be solved for each grid point, taking into account its neighboring radar and rain-gage data values. This process can be time-consuming if NG + NR is fairly large. Thus, we impose limits on NG as well as on NR. As far as the number of radar points is concerned, it seems reasonable to take into consideration the five surrounding data bins in order to utilize the closest radar information that is symmetric about the point to be estimated. For NG, the limit is also set to five, but because of the typical sparsity of the gage networks, usually fewer stations are taken into account. (We take only those gages which have significant correlation with respect to the grid point.) The computations can be simplified because, in each case, the five radar data bins have the same configuration with respect to the grid point to be estimated (exceptions are local situations associated with boundary effects at the edges of the field), so the covariance values, $C_{k\ell}(n)$ for n=1,...NR and C(i,n) for i=1,...,NR and n=1,...,NR are always the same and do not need to be recomputed for each point.

In order to test the procedure described, a numerical experiment has been designed (Greene et al., 1978) and performed. This procedure is described in the next section.

3. Numerical Experiment

A major problem generally encountered in developing and testing any procedure for rainfall estimation is lack of sufficient ground-truth data. The nature of rainfall phenomena and limited resources often do not allow for physical-type experiments, although many have been attempted. A numerical experiment can be less costly and more flexible in many aspects, and can have advantages over a physical-type experiment even with a very dense rain-gage network deployed. For example, it allows greater control of the data bases and precise knowledge of the truth field. However, the numerical experiment does have weaknesses. It is not always possible to account for all types of uncertainties met in the real world because of difficulties in, first, identifying them, and then defining them by means of mathematical models. Specifically, the single problem most often encountered in our approach is insufficient knowledge of the characteristics of the radar rainfall error field. Nevertheless, we tried to overcome this problem by making a few assumptions concerning the noise associated with radar rainfall measurements. Then, by imposing a certain amount of noise on the original rainfall field (O) [radar data from GATE (Hudlow and Patterson, 1979)], "radar" (R) and "gage" (G) fields were created. Various merging procedures can then be applied to use these data to derive the final rainfall estimates, which are compared against the original field.

(1) Generation of the "radar" field. Generation of the "radar" field (R) involves generation of a radar rainfall noise field which can be expressed as:

$$D(x,y) = S(x,y) \cdot \varepsilon(x,y) + m(x,y) , \tag{7}$$

where: $S(x,y)$ is the standard deviation of the noise field at the location (x,y),

$\varepsilon(x,y)$ is a zero mean, unit variance, correlated random field, and

$m(x,y)$ is a bias of the noise at the location (x,y).

In our case, $\varepsilon(x,y)$ was generated using the model described by Meija and Rodrigez-Iturbe (1974). According to that model, the stationary-correlated random field can be expressed as a series of N cosine functions (harmonics) of the same amplitude:

$$\varepsilon(x,y) = \left(\frac{2}{N}\right)^{1/2} \sum_{k=1}^{N} \cos[W_k(x \cos \Theta_k + y \sin \Theta_k) + \phi_k] , \qquad (8)$$

where W_k is an independent random variable with a known probability density function, Θ_k and ϕ_k are random variables uniformly distributed between 0 and 2π. $\varepsilon(x,y)$ can be simulated for a correlation structure chosen here as:

$$E[Z(x_1,y_2)\ Z(x_2,\ y_2)] = \exp\left\{-\alpha[(x_1-x_2)^2 + (y_1-y_2)^2]^{1/2}\right\} \qquad (9)$$

where α is the correlation parameter. The corresponding probability density function of W_k is:

$$G(W_k) = 1 - (1 + W^2/\alpha^2)^{-1/2} . \qquad (10)$$

Thus,

$$W_k = \alpha\{[1 - G(W_k)]^{-2} - 1\}^{1/2} , \qquad (11)$$

where: $G(W_k)$ is a uniformly distributed random variable over the interval (0,1).

Eqs. (8) - (11) allow the simulation of a zero-mean, unit variance isotropic field with correlation structure given by Eq. (9), as $N \to \infty$.

