OPTIMAL ESTIMATION OF RAINFALL FIELDS USING RADAR RAINFALL AND RAIN GAGE DATA

by

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ABSTRACT

Procedures for real-time estimation of rainfall fields using rain gage and radar rainfall data are described. Based on multiplicative decomposition of expectation of rainfall into conditional expectation of rainfall given raining and probability of rainfall, the procedures explicitly account for both within-storm variability of rainfall and variability due to fractional coverage of rainfall. As a result, in addition to the accuracy of radar rainfall data in estimating rainfall given that it actually rained, that in discerning rainfall from no rainfall can also be taken into account. The assumptions required are that the occurrence of rainfall is locally equally likely everywhere, and that positive rainfall is locally second-order homogeneous. To evaluate the estimation procedures, a cross-validation experiment was performed using hourly radar rainfall data from the Tulsa, Oklahoma, Weather Surveillance Radar - 1988 Doppler (WSR-88D)

and hourly rain gage data in the area. It is shown that, on the average, multi-sensor estimates are significantly more accurate than either mean field bias-corrected radar rainfall data or gage-only estimates, but that, for specific purposes of detection and estimation of large rainfall amounts, mean field bias-corrected radar rainfall data may be the most accurate.

INTRODUCTION

With the nationwide implementation of Weather Surveillance Radars - 1988 Doppler (WSR-88D), real-time radar rainfall data are now routinely available for operational hydrologic forecasting in the United States (Fread et al. 1995). Direct use of radar rainfall data in quantitative operational hydrologic forecasting, however, is in general unacceptable because of various sources of error associated with radar observation of rainfall (Wilson and Brandes 1979, Austin 1987, Smith et al. 1995). In the National Weather Service (NWS), to produce rainfall estimates that are of suitable quality to input to streamflow prediction models, the following steps are typically taken; a series of automatic quality control of raw radar rainfall and rain gage data, correction for mean field bias in radar rainfall data, multi-sensor estimation of rainfall fields using rain gage and bias-corrected radar rainfall data, and interactive quality control of rainfall fields from multi-sensor estimation (Hudlow 1988, Shedd and Smith 1991, NWS 1995).

Though both bias correction and multi-sensor estimation use radar rainfall and rain gage data, they serve fundamentally different purposes in that, whereas the former is to obtain radar rainfall data that are free of radar umbrella-wide multiplicative biases due, e.g., to lack of radar hardware calibration and temporal changes in the raindrop size distribution (Smith and Krajewski 1991), the latter is to estimate rainfall fields that would be observed by an extremely dense network of rain gages (say, one gage per 4x4 km^2). The combined effect of bias correction and multi-sensor estimation is that, on the average, the multi-sensor estimates are more accurate, at any scale of spatio-temporal aggregation (i.e., beyond the aggregation scale of the data itself), than rainfall estimates obtainable from either the radar rainfall or the rain gage data alone. The purpose of this work is to develop multi-sensor rainfall estimation procedures intended for operational implementation at NWS River Forecast Centers (RFC) and Weather Forecast Offices (WFO) in support of operational hydrologic forecasting.

Joint use of radar rainfall and rain gage data in rainfall estimation has been dealt with by a number of researchers (Wilson 1970, Crawford 1977, Brandes 1979, Eddy 1979, Krajewski 1987, Creutin et al. 1988, Azimi-Zonooz et al. 1989, Seo et al. 1990). Though optimal estimation procedures such as cokriging are shown to be superior to heuristic ones, none of the existing formulations offer an objective framework in which, in addition to within-storm variability of rainfall (or, inner variability, Barancourt et al. 1992), variability due to fractional coverage of rainfall (or, spatial intermittency) can be explicitly accounted for. It is an extremely important consideration for two reasons. The first is that, within the radar umbrella (for WSR-88D, the effective range is 230 km for rainfall estimation), the spatial coverage of, e.g., hourly rainfall is almost always fractional, and therefore accurate delineation of rain area (a spatial intermittency consideration) is as important as accurate estimation of rainfall over rain area (an inner variability consideration). The second is that radar rainfall data contain not only errors in radar estimation of rainfall given that rainfall is detected (an inner variability consideration), but also errors in radar detection of rainfall (a spatial intermittency consideration). Accuracy assessment of radar rainfall data as a function of range indicates that, at far ranges, the latter is at least as important as the former (Kitchen and Jackson 1993, Smith et al. 1995). The multi-sensor rainfall estimation procedures described in this work differ most significantly from the previous ones in that they explicitly account for both types of rainfall variability and both types of error in radar observation of rainfall. Mathematically, they are straightforward extensions of the gage-only rainfall estimation procedures of Seo (1995), to which frequent references are made throughout this paper.

This paper is organized in the following sections; description of the problem, estimation of the probability of rainfall, estimation of the amount of rainfall given raining, direct estimation of rainfall, operational considerations and parameter estimation, verification, and conclusions and future research recommendations.

PROBLEM DESCRIPTION

The problem of optimally estimating spatial distribution of rainfall using radar rainfall and rain gage data may be stated as follows. Estimate rainfall at an arbitrary location u_0 under the radar umbrella, using radar rainfall and rain gage data within the estimation domain, A, that would be measured by a rain gage if one existed at that location. We denote this unmeasured rainfall by Z_{g0}. Assuming, e.g., isotropy in the correlation structure of rainfall, we may define the estimation domain, A, to be the circle centered at the point of estimation, u_0, whose radius equals the spatial correlation scale of rainfall. Our goal is then to estimate $E[Z_{g0}|Z_{g1}=z_{g1},\ldots,Z_{gn}=z_{gn},Z_{r1}=z_{r1},\ldots,Z_{rm}=z_{rm}]$, where Z_{gi}'s and Z_{rj}'s are the rain gage and the radar rainfall data at locations, u_i's and u_j's within A, respectively, and the upper- and the lowercase letters signify random variables and their experimental values, respectively. For notational brevity, we define $Z_G \equiv \{Z_{g1}=z_{g1},\ldots,Z_{gn}=z_{gn}\}$ and $Z_R \equiv \{Z_{r1}=z_{r1},\ldots,Z_{rm}=z_{rm}\}$.

As in gage-only estimation of Seo (1995), the first step in our first approach to multi-sensor estimation is to rewrite $E[Z_{g0}|Z_G,Z_R]$ and $Var[Z_{g0}|Z_G,Z_R]$ as follows:

$$E[Z_{g0}|Z_G,Z_R]=E[Z_{g0}|Z_G,Z_R,z_{g0}>0]\cdot Pr[z_{g0}|Z_G,Z_R] \quad (1)$$

$$\begin{aligned} &Var[Z_{g0}|Z_G,Z_R] \\ &=Var[Z_{g0}|Z_G,Z_R,z_{g0}>0]\cdot Pr[z_{g0}|Z_G,Z_R]+E^2[Z_{g0}|Z_G,Z_R,z_{g0}>0]\{1-Pr[z_{g0}|Z_G,Z_R]\} \end{aligned} \quad (2)$$

We then estimate $Pr[z_{g0}|Z_G,Z_R]$, $E[Z_{g0}|Z_G,Z_R,z_{g0}>0]$, and $Var[Z_{g0}|Z_G,Z_R,z_{g0}>0]$ via optimal linear estimation, from which estimates of $E[Z_{g0}|Z_G,Z_R]$ and $Var[Z_{g0}|Z_G,Z_R]$ can be obtained via (1) and (2). The rationale behind the approach is given in Seo (1995) based on considerations of skewness in probability distribution of rainfall under fractional coverage conditions. Another motivation for the approach is that (1) mirrors the multiplicative decomposition of a rainfall estimate into the probability of rainfall and the conditional estimate given that it actually rained. It hence appeals as a natural multi-sensor nonlinear estimator when both the estimation accuracy and the detection accuracy are considered in radar rainfall data.

ESTIMATION OF $Pr[z_{g0}|Z_G,Z_R]$

$Pr[z_{g0}|Z_G,Z_R]$ in (1) and (2) is estimated via indicator cokriging (Journel 1983, Solow 1986, Seo 1996), based on the following conditional probability approximation of the conditional expectation of an indicator random variable:

$$Pr[z_{g0}|Z_G,Z_R]\approx E[I_{\{zg0>0\}}|I_G,I_R] \quad (3)$$

In the above, we defined $I_G \equiv \{I_{\{zg1>0\}}=i_{\{zg1>0\}},\ldots,I_{\{zgn>0\}}=i_{\{zgn>0\}}\}$ and $I_R \equiv \{I_{\{zr1>0\}}=i_{\{zr1>0\}},\ldots,I_{\{zrm>0\}}=i_{\{zrm>0\}}\}$, where the indicator random variables, $I_{\{zg>0\}}$ and $I_{\{zr>0\}}$, are defined as:

$$i_{\{zg>0\}} \equiv \begin{cases} 1 \text{ if } z_g>0 \\ 0 \text{ if } z_g=0 \end{cases} \tag{4a}$$

$$i_{\{zr>0\}} \equiv \begin{cases} 1 \text{ if } z_r>0 \\ 0 \text{ if } z_r=0 \end{cases} \tag{4b}$$

