Enhanced Freshwater Inflow to the Chesapeake Bay Through Operational Modifications: Raingage Network Design

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Table of Contents

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List of Figures

List of Tables

Executive Summary

The focus of this study is the development of raingage network design criteria for areas of spatially varying rainfall with the objective of providing better estimates of precipitation and streamflow for use in flood control operations. This study serves as a preliminary investigation into raingage network design for the North Branch basin of the Potomac River located in Maryland and West Virginia. The North Branch basin is the site of a major multipurpose impoundment and currently provides a situation in which the effects of better raingage networks may be felt downstream as far as the Chesapeake Bay. This is because the improvements in streamflow estimates would reduce the hydrologic uncertainty in flood control operations and thereby could reduce the flood control storage required for the routing of flood flows. This would provide additional storage for the supply of fresh water inflow to the Chesapeake Bay during extremely dry periods. In addition, there is a large potential for improving the estimates of precipitation and streamflow in the North Branch. The current operational raingage network is a sparse one which is used to represent a basin subjected to large spatial variations in rainfall.

This study involves the development of network design criteria which reduce the errors in streamflow estimates. Since streamflow estimates are obtained by routing precipitation estimates through a hydrologic model, the error in the precipitation estimates, otherwise called the "input error" was examined. The "input error" was divided into two contributing types of error; extrapolation error and capture error. Capture error results from not observing a storm event. The two types of error in addition to the density of a network are proposed as network design criteria.

Numerous raingage networks were derived for a hypothetical basin which resembles the North Branch. Using simulated rainfall and a hydrologic model to generate streamflow, the precipitation and streamflow estimates produced by the networks were analyzed to identify which design criteria consistently produced networks with smaller errors. The results may be summarized as follows:

1. Increased raingage density decreases errors in precipitation estimates; significant reductions in errors are observed when additional gages are added to sparse networks.

2. The distinction between the two types of input error is useful in the identification of networks which reduce errors in estimates of precipitation; the networks designed to minimize capture performed the best. This implies that raingage location is important in addition to raingage density.

3. The reduced errors in precipitation estimates were not consistently present in the streamflow estimates. There appears to be a specific number of gages beyond which streamflow estimates are not improved.

4. Raingage location was a contributing factor to reducing errors in streamflow estimates for a limited range of raingage densities.

These results demonstrate that raingage network design criteria developed for this study can be effective in generating networks which result in consistently reduced errors in precipitation estimates and reduced errors in streamflow estimates for a limited range of densities. These results form a foundation for the future work in this multi-year study in the North Branch basin. With design criteria in hand, the next step is to use existing technical tools and data in a similarly situated watershed to estimate rainfall variations throughout the North Branch basin. With this additional information, this investigation could be performed using the topographical and rainfall patterns of the North Branch basin. This would determine specific raingage networks which would reduce errors in streamflow estimates and would demonstrate how the current network performs in comparison to others with the same raingage density and with higher densities.

In addition, further investigation is necessary to determine why additional gages do not consistently improve streamflow estimates. This may be due to the structure of the hydrologic model which allows errors to accumulate. If this is the case, the use of the hydrologic model may be modified to incorporate true streamflow values at some regular time interval, a process which would be included in real-time application.

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Introduction

A portion of the reservoir volume dedicated to flood control storage is used as a hedge against hydrologic uncertainty. This means that in an environment of complete certainty (when the timing and magnitude of both downstream flows and reservoir inflows are known) the same storm could be routed through a smaller storage volume without increasing flood damage downstream. This suggests that more accurate information may be viewed as an alternative to structural changes as a means of providing additional water supply storage. Specifically, with the availability of better operational information, reservoirs designed for both water supply and flood control purposes could undergo a reallocation of storage from flood control to water supply without reducing the flood control benefits expected from the project (Schwartz(1986)).

This study examines raingage network design as a means of reducing the error in the streamflow estimates required for flood operations. Since streamflow estimates are directly linked to estimates of precipitation and since raingages provide the point estimates of rainfall, the number and the location of raingages within a basin can be important factors in reducing errors in both precipitation and streamflow estimates.

The physical phenomena which underlies this investigation is the spatial variability of rainfall. This variability results from an interaction between orographical and meteorological factors. While the mechanisms of the interactions are not fully understood, studies have been performed which explain the variation in average annual precipitation by a number of topographic parameters. Spreen(1947) identified elevation, maximum slope of the land, exposure, and orientation as significant factors; Schermerhorn(1967) identified terrain elevation, barrier elevation, and latitude to be dominant parameters; and Goulter(1984) observed distinct trends of increasing average annual rainfall with elevation.