The standard deviation of the noise, $S(x,y)$, was simulated as a non-homogenous variable defined as:

$$S(x,y) = \exp\left(-\frac{\beta_1}{A}\right) , \qquad (12)$$

where: $A = \dfrac{\nabla O(x,y)}{\nabla O_{max}} + \dfrac{O(x,y)}{O_{max}}$,

and

$\nabla O(x,y)$ is the average absolute value of the gradient computed in four directions around the point (x,y) in the original field (O),

∇O_{max} is the maximum absolute gradient in the O field,

$O(x,y)$ is the original field value at the point (x,y),

O_{max} is the maximum value of the original field, and

β_1 is a parameter which can be adjusted in order to obtain a radar field having a required amount of noise specified as:

$$\sigma_1^2 = \mathrm{Var}[\log \frac{O}{R}] \ . \tag{13}$$

The value of the parameter (β_1) can be obtained by solving the non-linear equation:

$$\hat{\sigma}_1^2 - \mathrm{Var}\left(\log \frac{O}{R(\beta_1)}\right) = 0.0 \ , \tag{14}$$

where the value for $\hat{\sigma}_1^2$ is specified a priori. It should be noted that because of the way we generate the standard deviation, S(x,y), the correlation structure of the noise field, D(x,y), does not obey Eq. (9). The noise field is non-stationary but still correlated.

Finally, the simulated "radar" field with noise is given by

$$R(x,y) = O(x,y).10^{D(x,y)} \ . \tag{15}$$

(2) <u>Generation of the "gage" field.</u> The "gage" field (G) was generated as a random sample from a conditionally simulated random field. Each value of this field is a log normal variable with the mean equal to the value of the original field at that location, and the variance proportional (with the proportionality parameter, β_2) to the variance of the original field in the area around the grid point, i.e.,

$$G(x,y) = O(x,y) \cdot 10^{\beta_2 \sigma^2(x,y)} \ , \tag{16}$$

The parameter β_2 can be estimated in similar fashion as β_1, i.e., by solving the equation:

$$\hat{\sigma}_2^2 - \mathrm{Var}\left(\log \frac{O}{G(\beta_2)}\right) = 0.0 \ , \tag{17}$$

where $\hat{\sigma}_2^2$ is an a priori assigned value of the variance of the noise in the G field.

4. Results

The described method for merging radar and rain-gage data was used to derive estimates which are compared to those obtained from the "radar" and "gage" values individually. The estimates from the gage data were derived with a common method currently used by the NWS, i.e., the inverse-square-distance weighting method. Mean Areal Precipitation (MAP) estimates were computed for areas varying from 16 km^2 to approximately 65,000 km^2. A number of statistics for rain areas have been computed for each area size including Root Mean Square (RMS) error, maximum RMS, and mean Absolute Percent Error (APE). Also, some global statistics were computed for the whole field, i.e., for the area of rainfall covered by the radar umbrella.

These are the field mean, the standard deviation, and the correlation coefficient with the original field.

The results presented here are meant to only illustrate the feasibility of the merging and testing procedures. They should not be regarded as definitive results of the method. These will be published in the near future.

Figures 1a and 1b show examples of analyzed fields for day 179 of GATE. The panels shown in Figures 1a and 1b are for subareas of approximately 75,000 km^2 extracted from the total radar field of view which is approximately 125,000 km^2 (compare Hudlow and Patterson, GATE Atlas, 1979). The original field is the radar field of hourly (Figure 1a) or daily (Figure 1b) accumulations of precipitation data. The "radar" field was obtained by imposing an amount of correlated noise on the original field corresponding to $\sigma_1^2 = 0.06$ for hourly data and $\sigma_1^2 = 0.03$ for daily data. The number of harmonics used in the simulations was set at 50. The noise magnitudes correspond roughly to 75 percent and 50 percent mean error for the hourly and daily estimates, respectively (for comparison, see the "radar" mean APE values for 16 km^2 in Figures 2 and 3 which give 62 percent and 45 percent, respectively).

The analyses of the "gage" fields shown in Figures 1a and 1b are based on 100 randomly located "rain gages" representing a sample from the field having $\sigma_1^2 = 0.0$ noise variance. In our analysis, we used the inverse-square-distance method as described in NOAA Technical Memorandum NWS HYDRO-14 (1972).

The merged fields were derived using the method described in Section 2. A visual comparison of the original field with the "radar," "gage," and merged fields demonstrates that significant improvement has been introduced by the merging procedure.

However, a more precise, i.e. quantitative, measure of that improvement for the hourly analysis is shown in Figure 2, which is a plot of mean APE's for MAP's for various sizes of averaging areas, and for the daily analysis in Figure 3, where absolute percent error is presented as a function of rain-gage density. The errors in MAP estimation for the "gage" field are due only to the interpolation technique used, since selection of zero noise means that we generate perfect "measurements." The zero noise case also provides us with some measure of the maximum improvement to be expected from the merging procedure.