$E[I_{\{zg0>0\}} | I_G,I_R]$ in (3) may be estimated by the following indicator cokriging estimator:

$$E^*[I_{\{zg0>0\}} | I_G,I_R]$$

$$= E[I_{\{zg0>0\}}] + \sum_{i=1}^{n} \lambda_{gi} (i_{\{zgi>0\}} - E[I_{\{zgi>0\}}]) + \sum_{j=1}^{m} \lambda_{rj} (i_{\{zrj>0\}} - E[I_{\{zrj>0\}}]) \tag{5}$$

where n and m are the numbers of rain gage and radar rainfall data in A, respectively. In (5), the optimal weights, λ_{gi}'s and λ_{rj}'s, that minimize $E[(I_{\{zg0>0\}} - E^*[I_{\{zg0>0\}} | I_G,I_R])^2 | I_G,I_R]$ are given by:

$$(\lambda_{g1},\ldots,\lambda_{gn},\lambda_{r1},\ldots,\lambda_{rm}) = [P_{G0}\ P_{R0}] \begin{bmatrix} P_{GG} & P_{GR} \\ P_{RG} & P_{RR} \end{bmatrix}^{-1} \tag{6}$$

where P_{GG}, P_{GR} $(=P_{RG}^T)$, and P_{RR} the nxn, nxm, and mxm indicator covariance matrices whose ij-th entries are given by $Cov[I_{\{zgi>0\}},I_{\{zgj>0\}}]$, $Cov[I_{\{zgi>0\}},I_{\{zrj>0\}}]$, and $Cov[I_{\{zri>0\}},I_{\{zrj>0\}}]$, respectively, and P_{G0} and P_{R0} are the 1xn and 1xm indicator covariance vectors whose i-th entries are given by $Cov[I_{\{zgi>0\}}, I_{\{zg0>0\}}]$, $Cov[I_{\{zri>0\}}, I_{\{zg0>0\}}]$, respectively. $Cov[I_{\{zgi>0\}}, I_{\{zgj>0\}}]$, $Cov[I_{\{zgi>0\}}, I_{\{zrj>0\}}]$, and $Cov[I_{\{zri>0\}}, I_{\{zrj>0\}}]$ are written as:

$$Cov[I_{\{zgi>0\}}, I_{\{zgj>0\}}] = \sigma_{Ig}^2 \cdot \rho_{Ig}(|u_i - u_j|) \tag{7a}$$

$$Cov[I_{\{zgi>0\}}, I_{\{zrj>0\}}] = \sigma_{Ig} \cdot \sigma_{Ir} \cdot \rho_{Ic}(|u_i - u_j|) \tag{7b}$$

$$Cov[I_{\{zri>0\}}, I_{\{zrj>0\}}] = \sigma_{Ir}^2 \cdot \rho_{Ir}(|u_i - u_j|) \tag{7c}$$

where σ_{Ig} and σ_{Ir} are the standard deviations of $I_{\{zg>0\}}$ and $I_{\{zr>0\}}$, respectively, $|u_i - u_j|$ is the Euclidean distance between u_i and u_j, and $\rho_{Ig}(|\cdot|)$, $\rho_{Ic}(|\cdot|)$, and $\rho_{Ir}(|\cdot|)$ are the spatial correlation functions of $I_{\{zg>0\}}$, between $I_{\{zg>0\}}$ and $I_{\{zr>0\}}$, and of $I_{\{zr>0\}}$, respectively. Under the assumption that occurrence of rainfall is equally likely everywhere in A, we define $m_{Ir} \equiv E[I_{\{zrj>0\}}]$, which may now be interpreted as the fraction of rain area within A. Then, we may also write $\sigma_{Ir}^2 = m_{Ir}(1 - m_{Ir})$.

ESTIMATION OF $E[Z_{g0} | Z_G, Z_R, z_{g0} > 0]$

$E[Z_{g0} | Z_G, Z_R, z_{g0} > 0]$ in (1) and (2) is estimated by the following linear estimator:

$$E^*[Z_{g0}|Z_G,Z_R,z_{g0}>0]$$

$$=E[Z_{g0}|z_{g0}>0]+\sum_{i=1}^{n}\Gamma_{gi}(z_{gi}-E[Z_{gi}|z_{g0}>0])+\sum_{j=1}^{m}\Gamma_{rj}(z_{rj}-E[Z_{rj}|z_{g0}>0]) \tag{8}$$

In (8), the optimal weights, Γ_{gi}'s and Γ_{rj}'s, that minimize $E[(Z_{g0}-E^*[Z_{g0}|Z_G,Z_R,z_{g0}>0])^2|Z_G,Z_R,z_{g0}>0]$ are given by:

$$(\Gamma_{g1},\ldots,\Gamma_{gn},\Gamma_{r1},\ldots,\Gamma_{rm})=[Q_{0G}\ Q_{0R}]\begin{bmatrix} Q_{GG} & Q_{GR} \\ Q_{RG} & Q_{RR} \end{bmatrix}^{-1} \tag{9}$$

where Q_{GG}, Q_{GR} ($=Q_{RG}^T$), and Q_{RR} are the nxn, nxm, and mxm conditional covariance matrices, whose ij-th entries are given by $Cov[Z_{gi},Z_{gj}|z_{g0}>0]$, $Cov[Z_{gi},Z_{rj}|z_{g0}>0]$, and $Cov[Z_{ri},Z_{rj}|z_{g0}>0]$, respectively, and Q_{0G} and Q_{0R} are the 1xn and 1xm conditional covariance vectors, whose i-th and j-th entries are given by $Cov[Z_{g0},Z_{gi}|z_{g0}>0]$ and $Cov[Z_{g0},Z_{rj}|z_{g0}>0]$, respectively.

For specification of $E[Z_{gi}|z_{g0}>0]$ in (8), the reader is kindly referred to (23) of Seo (1995). $E[Z_{rj}|z_{g0}>0]$ in (8) is specified analogously as follows:

$$E[Z_{rj}|z_{g0}>0]$$

$$=E[Z_{rj}|z_{rj}>0,z_{g0}>0]\cdot Pr[z_{rj}>0|z_{g0}>0]+E[Z_{rj}|z_{rj}=0,z_{g0}>0]\cdot Pr[z_{rj}=0|z_{g0}>0] \tag{10a}$$

$$=E[Z_{rj}|z_{rj}>0]\cdot Pr[z_{rj}>0|z_{g0}>0] \tag{10b}$$

$$=m_r\cdot\{(1-m_{Ir})\cdot\rho_{Ir}(|u_j-u_0|)+m_{Ir}\} \tag{10c}$$

In obtaining (10c) from (10b), we have used the definition, $m_r\equiv E[Z_{rj}|z_{rj}>0]$, and the assumption that the fraction of rain area observed by radar is the same as that observed by a dense network of rain gages (see also Operational Considerations and Parameter Estimation Section), i.e., $m_{Ir}=m_{Ig}$, where $m_{Ig}\equiv E[I_{\{zgi>0\}}]$.

For specification of $Cov[Z_{gi},Z_{gj}|z_{g0}>0]$ in (9), the reader is kindly referred to (24) through (27) of Seo (1995). To specify $Cov[Z_{gi},Z_{rj}|z_{g0}>0]$ in (9), we first write:

$$Cov[Z_{gi},Z_{rj}|z_{g0}>0]$$
$$=E[Z_{gi}Z_{rj}|z_{g0}>0]-E[Z_{gi}|z_{g0}>0]\cdot E[Z_{rj}|z_{g0}>0] \quad (11)$$

In the above, $E[Z_{gi}Z_{rj}|z_{g0}>0]$ can be written as:

$$E[Z_{gi}Z_{rj}|z_{g0}>0]$$
$$=E[Z_{gi}Z_{rj}|z_{gi}>0,z_{rj}>0,z_{g0}>0]\cdot Pr[z_{gi}>0,z_{rj}>0|z_{g0}>0] \quad (12a)$$
$$=E[Z_{gi}Z_{rj}|z_{gi}>0,z_{rj}>0,z_{g0}>0]\cdot Pr[z_{g0}>0|z_{gi}>0,z_{rj}>0]\cdot Pr[z_{rj}>0|z_{gi}>0]\cdot Pr[z_{gi}>0]/Pr[z_{g0}>0] \quad (12b)$$
$$=E[Z_{gi}Z_{rj}|z_{gi}>0,z_{rj}>0]\cdot Pr[z_{g0}>0|z_{gi}>0,z_{rj}>0]\cdot Pr[z_{rj}>0|z_{gi}>0] \quad (12c)$$

The three terms in (12c) are specifies as follows. $Pr[z_{rj}>0|z_{gi}>0]$ is given by the second term in (10c). $E[Z_{gi}Z_{rj}|z_{gi}>0,z_{rj}>0]$ is given by:

$$E[Z_{gi}Z_{rj}|z_{gi}>0,z_{rj}>0]=\sigma_g\sigma_r\cdot\rho_c(|u_i-u_j|) \quad (13)$$

where σ_g and σ_r are the standard deviations of positive gage and positive radar rainfall, respectively, and $\rho_c(|u_i-u_j|)$ denotes the conditional cross-correlation coefficient between Z_{gi} and Z_{rj}. $\Pr[z_{g0}>0|z_{gi}>0,z_{rj}>0]$ is estimated by the indicator cokriging estimator described by (3) through (6):

$$E[z_{g0}>0|z_{gi}>0,z_{rj}>0]$$

$$\approx E[I_{\{zg0>0\}}|I_{\{zgi>0\}}=1,I_{\{zrj>0\}}=1] \quad (14a)$$

$$=m_{Ig}+\omega_{0g}(1-m_{Ig})+\omega_{0r}(1-m_{Ir}) \quad (14b)$$

where

$$\omega_{0g}=\{\rho_{Ig}(|u_0-u_i|)-\rho_{Ic}(|u_i-u_j|)\cdot\rho_{Ic}(|u_0-u_j|)\}/\{1-\rho_{Ic}^2(|u_i-u_j|)\} \quad (15a)$$

$$\omega_{0r}=\{\rho_{Ic}(|u_0-u_j|)-\rho_{Ic}(|u_i-u_j|)\cdot\rho_{Ig}(|u_0-u_i|)\}/\{1-\rho_{Ic}^2(|u_i-u_j|)\} \quad (15b)$$

Specification of $\mathrm{Cov}[Z_{ri},Z_{rj}|z_{g0}>0]$ is completely analogous, and is not given here.

As in gage-only estimation of Seo (1995), a simpler and computationally less expensive alternative to the above estimation procedure, which we now call Double Optimal Estimation (DOE), is to directly estimate $E[Z_{g0}|Z_G,Z_R]$ and $\mathrm{Var}[Z_{g0}|Z_G,Z_R]$ using the correlation structure that reflects both within-storm variability and variability due to fractional coverage. This estimation procedure, which we now refer to as Single Optimal Estimation (SOE), is described in the next section.