As was anticipated, the errors generally drop as gage density increases. The reason that the APE increases, for the gage only analysis, with gage density up to 0.8 gages/1000 km^2, is believed to be fortuitous for this single replication, and a monotonically decreasing function would be expected to emerge, statistically, with a greater number of replications. Figures 2 and 3 also illustrate that the APE decreases with increasing size of the averaging area, for a particular type of estimate and, in general, with the addition of radar information. Improvements in error statistics for the merged gage/radar analysis compared to those for the radar-only analysis are not that dramatic. This is especially true of the smallest size areas. We anticipate that additional improvements will result from refinements planned for the interpolation procedures in the local vicinity

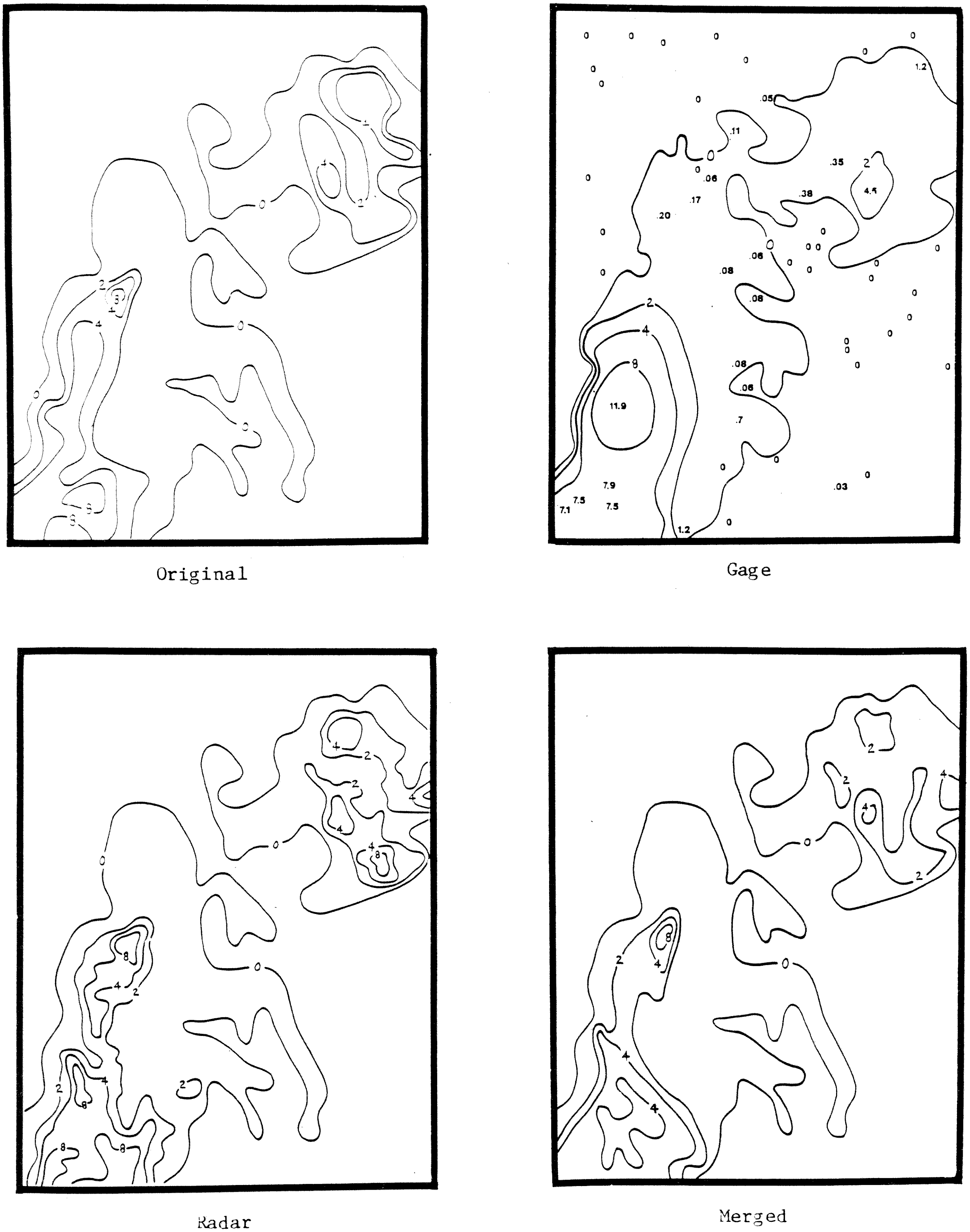

Figure 1a. Comparison of hourly rainfall analyses (mm of rain) from numerical experiment for day 179 (June 28, 1974, 1600-1700 hrs.) of GATE.

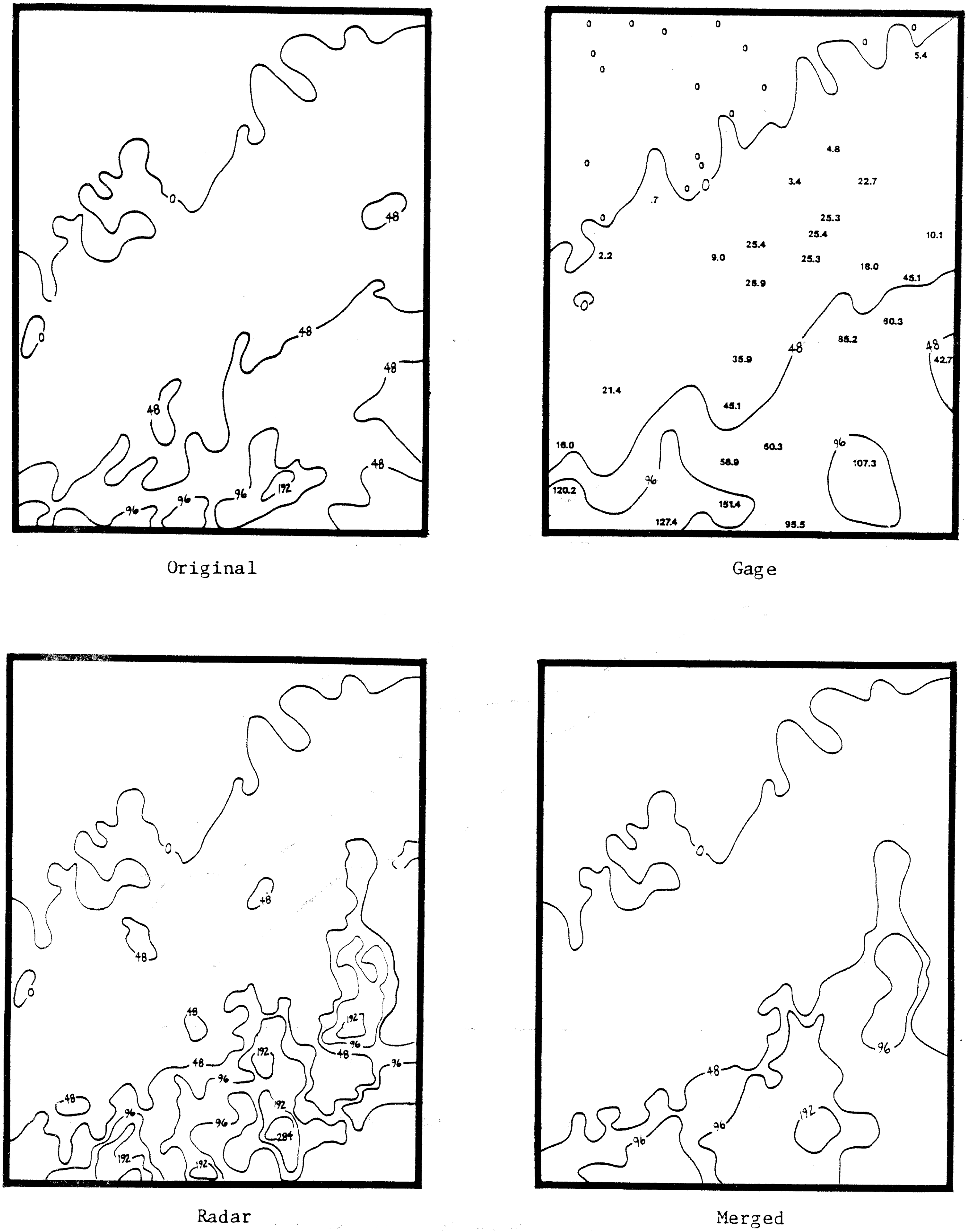

Figure 1b. Comparison of daily rainfall analyses (mm of rain) from numerical experiment for day 179 (June 28, 1974) of GATE.