DIRECT ESTIMATION OF $E[Z_{g0}|Z_G,Z_R]$

For SOE, we first write:

$$E^*[Z_{g0}|Z_G,Z_R]$$

$$=E[Z_{g0}]+\sum_{i=1}^{n}\lambda_{gi}(z_{gi}-E[Z_{gi}])+\sum_{j=1}^{m}\lambda_{rj}(z_{rj}-E[Z_{rj}]) \tag{16}$$

In the above, $E[Z_{gi}]$ and $E[Z_{rj}]$ can be written as:

$$E[Z_{gi}]$$

$$=E[Z_{gi}|z_{gi}>0]\cdot Pr[z_{gi}>0] \tag{17a}$$

$$=m_g\cdot m_{Ig} \tag{17b}$$

$$E[Z_{rj}]$$

$$=E[Z_{rj}|z_{rj}>0]\cdot Pr[z_{rj}>0] \tag{18a}$$

$$=m_r\cdot m_{Ir} \tag{18b}$$

In (16), the optimal weights, Λ_{gi}'s and Λ_{rj}'s, that minimize $E[(Z_{g0}-E^*[Z_{g0}|Z_G,Z_R])^2|Z_G,Z_R]$ are given by:

$$(\Lambda_{g1},\ldots,\Lambda_{gn},\Lambda_{r1},\ldots,\Lambda_{rm})=[C_{0G}\ C_{0R}]\begin{bmatrix} C_{GG} & C_{GR} \\ C_{RG} & C_{RR} \end{bmatrix}^{-1} \tag{19}$$

where C_{GG}, C_{GR} ($=C_{RG}^{T}$), and C_{RR} are the nxn, nxm, and mxm unconditional covariance matrices whose ij-th entries are given by $Cov[Z_{gi},Z_{gj}]$, $Cov[Z_{gi},Z_{rj}]$, and $Cov[Z_{ri},Z_{rj}]$, respectively, and C_{0G} and C_{0R} are the 1xn and 1xm unconditional covariance vectors whose i-th and j-th entries are given by $Cov[Z_{g0},Z_{gi}]$ and $Cov[Z_{g0},Z_{ri}]$, respectively. Specification of $Cov[Z_{gi},Z_{gj}]$, as a function of σ_g^2, m_{Ig}, $\rho_g(|u_i-u_j|)$, and $\rho_{Ig}(|u_i-u_j|)$, is given by (33) of Seo (1995). $Cov[Z_{gi},Z_{rj}]$ and $Cov[Z_{ri},Z_{rj}]$ are specified in an analogous manner. For example, we have for $Cov[Z_{gi},Z_{rj}]$:

$$Cov[Z_{gi},Z_{rj}]$$

$$=E[Z_{gi},Z_{rj}]-E[Z_{gi}]E[Z_{rj}] \tag{20a}$$

$$=E[Z_{gi},Z_{rj}|z_{gi}>0,z_{rj}>0]\cdot Pr[z_{gi}>0,z_{rj}>0]-E[Z_{gi}|z_{gi}>0]\cdot Pr[z_{gi}>0]\cdot E[Z_{rj}|z_{rj}>0]\cdot Pr[z_{rj}>0] \tag{20b}$$

$$=\sigma g\cdot\sigma r\cdot\{m_{Ig}(1-m_{Ig})\}^{1/2}\cdot\{m_{Ir}(1-m_{Ir})\}^{1/2}\cdot\rho_c(|u_i-u_j|)\cdot\rho_{Ic}(|u_i-u_j|)$$

$$+m_g\cdot m_r\cdot\sigma g\cdot\sigma r\cdot\rho_{Ic}(|u_i-u_j|)+\sigma g\cdot\sigma r\cdot m_{Ig}\cdot m_{Ir}\cdot\rho_c(|u_i-u_j|) \tag{20c}$$

Specification of $Cov[Z_{ri},Z_{rj}]$ is completely analogous to that of $Cov[Z_{gi},Z_{gj}]$, and is not given here.

OPERATIONAL CONSIDERATIONS AND PARAMETER ESTIMATION

To estimate rainfall at a single point using SOE and DOE as described above in generality, a linear system of dimension (n+m) will have to be solved once and twice, respectively, where n and m denote the numbers of rain gage and radar rainfall data in A, respectively. Such an approach, however, makes the size of the linear system much too large for operational implementation. To minimize the computational requirements, we use only the single radar rainfall datum collocated with the point of estimation, u_0 (i.e., m=1). Under this simplification, both SOE and DOE require specification of the following parameters;

m_g - mean of positive gage rainfall in A, m_r - mean of positive radar rainfall in A, σ_g^2 - variance of positive gage rainfall in A, σ_r^2 - variance of positive radar rainfall in A, m_{Ig} - fraction of rain area in A as would be observed by a dense network of gages, m_{Ir} - fraction of rain area in A observed by radar, $\rho_g(|\cdot|)$ - spatial correlation function of positive gage rainfall in A, $\rho_{Ig}(|\cdot|)$ - spatial correlation function of indicator gage rainfall in A, $\rho_c(|0|)$ - lag-zero cross-correlation coefficient between positive gage and positive radar rainfall in A, and $\rho_{Ic}(|0|)$ - lag-zero cross-correlation coefficient between indicator gage and indicator radar rainfall in A.

Estimation of $\rho_g(|\cdot|)$ and $\rho_{Ig}(|\cdot|)$, either in real time or climatologically, is practically impossible because of sparsity of gage networks. To circumvent the problem, we use both radar rainfall and rain gage data to infer statistics of gage rainfall under a set of simplifying assumptions. Such an approach seems inevitable in that, if there exist enough rain gage data to allow reliable estimation of the second-order statistics of gage rainfall, multi-sensor estimation may not be necessary in the first place (i.e., gage-only estimation may suffice). The assumptions used are:

$$\rho_g(|\cdot|)=\rho_r(|\cdot|) \tag{21}$$

$$\rho_{Ig}(|\cdot|)=\rho_{Ir}(|\cdot|) \tag{22}$$

$$m_g=m_r \tag{23}$$

$$m_{Ig}=m_{Ir} \tag{24}$$

$$\sigma_g^2=\sigma_r^2 \tag{25}$$

It can be easily shown that (21) holds when radar rainfall is a linear sum of gage rainfall and a white-noise error in space (Creutin et al. 1988, Seo and Smith 1991). The sufficient condition for (22) is that the bivariate probability distribution of occurrence of rainfall observed by radar is the same as that observed by a dense network of gages. (23) implies that mean field bias-corrected radar rainfall data are also locally unbiased. (24) states that, locally, the fraction of rain area observed by radar is the same as that observed by a dense network of gages. (25) states that, locally, hourly radar rainfall has approximately the same magnitude of variability as hourly gage rainfall. Because of range degradation, beam blockage, spatial variability in raindrop size distribution, etc., the above assumptions are not true in general. Nevertheless, use of radar rainfall data in parameter estimation via, e.g., (21) through (25) can easily be justified by the fact that estimation of local second-order statistics of gage rainfall, based on rain gage data alone, is practically impossible due to sparsity of gage networks.

Real-time estimation of locally varying $\rho_r(|\cdot|)$ and $\rho_{Ir}(|\cdot|)$ also poses a difficulty because the number of radar rainfall data in A, i.e., within the circle whose radius equals the spatial correlation scale of rainfall (or, equivalently, the greater of the correlation scale of positive rainfall and the indicator correlation scale of rainfall), would typically be too small to obtain reliable estimates of them. Also, even if $\rho_r(|\cdot|)$ and $\rho_{Ir}(|\cdot|)$ may be estimated locally, the associated computational burden would be too heavy for operational implementation. For these reasons, $\rho_r(|\cdot|)$ and $\rho_{Ir}(|\cdot|)$ are treated in this work as spatially uniform, and hence estimated once only from the current hourly radar rainfall field under the assumptions of translation invariance and isotropy.

Estimation of m_g and σ_g^2 amounts to estimating $E[m_g|Z_g,Z_r]$ and $E[\sigma_g^2|Z_g,Z_r]$, where Z_g

and Z_r are the rain gage and the radar rainfall data in A, respectively. With (21) through (25), m_g may be estimated via the following maximum likelihood estimator (Kitanidis 1986):

$$m_g = U^T \, Corr^{-1} \, Z \, / \, \{U^T \, Corr^{-1} \, U\} \tag{26}$$

where U is the 1x(n+m) unit vector, i.e., $U=(1,...,1)^T$, Corr is the (n+m)x(n+m) spatial correlation coefficient matrix, and Z is the (n+m)x1 vector of rain gage and radar rainfall data, i.e., $Z=(Z_g,Z_r)$. Similarly, following a number of assumptions concerning the prior probability distribution of σ_g^2 and the likelihood function of Z (Raiffa and Shlaifer 1961, Kitanidis 1986), σ_g^2 may be estimated via the following Bayesian estimator:

$$\sigma_g^2 = \{1/(n+m-2)\} \, (Z-Um_g)^T \, Corr^{-1} \, Z \tag{27}$$

If rain gage and radar rainfall data are sampled sparsely in space such that Corr reduces to an identity matrix, we have for (26) and (27):

$$m_g = \{1/(n+m)\} \, \left(\sum_{i=1}^{n} z_{gi} + \sum_{j=1}^{m} z_{rj} \right) \tag{28}$$

$$\sigma_g^2 = \{1/(n+m-2)\} \, \left\{ \sum_{i=1}^{n} (z_{gi} - m_g)^2 + \sum_{j=1}^{m} (z_{rj} - m_g)^2 \right\} \tag{29}$$

Computationally, (26) and (27) are too expensive for operational implementation: as approximations, we used in this work (28) and (29) instead. Estimation of m_{Ig} is completely analogous to (26) and (28), with z_{gi} and z_{rj} replaced by $i_{\{zgi>0\}}$ and $i_{\{zrj>0\}}$, respectively.

$\rho_c(|0|)$ and $\rho_{Ic}(|0|)$ are estimated climatologically from long-term records of synchronized and collocated pairs of hourly radar rainfall and rain gage data. It is important to point out that, though not considered in this work for the sake of simplicity, $\rho_c(|0|)$ and $\rho_{Ic}(|0|)$ can be stratified according to range so that range degradation in radar estimation of rainfall given raining and radar detection of rainfall (Kitchen and Jackson 1993, Smith et al. 1995) can be taken into account.

VALIDATION

To evaluate the estimation procedures, a cross-validation experiment was performed using hourly radar rainfall data from the Tulsa, Oklahoma, WSR-88D and hourly rain gage data in the area. This site has one of the densest operational rain gage networks in the country, and therefore is well-suited for cross validation. The reader is kindly referred to Fig 1 of Seo (1995) for the rain gage network and the radar umbrella. The data used cover April through November of 1994.

As noted, the multi-sensor estimation procedures described in this work use mean field bias-corrected radar rainfall data. Owing to the large number of rain gages available at this site (about 200), it was concluded that the sophisticated, operational bias estimation procedure (Smith and Krajewski 1991) may be substituted by the following, simple sample bias estimator:

$$\beta^{*}=(1/k)\sum_{i=1}^{k}\{z_{gi}/z_{ri}\} \tag{30}$$

where β^{*} is the estimated bias at the current hour, and k is the number of radar-gage pairs. β^{*} is then multiplied to the radar rainfall data at the current hour to obtain bias-corrected radar rainfall data.