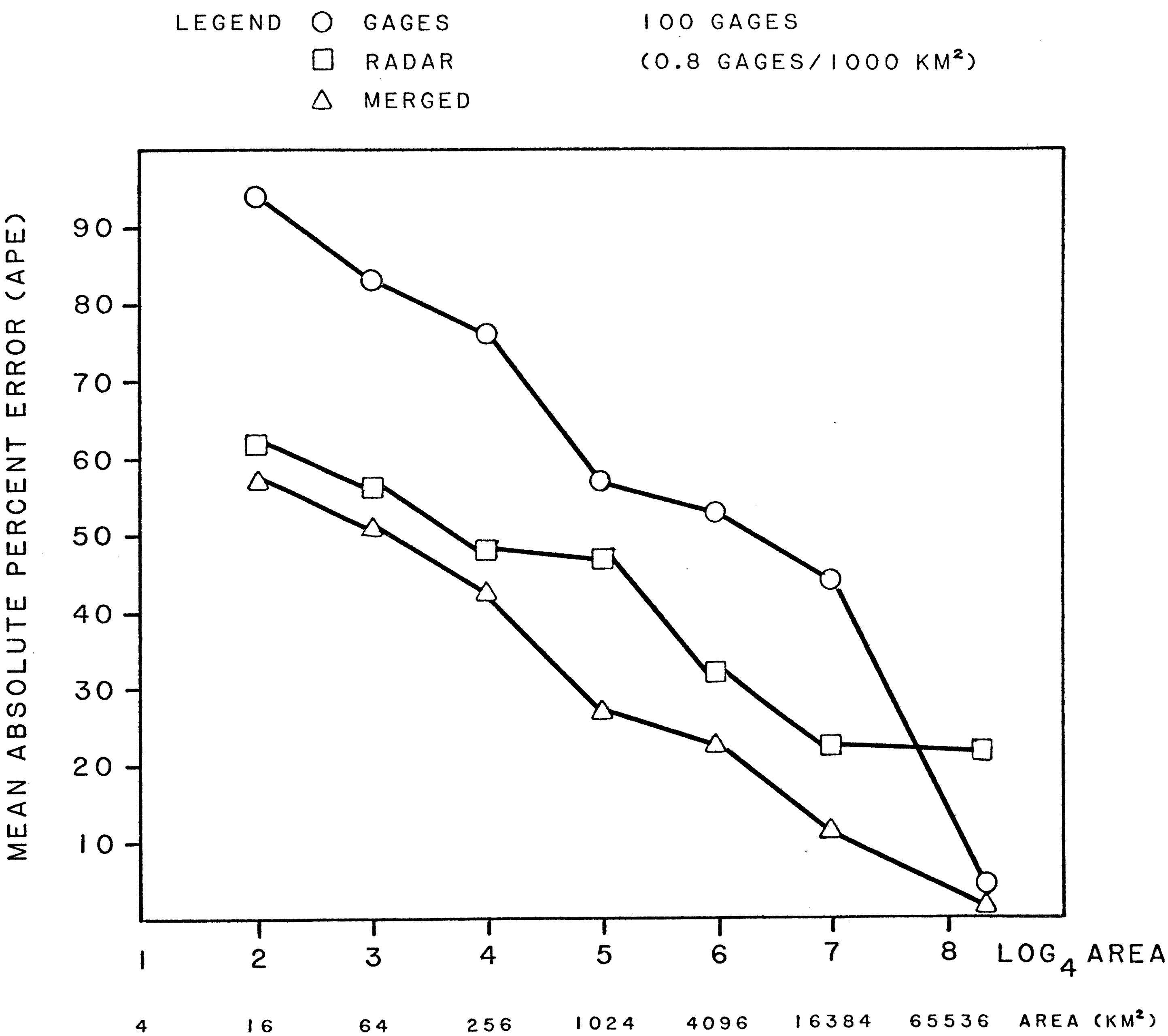

Figure 2. Mean Absolute Percent Error (APE) of Mean Areal Precipitation (MAP) values over rain areas as a function of various sizes of total areas. Hourly data of day 179 (June 28, 1974, 1600-1700 hrs) of GATE was used, with $\sigma_1^2 = 0.060$, $\sigma_2^2 = 0.0$, $\alpha = 0.02$.