For intercomparison purposes, four estimation procedures were included in the cross-validation experiment; gage-only estimation using the reciprocal distance-squared method (Chow et al. 1988, NWS 1993), radar-only estimation using the bias-corrected radar rainfall data directly above the withheld rain gages, multi-sensor estimation using SOE, and multi-sensor estimation using DOE. They are denoted as GAG, RAD, SOE, and DOE, respectively. Because of space limitations, we are not able to provide examples of rainfall fields as obtained from GAG, RAD, and SOE/DOE: the reader is referred to, e.g., the Arkansas-Red River Basin River Forecast Center's (ABRFC) Home Page on the World-Wide Web at 'http://gopherpc.abrfc.noaa.gov/abrfc.html.'

Figs 1, 2, and 3 show, for each month, the mean error of the estimates (a positive mean error implies underestimation), the root mean square error of the estimates, and the cross-correlation coefficient between observed and estimated rainfall, respectively. The reduction in root mean square error by SOE over RAD estimates ranges from 0.1 to as much as 0.4 mm per hour. It is seen that, in June, July, and August, multi-sensor estimation is not as effective as in other months whereas bias-corrected radar rainfall data are prominently superior to rain gage-only estimates: it can be explained by the rainfall climatology that summer rainfall in the area occurs primarily due to localized convection, and hence the spatial correlation scale tends to be small. Comparatively large biases in DOE estimates in the summer months (Fig 1) is peculiar, and suggests that DOE may not be as robust as SOE when data exhibit very large variabilities. Figs 4, 5, and 6 show scatter-plots for November 1994 between observed rainfall and GAG, RAD, and SOE estimates, respectively. The scatter-plot for DOE estimates is very similar to that for SOE estimates, and hence is not shown. A perfect estimator would produce a scatter on the 45-degree line. It can be seen that the multi-sensor estimates produce a significantly tighter scatter.

Figs 7 and 8 show the mean and the root mean square errors of the estimates, respectively, over various ranges, bounded from below, of observed rainfall. They are useful for assessing performance in estimation of large rainfall amounts. Fig 9 shows, at various cutoffs, the conditional probability that the estimated rainfall is greater than the cutoff given that the observed rainfall is. It is useful for assessing performance in detection of large rainfall amounts. Figs 10 and 11 are completely analogous to Figs 7 and 8, respectively, except that the ranges of observed rainfall are bounded from above. They are useful for assessing performance in estimation of small to moderate rainfall amounts. The five figures may be summarized as follows: 1) RAD estimates are, expectedly, substantially better than GAG estimates under all criteria considered except for overall unbiasedness (see Fig 7) and detection of small rainfall amounts (see Fig 9), 2) DOE estimates provide little or no improvement over SOE estimates under all criteria considered except for estimation of no to small rainfall amounts (see Fig 11), 3) multi-sensor estimates have a more pronounced tendency to underestimate large rainfall amounts than RAD estimates (see Fig 7): for specific purposes of estimation and detection of rainfall amounts of a half an inch or more, RAD estimates are better (Figs 8 and 9), 2) on the average, however, multi-sensor estimates are significantly better than RAD estimates over any areas of rainfall and/or no-rainfall (see Fig 11).

Fig 12 show the root mean square errors of the estimates for various gage network densities. The network density was varied by randomly eliminating a half and three quarters of the gages in the original network of about 200. They suggest that, as long as there exists at least a single rain gage within the radius of influence, defined as the spatial correlation scale of rainfall, effectiveness of multi-sensor estimation is not very sensitive to the number of additional rain gages available.

Figs 13 and 14 show scatter-plots between (observed - estimated rainfall)^2 and estimation variances from SOE and DOE, respectively. An ideal estimator would produce a tight scatter centered around the 45-degree line. They indicate that DOE variance estimates are slightly more accurate than SOE variance estimates.

CONCLUSIONS AND FUTURE RESEARCH RECOMMENDATIONS

The conclusions may be summarized as follows:

1) On the average, multi-sensor estimates are significantly more accurate than either the bias-corrected radar rainfall data or the gage-only estimates. Therefore, streamflow prediction models, such as those used at the National Weather Service River Forecast Centers, are better-served by inputting multi-sensor estimates.
2) For specific purposes of detection and estimation of large rainfall amounts, however, bias-corrected radar rainfall data may provide the most accurate rainfall estimates: it points out the

importance of accurate correction of mean field bias in radar rainfall data, e.g., for flash-flood forecasting at the National Weather Service Weather Forecast Offices.

3) Multi-sensor estimation based on double optimal estimation (DOE) of the probability of rainfall and the amount of rainfall given raining offers little or no improvement over that based on direct, single optimal estimation (SOE). DOE, nevertheless, offers a methodology that allows objective assimilation of both continuous (e.g., rainfall amount) and binary variables (e.g., rain or no-rain).

Areas of further enhancement include the following:

1) Incorporate climatological correction for orographic enhancement,
2) Account for range degradation of radar rainfall data by stratifying lag-zero conditional and indicator correlation coefficients according to range,
3) Investigate stratification of lag-zero conditional and indicator cross-correlation coefficient according to amount of radar rainfall to reduce the tendency for multi-sensor estimates to underestimate large rainfall amounts.

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REFERENCES

Austin, P. M., Relation between measured radar reflectivity and surface rainfall, Mon. Wea. Rev., 115, 1053-1070, 1987.

Azimi-Zonooz, A., W. F. Krajewski, D. S. Bowles, and D.-J. Seo, Spatial rainfall estimation by linear and non-linear co-kriging of radar-rainfall and raingage data, Stoch. Hydrol. Hydraul., 3, 51-67, 1989.

Barancourt, C., J. D. Creutin and J. Rivoirard, A method for delineating and estimating rainfall fields, Water Resour. Res., 28(4), 1133-1144, 1992.

Brandes, E. A., Optimizing rainfall estimate with the aid of radar, J. Appl. Meteor., 14, 1339-1345, 1975.

Chow, V. T., D. R. Maidment, and L. W. Mays, Applied Hydrology, McGraw-Hill, 1988.

Crawford, K. C., Consideration for the design of a hydrologic data network using multivariate sensors, Water Resour. Res., 15(6), 1752-1762, 1979.

Creutin, J. D., G. Delrieu, and T. Lebel, Rain measurement by raingage-radar combination: a geostatistical approach, J. Atmos. Oceanic Technol., 5(1), 102-115, 1988.

Eddy, A., Objective analysis of convective scale rainfall using gages and radar, J. Hydrol., 44, 125-134, 1979.

Fread, D. L, R. C. Shedd, G. F. Smith, R. Farnsworth, C. N. Hoffeditz, L. A. Wenzel, S. M. Wiele, J. A. Smith, and G. N. Day, Modernization in the National Weather Service River and Flood Program, Weather and Forecasting, 10(3), 477-484, 1995.

Hudlow, M. D., Technological developments in real-time operational hydrologic forecasting in the United States, J. Hydrol., 102, 69-92, 1988.

Journel, A. G., Nonparametric estimation of spatial distributions, Mathematical Geology, 15(3), 445-468, 1983.

Kitanidis, P. K., Parameter uncertainty in estimation of spatial function: Bayesian analysis, Water Resour. Res., 22(4), 499-507, 1986.

Kitchen, M., and P. M. Jackson, Weather radar performance at long range - Simulated and observed, J. Appl. Meteor., 32, 975-985, 1993.

Krajewski, W. F., Cokriging of radar-rainfall and rain gage data, J. Geophys. Res., 92(D8), 9571-9580, 1987.

National Weather Service, National Weather Service River Forecast System (NWSRFS) User's Manual, Office of Hydrology, National Weather Service, 1993.

National Weather Service, Stage III User's Guide, Office of Hydrology, August 1995.

Raiffa, H., and R. Schlaifer, Applied statistical decision theory, The MIT Press, Cambridge, MA, 1961.

Seo, D.-J., Real-time estimation of rainfall fields using rain gage data under fractional coverage conditions, submitted to Water Resour. Res., September 1995.

Seo, D.-J., Nonlinear estimation of spatial distribution of rainfall - An indicator cokriging approach, to appear in Stoch. Hydrol. Hydraul., 1996.

Seo, D.-J., Krajewski, W. F., D. S. Bowles, Stochastic interpolation of rainfall data from rain gages and radar using cokriging, 1. Design of experiments, Water Resour. Res., 26, 469-477, 1990.

Seo, D.-J., W. F. Krajewski, A. Azimi-Zonooz, and D. S. Bowles, Stochastic interpolation of rainfall data from rain gages and radar using cokriging, 2. Results, Water Resour. Res., 26, 915-924, 1990.

Seo, D.-J., and J. A. Smith, Rainfall estimation using raingages and radar - A Bayesian approach: 2. An application, Stoch. Hydrol. Hydraul., 5, 31-44, 1991.

Seo, D.-J., and J. A. Smith, Characterization of the climatological variability of mean areal rainfall through fractional coverage, to appear in Water Resour. Res., 1996.

Shedd, R. C., and J. A. Smith, Interactive precipitation processing for the modernized National Weather Service, Preprints, 7th Inter. Conf. On Interactive Information and Processing Systems for Meteorology, Oceanography, and Hydrology, AMS, New Orleans, January 13-18, 1991.

Smith, J. A., and W. F. Krajewski, Estimation of the mean field bias of radar rainfall estimates, J. Appl. Meteor., 30(4), 397-412, 1991.

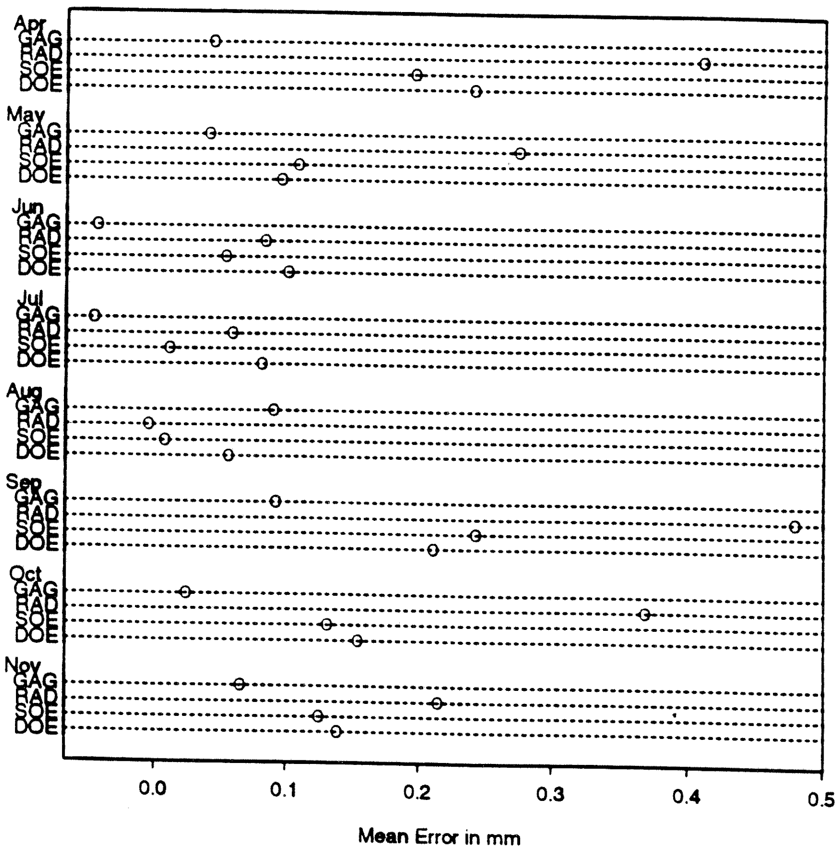
Smith, J. A., D.-J. Seo, M. L. Baeck, and M. D. Hudlow, An intercomparison study of NEXRAD precipitation estimates, submitted to Water Resour. Res., 1995.

Solow, A. R., Mapping by indicator kriging, Math. Geol., 18(3), 335-352, 1986.

Wilson, J. W., Integration of radar and raingage data for improved rainfall measurement, J. Appl. Meteor., 9(3), 489-497, 1970.

Wilson, J. W., and E. A. Brandes, Radar measurement of rainfall, Bull. Amer. Meteor. Soc., 60, 1048-1058, 1979.

List of Figures and Their Captions



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GAG
RAD
SOE
DOE
May
GAG
RAD
SOE
DOE
Jun
GAG
RAD
SOE
DOE
Jul
GAG
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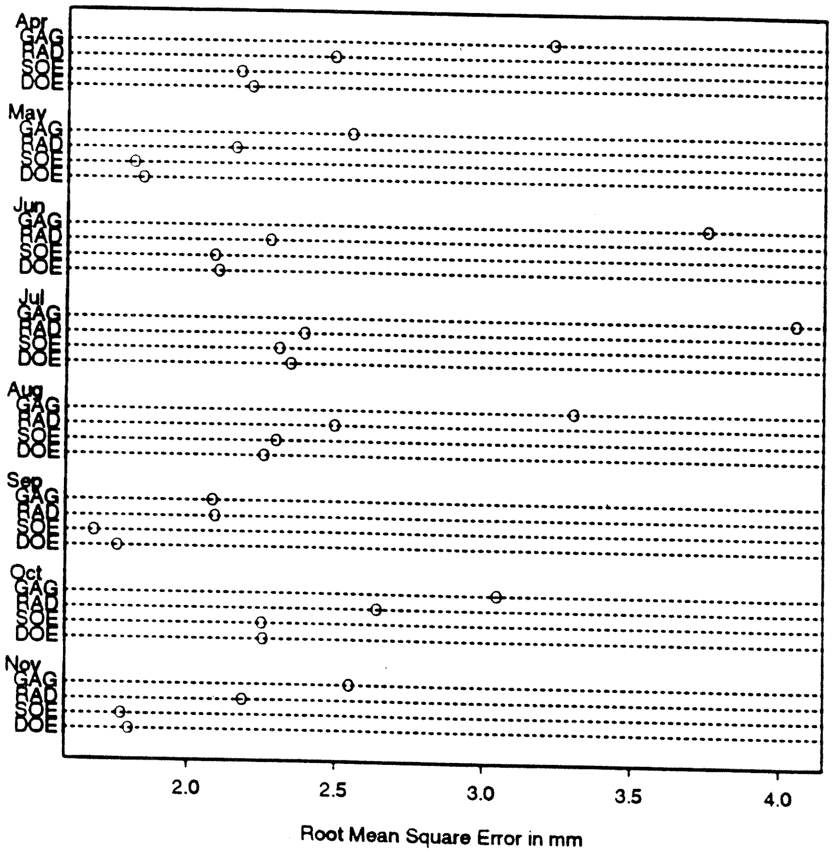
SOE
DOE
Aug
GAG
RAD
SOE
DOE
Sep
GAG
RAD
SOE
DOE
Oct
GAG
RAD
SOE
DOE
Nov
GAG
RAD
SOE
DOE
0.0
0.1
0.2
0.3
0.4
0.5
Mean Error in mm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GAG
RAD
SOE
DOE
May
GAG
RAD
SOE
DOE
Jun
GAG
RAD
SOE
DOE
Jul
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SOE
DOE
Aug
GAG
RAD
SOE
DOE
Sep
GAG
RAD
SOE
DOE
Oct
GAG
RAD
SOE
DOE
Nov
GAG
RAD
SOE
DOE
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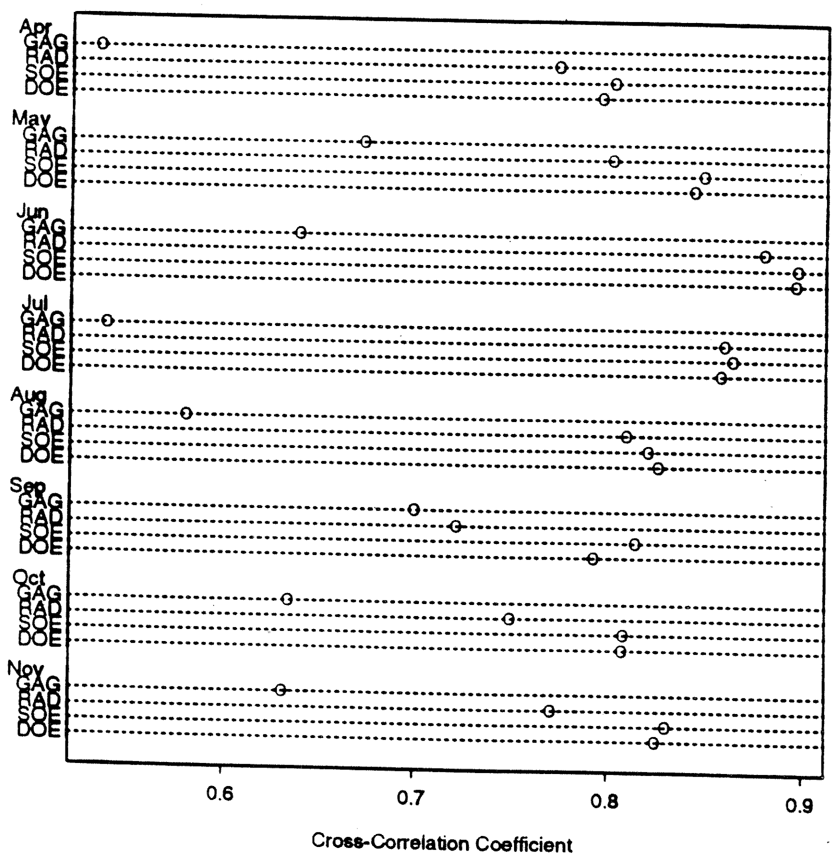
2.5
3.0
3.5
4.0
Root Mean Square Error in mm


Apr
GAG
RAD
SOE
DOE
May
GAG
RAD
SOE
DOE
Jun
GAG
RAD
SOE
DOE
Jul
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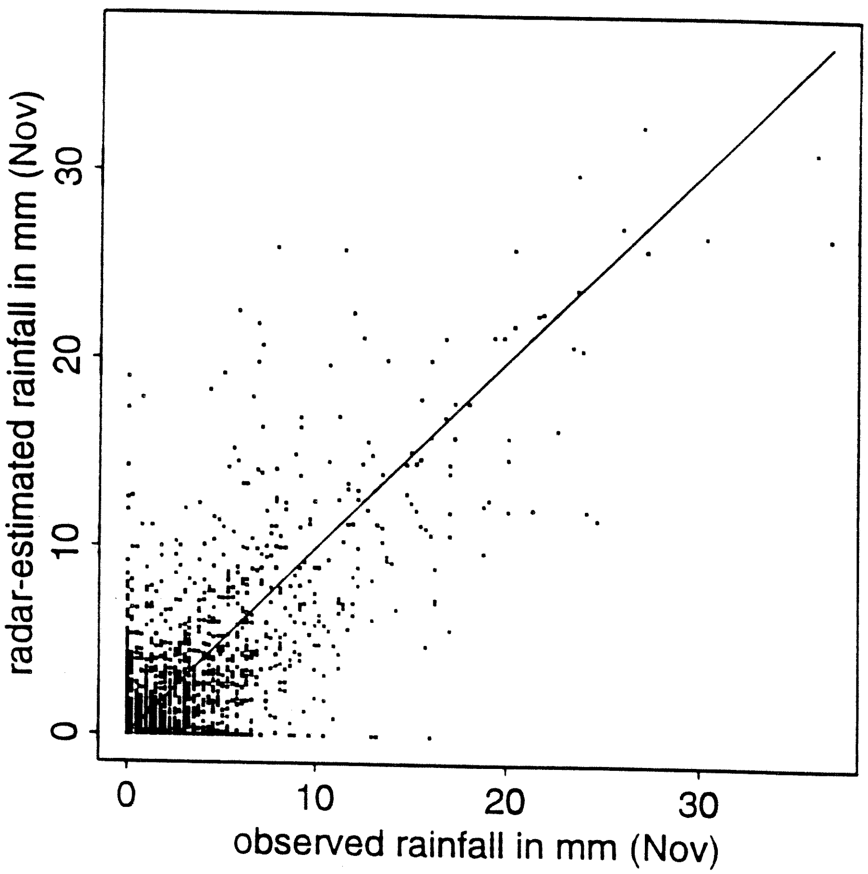
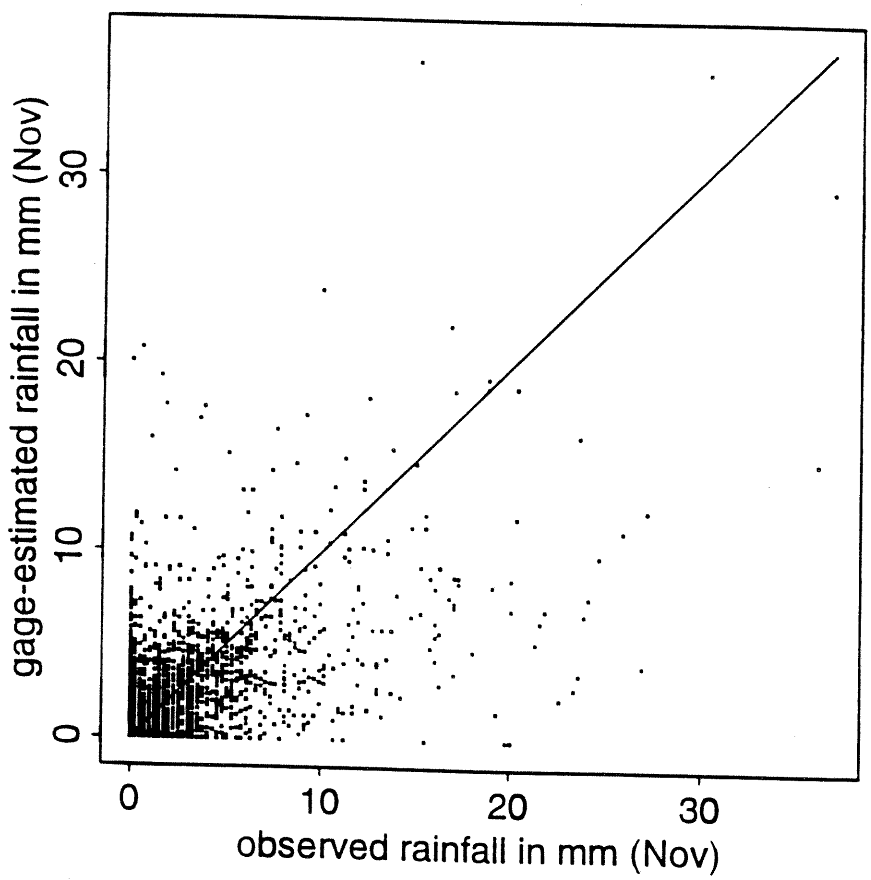
DOE
Aug
GAG
RAD
SOE
DOE
Sep
GAG
RAD
SOE
DOE
Oct
GAG
RAD
SOE
DOE
Nov
GAG
RAD
SOE
DOE
0.6
0.7
0.8
0.9
Cross-Correlation Coefficient