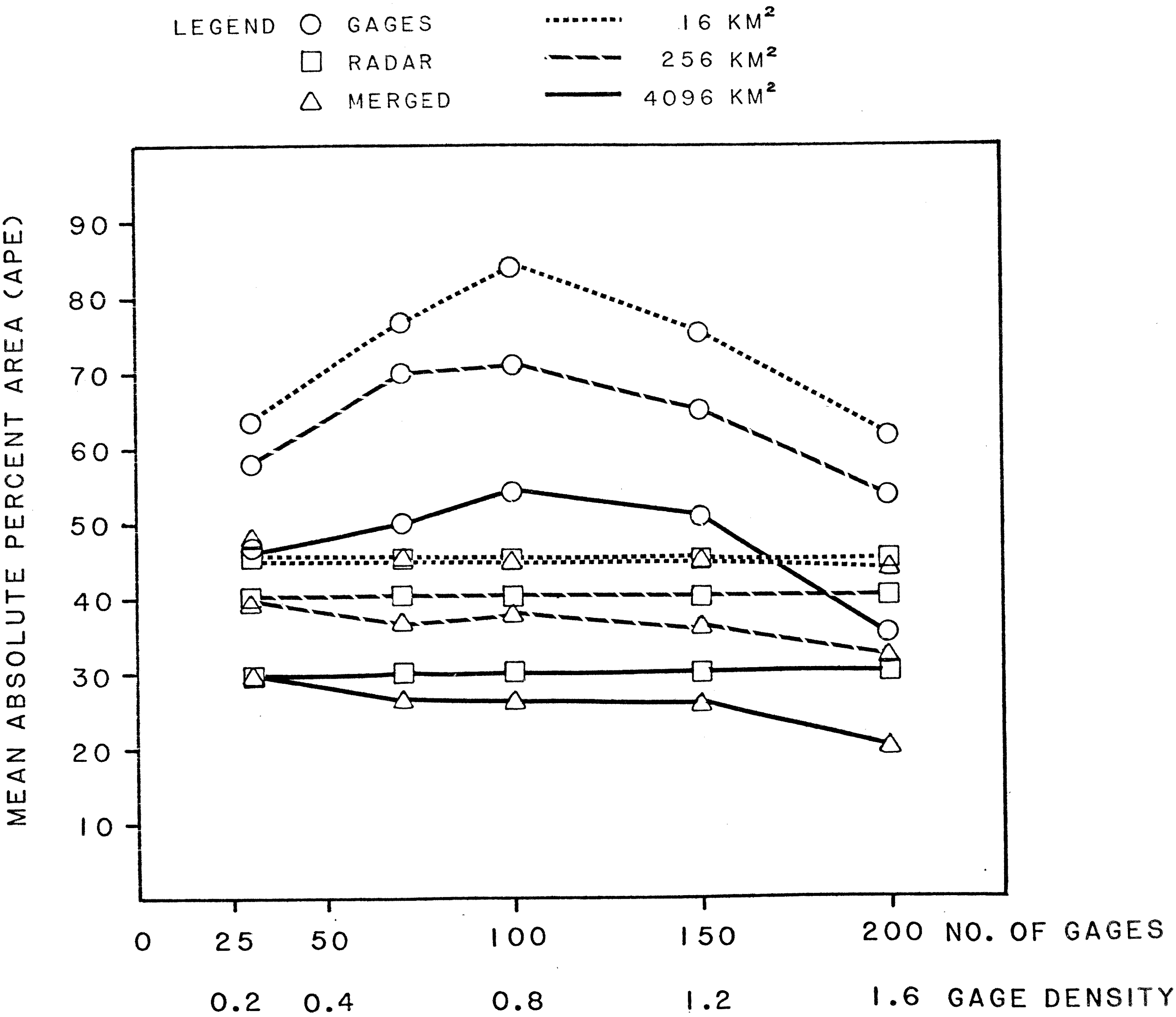

Figure 3. Mean Absolute Percent Error (APE) of Mean Areal Precipitation (MAP) values over rain areas as a function of gage density (gages/1000 km^2) for various sizes of total areas. Daily data of day 179 of GATE (28 June 1974) was used, with $\sigma_1^2 = 0.030$, $\sigma_2^2 = 0.0$, $\alpha = 0.02$.

of the gages as mentioned in Section 5. Nevertheless, significant visual improvements in the merged analysis using current procedures can be seen for both the hourly and daily cases shown in Figures 1a and 1b.

Tables 1a and 1b contain a more complete summary of field and error statistics obtained for the previously shown analyses, for the case of 100 gages (0.8 gages/1000 km^2).

It should be noted that the RMS error statistic can be heavily influenced by a small number of estimates at the high rainfall amounts which may be in error by only relatively small percentages. Therefore, we believe that the mean APE is a better statistic for this study as an overall measure for evaluation and relative comparison procedures. Nevertheless, all the statistics should be examined carefully with appropriate interpretation before final conclusions are drawn. While these statistical results are informative for relative comparisons and to illustrate the need for additional refinements in the procedures, a much larger number of cases will be analyzed in the future in order to arrive at definitive conclusions.

5. Concluding Remarks and Future Directions

As was mentioned before, one of the major problems in evaluating any procedure for rainfall analysis is lack of sufficient ground truth data. Nevertheless, extensive testing of the described procedures, as well as other procedures, is necessary prior to operational implementation, which is our ultimate goal. As described in Section 3, a numerical experiment has been devised to facilitate testing the performance of procedures for various network configurations, magnitudes of data errors, and spatial and temporal scales. The results obtained so far, part of which are presented here, are very encouraging although there still are many problems to be solved. Many of these problems result from the fact that the method is to be implemented in an operational environment. This imposes very severe restrictions concerning high reliability and efficiency of the method. The results to date appear to indicate that most of the characteristics desired of a multivariate analysis system (given in Section 1) can be met with the described method, although additional refinements will be required to achieve a totally robust system. For example, if the number of gages available for deriving the covariance matrix of the gage field is too small, the method should not be used as described, and default to a simpler procedure may be appropriate. The kind of procedure and the criteria for the switchover have not been determined yet. Also, improvements in the interpolation procedures in the local vicinity of the gages should be possible. The reason for this is that not all of the assumptions underlying the method are always met. For example, the assumption of homogeneity of the covariance structure for the rainfall field is generally not met. Another assumption, which is not completely valid for this experiment, is that the systematic bias has been removed from the radar field. For the final processing system described by Ahnert et al. (1983) and Hudlow et al. (1983), the systematic bias should be removed in advance of applying the method described in this paper.

An important constraint is the requirement of efficiency in terms of computer time. Considering that the analysis will be done for hourly data from multiple radars, accompanied by other computations and preceded by data transmission, it becomes understandable that the actual computer time has to

Table 1a. Summary of the results for hourly accumulations for day 179 of GATE (June 28, 1974, 1600-1700 hrs.). Number of gages 100; $\sigma_1^2 = 0.060$, $\sigma_2^2 = 0.0$, $\alpha = 0.02$.

Statistic *	Field			
	Original	Gages	Radar	Merged
Mean of the Field	2.26	2.28	2.80	2.24
Standard Deviation	2.90	2.76	5.04	3.15
Correlation Coefficient With the Original Field	1.00	0.57	0.74	0.72
RMS Error for Area of:				
16 km^2	0.0	1.54	1.77	1.11
64 km^2	0.0	1.39	1.42	0.91
256 km^2	0.0	1.25	1.16	0.76
1024 km^2	0.0	1.05	0.81	0.49
4096 km^2	0.0	0.72	0.44	0.28
16384 km^2	0.0	0.49	0.23	0.13
Maximum RMS Error				
16 km^2	0.0	18.54	40.00	12.70
64 km^2	0.0	9.94	21.98	7.37
256 km^2	0.0	7.27	11.11	4.43
1024 km^2	0.0	4.88	5.25	2.42
4096 km^2	0.0	2.16	1.71	0.85
16384 km^2	0.0	0.96	0.45	0.26
Mean Absolute Percent Error				
16 km^2	0.0	92.40	61.44	58.58
64 km^2	0.0	84.84	57.22	51.82
256 km^2	0.0	73.28	49.36	40.18
1024 km^2	0.0	58.13	46.20	27.50
4096 km^2	0.0	53.07	34.00	23.18
16384 km^2	0.0	44.79	23.15	12.67

*All the statistics except the correlation coefficient and absolute percent error are in mm/hr.

Table 1b. Summary of the results for daily accumulations for day 179 of GATE (June 28, 1974). Number of gages 100; $\sigma_1^2 = 0.030$, $\sigma_2^2 = 0.0$, $\alpha = 0.02$.