4

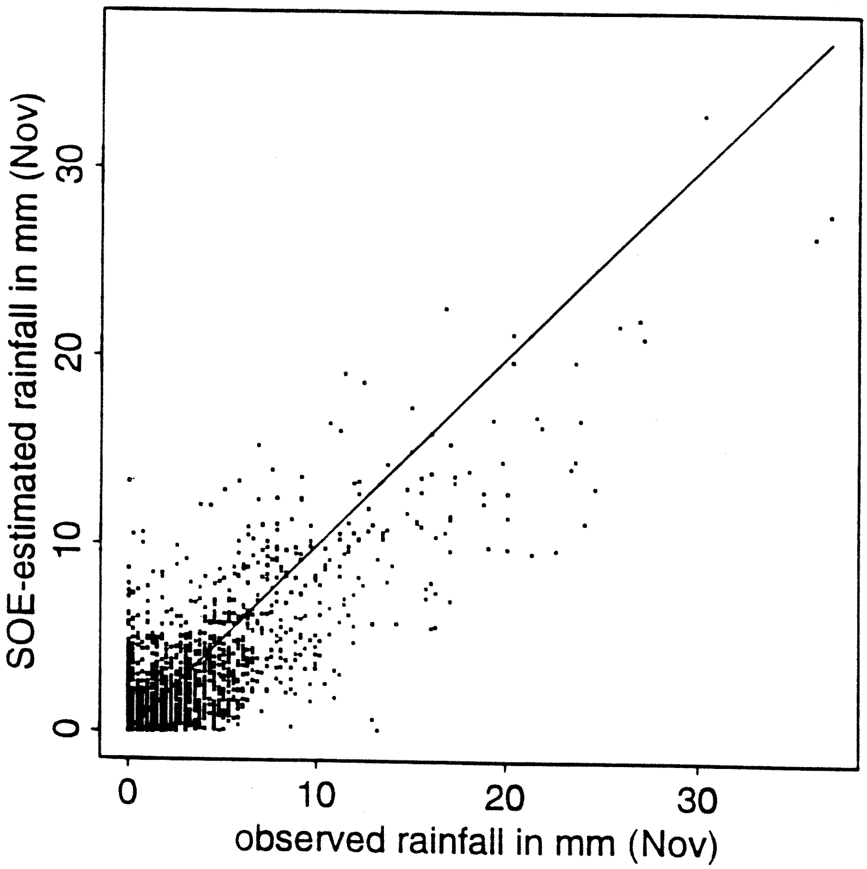


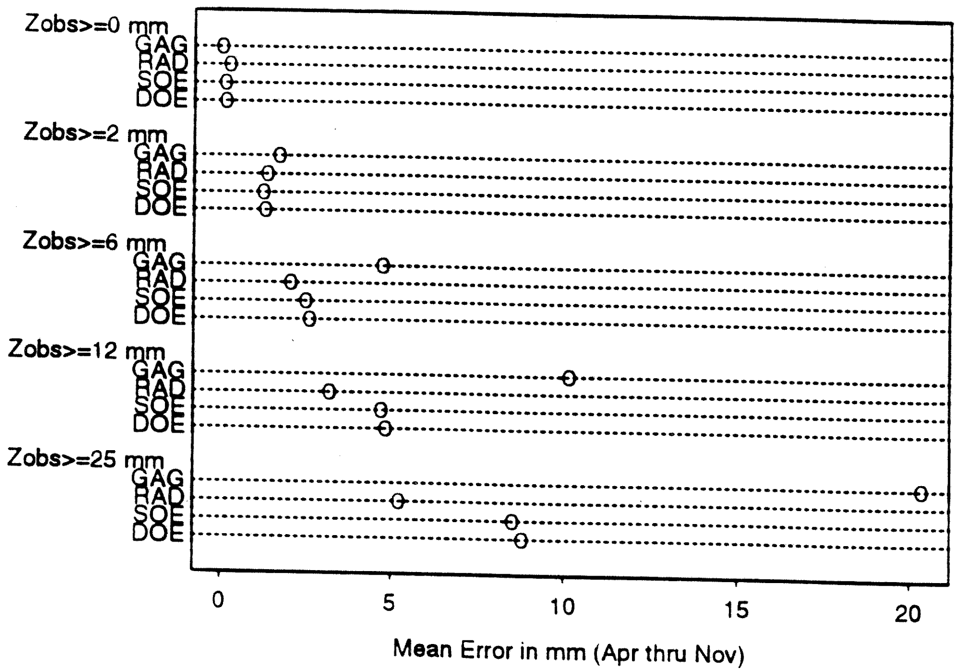
radar-estimated rainfall in mm (Nov)
0
10
20
30
observed rainfall in mm (Nov)

5

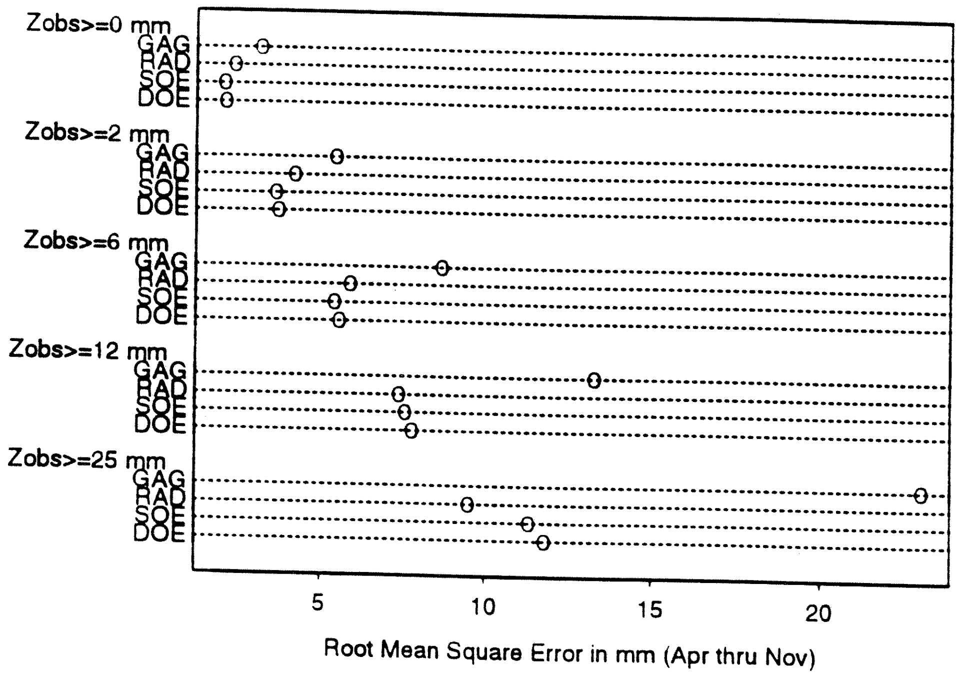

gage-estimated rainfall in mm (Nov)
0
10
20
30
observed rainfall in mm (Nov)

6


SOE-estimated rainfall in mm (Nov)
0
10
20
30
observed rainfall in mm (Nov)


Zobs>=0 mm
GAG
RAD
SOE
DOE
Zobs>=2 mm
GAG
RAD
SOE
DOE
Zobs>=6 mm
GAG
RAD
SOE
DOE
Zobs>=12 mm
GAG
RAD
SOE
DOE
Zobs>=25 mm
GAG
RAD
SOE
DOE
0
5
10
15
20
Mean Error in mm (Apr thru Nov)

8


Zobs>=0 mm
GAG
RAD
SOE
DOE
Zobs>=2 mm
GAG
RAD
SOE
DOE
Zobs>=6 mm
GAG
RAD
SOE
DOE
Zobs>=12 mm
GAG
RAD
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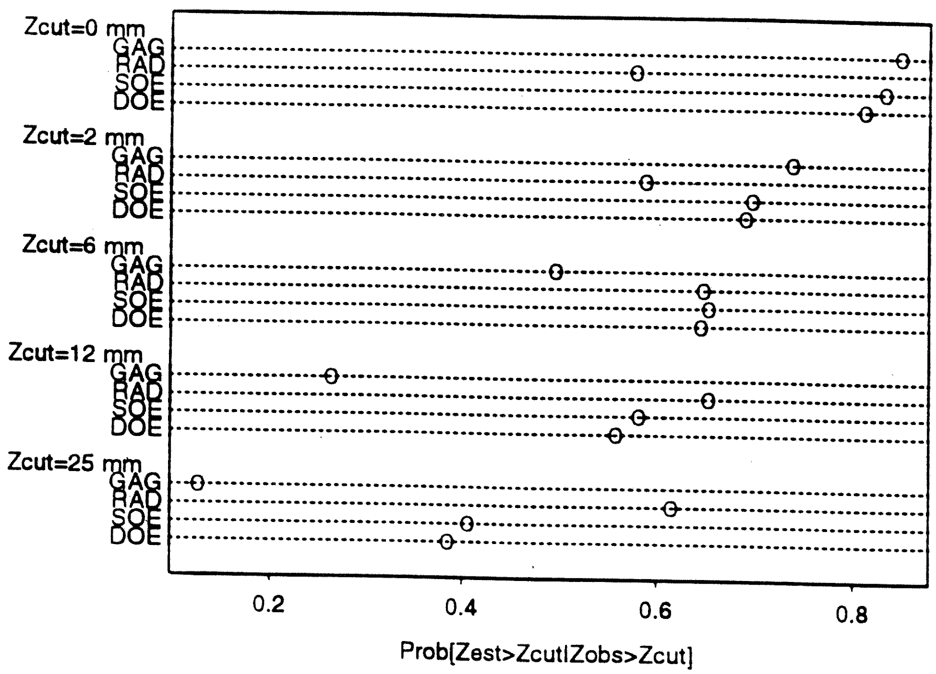
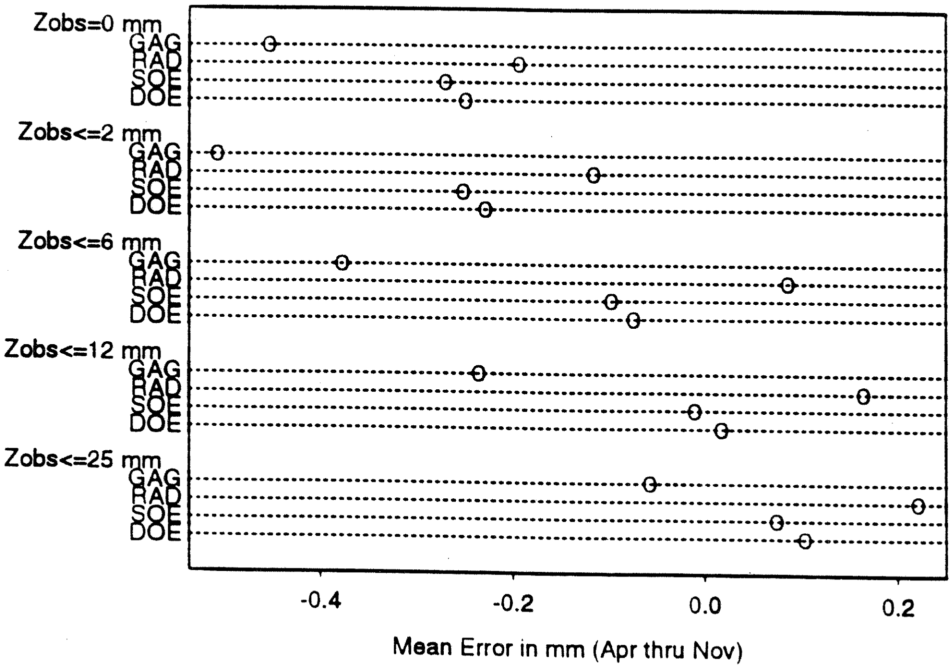
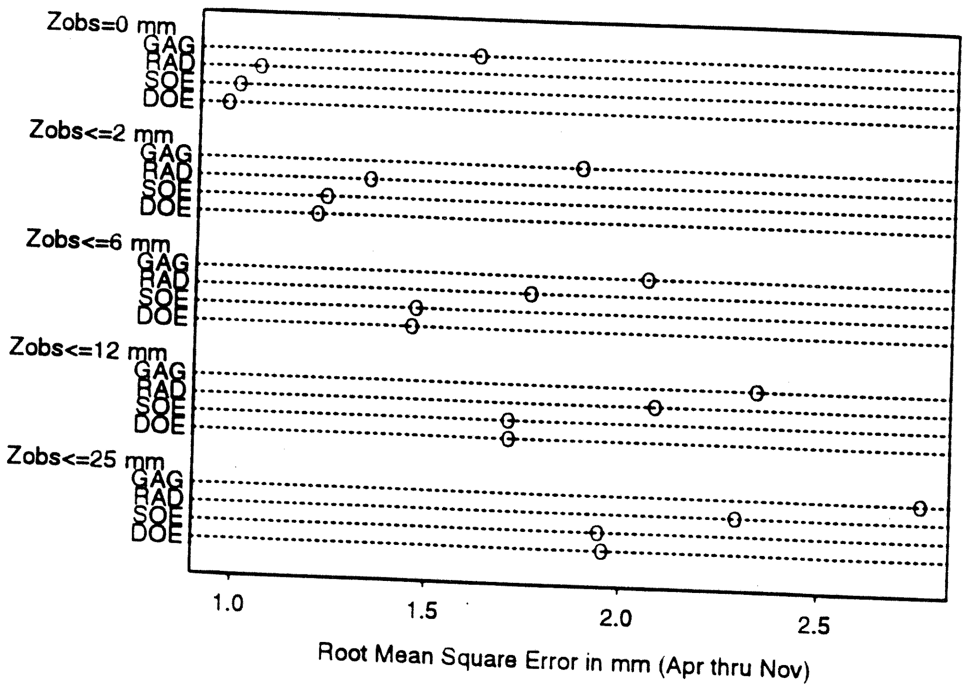
Zobs>=25 mm
GAG
RAD
SOE
DOE
5
10
15
20
Root Mean Square Error in mm (Apr thru Nov)


Zcut=0 mm
GAG
RAD
SOE
DOE
Zcut=2 mm
GAG
RAD
SOE
DOE
Zcut=6 mm
GAG
RAD
SOE
DOE
Zcut=12 mm
GAG
RAD
SOE
DOE
Zcut=25 mm
GAG
RAD
SOE
DOE
0.2
0.4
0.6
0.8
Prob[Zest>Zcut|Zobs>Zcut]


Zobs=0 mm
GAG
RAD
SOE
DOE
Zobs<=2 mm
GAG
RAD
SOE
DOE
Zobs<=6 mm
GAG
RAD
SOE
DOE
Zobs<=12 mm
GAG
RAD
SOE
DOE
Zobs<=25 mm
GAG
RAD
SOE
DOE
-0.4
-0.2
0.0
0.2
Mean Error in mm (Apr thru Nov)

11



Zobs=0 mm
GAG
RAD
SOE
DOE
Zobs<=2 mm
GAG
RAD
SOE
DOE
Zobs<=6 mm
GAG
RAD
SOE
DOE
Zobs<=12 mm
GAG
RAD
SOE
DOE
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GAG
RAD
SOE
DOE
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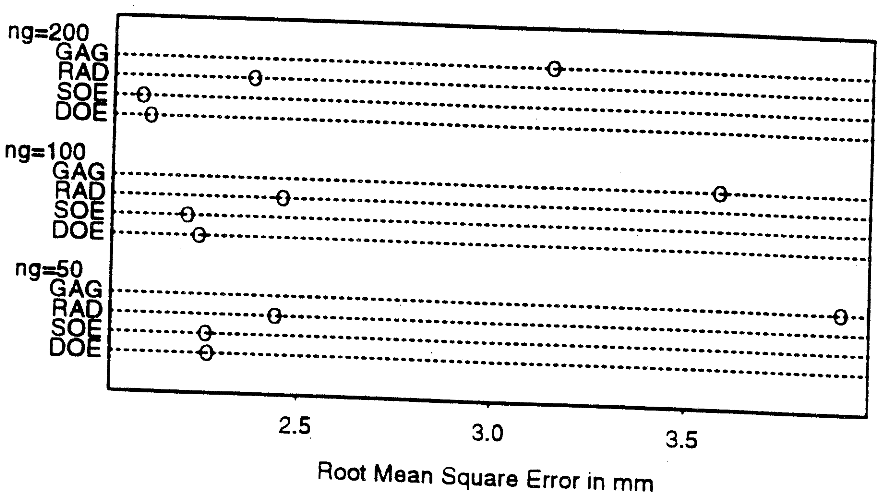
1.5
2.0
2.5
Root Mean Square Error in mm (Apr thru Nov)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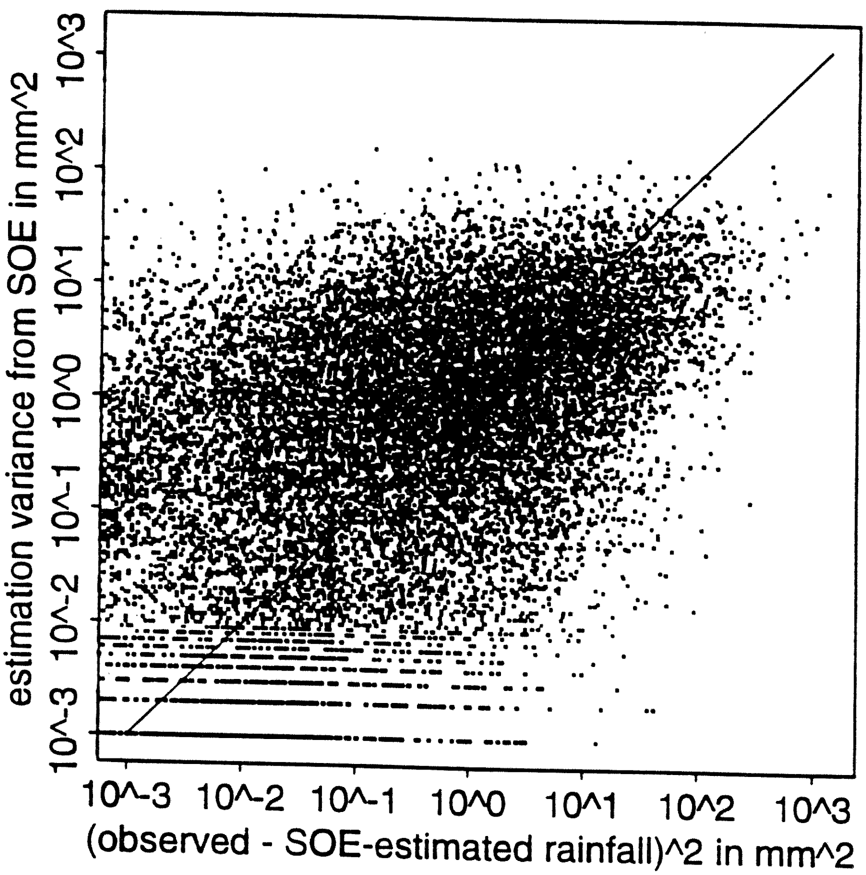
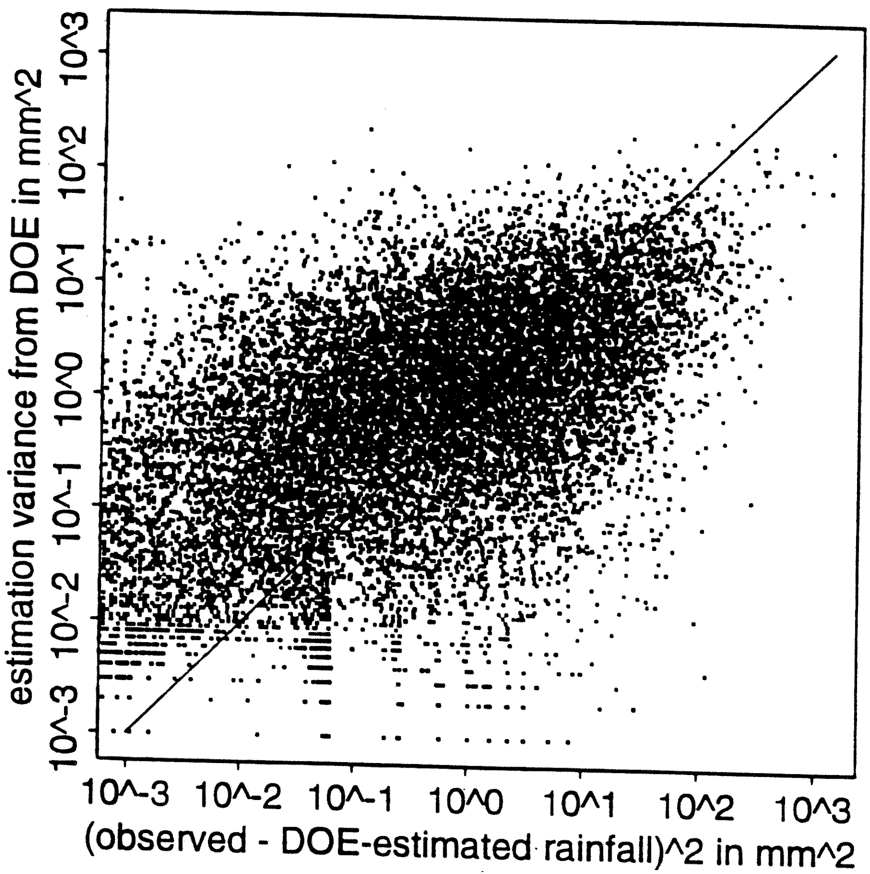
GAG
RAD
SOE
DOE
ng=100
GAG
RAD
SOE
DOE
ng=50
GAG
RAD
SOE
DOE
2.5
3.0
3.5
Root Mean Square Error in mm