Statistic *	Field			
	Original	Gages	Radar	Merged
Mean of the Field	34.80	40.5	45.36	43.20
Standard Deviation	37.44	37.20	55.44	50.80
Correlation Coefficient With the Original Field	1.00	0.81	0.84	0.86
RMS Error for Area of:				
16 km^2	0.0	14.64	18.24	17.28
64 km^2	0.0	13.20	14.32	13.38
256 km^2	0.0	11.27	12.72	11.52
1024 km^2	0.0	8.88	9.05	8.70
4096 km^2	0.0	6.87	6.48	6.24
16384 km^2	0.0	5.28	5.40	4.99
Maximum RMS Error				
16 km^2	0.0	313.70	476.20	476.20
64 km^2	0.0	156.72	272.51	272.51
256 km^2	0.0	69.57	111.28	111.28
1024 km^2	0.0	37.92	52.31	51.21
4096 km^2	0.0	23.28	19.36	18.59
16384 km^2	0.0	9.60	9.82	8.16
Mean Absolute Percent Error				
16 km^2	0.0	84.57	45.28	45.20
64 km^2	0.0	77.68	42.96	40.29
256 km^2	0.0	71.23	40.11	37.62
1024 km^2	0.0	62.47	36.12	30.19
4096 km^2	0.0	54.32	30.22	26.32
16384 km^2	0.0	37.56	22.72	18.36

*All the statistics except the correlation coefficient and absolute percent error are in mm/day.

be less than 1 min. per radar umbrella. This eliminates many methodologies potentially useful from theoretical points of view, such as universal kriging or disjunctive kriging.

This work has produced useful scientific observations which should assist the direction of future research and development efforts. Most importantly, it has shown that more basic knowledge is needed about the structure of the radar measurement noise. Such knowledge would improve our capability to conduct numerical experiments like the one used in this study, as well as facilitate improvement of the analysis method itself.

As far as plans for the near future are concerned, we will continue testing to make the conclusions statistically more valid. Sensitivity analyses will include additional numerical simulation tests and evaluation will proceed as quickly as possible to analysis using real data.

As mentioned before and described in Hudlow et al. (1983) and Ahnert et al. (1983), the method presented here is only a component of a larger system and thus depends on the configuration of that system. However, it is possible to develop a similar method using a different configuration of the rainfall analysis system; for example, a simplified system with local (on-site) processing using mini- or micro-computers.

Finally, it may be worthwhile to make several observations concerning the overall merit of this analysis method, as well as the use of radar in general, for hydrologic forecasting applications. To the extent possible, these observations will be keyed to the levels of technological capabilities existing within the organizations and countries attempting to implement radar technology. As mentioned earlier, total benefits from radar will be dependent on whether it is being used as a multipurpose system to support both meteorological and hydrological applications. The purchase of a radar system solely to support hydrologic forecasting applications may be difficult to justify compared to the purchase of an automated rain-gage network, especially if the area of interest is confined to a fairly small region which is physically accessible. Conversely, if networks of radars exist, or are planned, for a nation to provide meteorological coverage for most, if not all, of the country, then it seems only prudent that the hydrologists attempt to develop procedures to effectively use this source of precipitation information. This is logical since insufficient rain-gage data generally exist to obtain the best estimates of precipitation. However, a word of caution is in order: to obtain consistently reliable and accurate quantitative precipitation estimates from a radar, or combined radar and gage, system will require stable and well calibrated radar hardware and comprehensive software. The software system must provide the capabilities to automatically perform numerous preprocessing, quality control, and analysis tasks. Without these capabilities, the radar estimates will not be consistently reliable because errors originating from variations in equipment and/or hydrometeorological conditions can go undetected. Achieving these quantitative real-time capabilities, at the current state-of-the-art, is possible only with a relatively high-level technology system. This means that the user country/organization will incur the need for considerable expertise in radar meteorology and hydrology, computer processing, and systems integration and analysis.

In conclusion, we believe that the analysis method described herein, with suitable modifications and refinements, as part of a larger analysis system (Hudlow et al., 1983), offers considerable promise for providing improved precipitation estimates in the future for large portions of the U.S. Rainfall information has been available from various types of in situ and remote sensors for numerous years, but accurate assimilation and analysis of this information has often been deficient. A major deficiency has been the lack of a real-time computer processing system which would allow the numerical merging of precipitation data from multiple types of sensors. Development work and operational implementation will proceed to remove these deficiencies. Areas covered by the existing RADAP II network will be used as a test bed in anticipation of National coverage once the NEXRAD network comes on line in the late 1980's.

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