13



estimation variance from SOE in mm^2
10^-3
10^-2
10^-1
10^0
10^1
10^2
10^3
10^-3 10^-2 10^-1 10^0 10^1 10^2 10^3
(observed - SOE-estimated rainfall)^2 in mm^2

14


estimation variance from DOE in mm^2
10^-3 10^-2 10^-1 10^0 10^1 10^2 10^3
10^-3 10^-2 10^-1 10^0 10^1 10^2 10^3
(observed - DOE-estimated rainfall)^2 in mm^2

Adaptable Parameters - Gage-Only Analysis

Parameter	Current Default	Description
distmin	0.1	Specifies the separation distance in km in correlation modeling. No changes are recommended.
itype	2	Specifies the type of gage-only analysis procedure to be used (**itype**=1: Reciprocal Distance-Squared method (RDS), **itype**=2: Single Optimal Estimation (SOE), **itype**=3: Double Optimal Estimation (DOE)). Computationally, RDS is the least expensive, DOE the most expensive.

If there are less than 50 gages or so under the radar umbrella (assuming that they are fairly well-scattered), RDS is recommended. If there are more gages, SOE is recommended. DOE, developed primarily to assimilate satellite and lightning data in the future, is twice as computationally expensive as SOE, and hence is not recommended at this time.

Parameter	Current Default	Description
nbors	4	Specifies the number of surrounding rain gage measurements to be used in the estimation procedure (if that many gages indeed exist within the radius of **radius** (see below)). The maximum is 20.

This parameter has a huge impact on both the accuracy of estimates and how the estimated rainfall field looks like. If **nbors=1**, the estimate will be the same as the nearest rain gage datum (if there exists at least a single rain gage within the radius of **radius**): it will produce something that looks nothing like a rainfall field. Theoretically, the larger **nbors** is, the more accurate the estimates are (if that many rain gages indeed exist within the radius of **radius**). Computationally, however, the larger **nbors**, the more expensive. With the recommended value of 4, this trade-off between accuracy and computational burden should not be an issue at most sites because of the sparsity of rain gage networks.

Parameter	Current Default	Description
rainmin	0.01	Specifies the minimum detectable rainfall depth in mm. No changes are recommended.
rangei	52.	Specifies the indicator correlation scale in

km. It represents a characteristic scale for spatial intermittency of rainfall. The default value is obtained from climatological analyses of WSR-88D hourly rainfall data in the Southern Plains. Until site- and seasonality-specific estimates of **rangei** can be obtained, no changes are recommended.

cor0i	1.	Specifies the lag-0 indicator correlation coefficient. No changes are recommended.
cor0pi	0.75.	Specifies the lag-0+ indicator correlation coefficient. No changes are recommended.
rangec	36.	Specifies the conditional correlation scale in km. It represents a characteristic scale for within-storm variability of rainfall. The default value is obtained from climatological analyses of WSR-88D hourly rainfall data in the Southern Plains. Until site- and seasonality-specific estimates of **rangec** can be obtained, no changes are recommended.
cor0c	1.	Specifies the lag-0 conditional correlation coefficient. No changes are recommended.
cor0pc	1.	Specifies the lag-0+ conditional correlation coefficient. No changes are recommended.
radius	52.	Specifies the radius of influence in km. For example, with the default value of 52, rain gage data outside of the circle of radius of 52 km are not used in estimation. Theoretically speaking, **radius** should always be equal to max{**rangei**,**rangec**}. However, because we do not have site- and seasonality-specific estimates of **rangei** and **rangec** yet, it is recommended that **radius** be adjusted to account for differences between, e.g., cellular/convective and widespread/stratiform rainfall fields. Generally speaking, **radius** for a convective storm should be smaller than for a stratiform storm.

It is recommended that the sensitivity of the analysis field on **radius** be familiarized by displaying gage-only analysis fields for a range of values of **radius** (say, 20 to 100 km) so that a visual 'feel' may be acquired for what the appropriate values of **radius** should be for the regional and seasonal climatology of rainfall (and, ideally, synoptic conditions as well).

Adaptable Parameters - Multi-Sensor Analysis

Parameter	Current Default	Description
itype	1	Specifies the type of multi-sensor estimation procedure (**itype**=1: Single Optimal Estimation (SOE), **itype**=2: Double Optimal Estimation (DOE)).

DOE, developed primarily to assimilate satellite and lightning data in the future, is computationally twice as expensive as SOE, and hence is not recommended at this time.

Parameter	Current Default	Description
nbors	3	Specifies the number of the nearest gage measurements to be used in estimation (if that many gages indeed exist within the radius of influence: in multi-sensor estimation, the radius of influence is computed in real time from radar rainfall data).

Theoretically speaking, the larger the value of **nbors**, the more accurate the estimates will be. As in gage-only estimation, however, the larger the value of **nbors** (if that many gages indeed exist within the radius of influence), the more computationally expensive. Changing **nbors** does not have as great an impact in multi-sensor estimation as it does in gage-only estimation. The current default of 3 (if that many gages indeed exist within the radius of influence) is strongly recommended unless excessive CPU/elapsed time becomes a problem, in which case **nbors** may be lowered to 2 (the procedure will still produce reasonable-looking rainfall fields even with **nbors**=1).

Parameter	Current Default	Description
distmin	0.1	Specifies the separation distance in correlation model in km. No changes are recommended.
rainmin	0.01	Specifies the minimum detectable rainfall depth in mm. No changes are recommended.
crscori	0.80	Specifies the lag-0 indicator cross-correlation coefficient. Loosely speaking, this quantifies, on the scale of 0 to 1, how accurate radar rainfall data are, on the average, in discerning rainfall/no-rainfall from no-rainfall/rainfall.

The default value is obtained from climatological analyses of hourly rain gage data and WSR-88D radar rainfall data in the Southern Plains. Data analysis-permitting, **crscori** should be estimated for each site as a function of range and seasonality (ideally, it should also be stratified according to storm type; e.g., convective versus stratiform). In the meantime, no changes are recommended.

crscorc 0.85 Specifies the lag-0 conditional cross-correlation coefficient. Loosely speaking, this quantifies, on the scale of 0 to 1, how accurate radar rainfall data are, on the average, in estimating rainfall amount over rain area (i.e., given that it is raining).

The default value is obtained from climatological analyses of hourly rain gage data and WSR-88D radar rainfall data in the Southern Plains. Data analysis-permitting, **crscorc** should be estimated for each site as a function of range and seasonality (ideally, it should also be stratified according to storm type; e.g., convective versus stratiform). In the meantime, no changes are recommended.

scali_def 36. Specifies the default indicator correlation scale in km. It is used whenever the indicator correlation scale (the same as **rangei** in gage-only estimation) cannot be obtained in real time. Until site- and seasonality-specific estimation of the parameter, no changes are recommended.

scale_def 28. Specifies the default conditional correlation scale in km. It is used whenever the conditional correlation scale (the same as **rangec** in gage-only estimation) cannot be obtained in real time. Until site- and seasonality-specific estimation of the parameter, no changes are recommended.

scali_max 70. Specifies the maximum indicator correlation scale in km. It is the upper bound for the indicator correlation scale. No changes are recommended.

scale_max 50. Specifies the maximum conditional correlation scale in km. It is the upper bound for the conditional correlation scale. No changes are recommended.

threshmin 0.25 Specifies the minimum threshold value in mm for multi-sensor estimates (display purposes only). No changes are recommended.