The degree of spatial variability of rainfall plays a major role in determining how extensive a network is required to obtain estimates of a particular level of accuracy. Silverman et al.(1981) show that the sampling variance of raingage networks is quantitatively related to the characteristics of the isohyetal pattern in addition to the raingage density. That is, the sampling variance is directly proportional to the rainfall gradient and inversely proportional to the number of gages. Therefore, the greater the spatial variations in rainfall, the greater the number of raingages required to produce an adequate estimate of areal precipitation.

The spatial variability of rainfall is of particular concern in the design of networks which produce precipitation estimates for operational purposes. In this case, networks are required which can characterize individual storms, particularly in areas experiencing high percentages of thunderstorm rainfall. Since these convective storm systems may be very intense and of limited areal extent, they provide a large potential for either not being observed by a raingage or for being overweighted in a sparse raingage network. Dense networks are required for accurate representation of these systems. For example, Osborn(1972) recommends that raingages be located at 1000 foot intervals to adequately represent thunderstorm rainfall in southeastern Arizona.

Capturing the spatial variability of rainfall with a raingage network is also important for reducing errors in streamflow estimates. Wilson et al.(1979) examined the effect of spatially varying rainfall on runoff. They questioned whether or not the spatial variability of actual rainfall is dampened out by means of the runoff process. By generating spatially varying rainfall and routing it through a rainfall-runoff model, they conclude that this dampening effect is not present and that the use of networks which do not reflect the variability in rainfall may lead to serious errors in the total volume of flow, the peak flow, and the time-to-peak of the estimated runoff hydrograph (critical operational measures).

Others have investigated the characteristics of raingage networks, for areas with heterogeneous rainfall, which provide reduced errors in streamflow estimates. Troutman(1983) has used a stochastic rainfall model in an examination which yields runoff prediction error as a function of raingage number and location. Troutman observes that errors in precipitation prediction become less dramatic as more gages are added to the network and that this phenomena is directly carried over to the runoff predictions. Troutman concludes that the gage network is an important factor in reducing prediction errors and he emphasizes that the number of gages as opposed to the location of the gages is the more crucial element. Bras and Rodriguez-Iturbe(1976) reach a contradicting conclusion. They find that location plays an important role and in some cases a more important role than the number of gages.

Given this background, it is necessary to examine raingage networks in the context of the North Branch basin, the site of the only major multipurpose impoundment in the Potomac River basin and an area in which a sparse network represents a region of wide variations in rainfall. This report is a report of a preliminary investigation; it provides an indication of whether or not the knowledgable selection of a raingage network for the North Branch basin can reduce errors in streamflow estimates given the rainfall-runoff models which are currently used to generate the streamflow estimates. For the purposes of this study, a hypothetical basin with spatially varying rainfall was designed. This basin conforms to as many of the characteristics of the North Branch as could reasonably be incorporated in a preliminary investigation.

In Section 1, the components of the process by which the rainfall occuring in a basin is transformed into streamflow estimates are described. This includes the identification of the types of error which are introduced at various points in this process and the development of network design criteria which correspond to components of the input error to hydrologic models.

The methodology used in this analysis is outlined in Section 2. A series of models simulate rainfall, locate raingages based on the design criteria, and transform rainfall estimates into streamflow estimates. Simulation of rainfall allows the generation of "true" rainfall and "true" streamflow for comparison purposes.

The results of the analysis performed using the hypothetical basin are presented in Section 3. The relationships between the network design criteria and both precipitation estimates and streamflow estimates are presented. Both the errors in the estimation of extreme events and the expected daily errors associated with the various networks are presented. In Section 4 these results and an assessment of the current network are used to direct further study in the North Branch basin.

1.0 The Development of Network Design Criteria

Producing streamflow estimates is a multistep process which introduces errors at each step, see figure 1. The process is one which begins with the physical phenomena of rainfall. This rainfall is measured by raingages, discrete points which yield point estimates of the rainfall. The use of raingages introduces two types of error. First is the measurement error associated with the individual raingages, the difference between the actual precipitation at the raingage and the depth the raingage registers. This error is usually small as compared with other types of error. A discussion of the topographical and meteorological factors affecting this type of error may be found in Merva et al.(1976) and McGuinness and Vaughan(1969). These errors are excluded from this analysis.

The second type of error introduced by the use of raingages applies to the network as a whole. This error is termed capture error and refers to the event in which a storm occurs within a gaged area but is not observed by any of the raingages. This is a likely event when the storms are convective in nature; this error is of major concern in this study.

The next step is one of transforming the point estimates of rainfall into a mean areal precipitation (MAP) estimate. This is usually performed by using areal weights derived from Thiesson polygons.

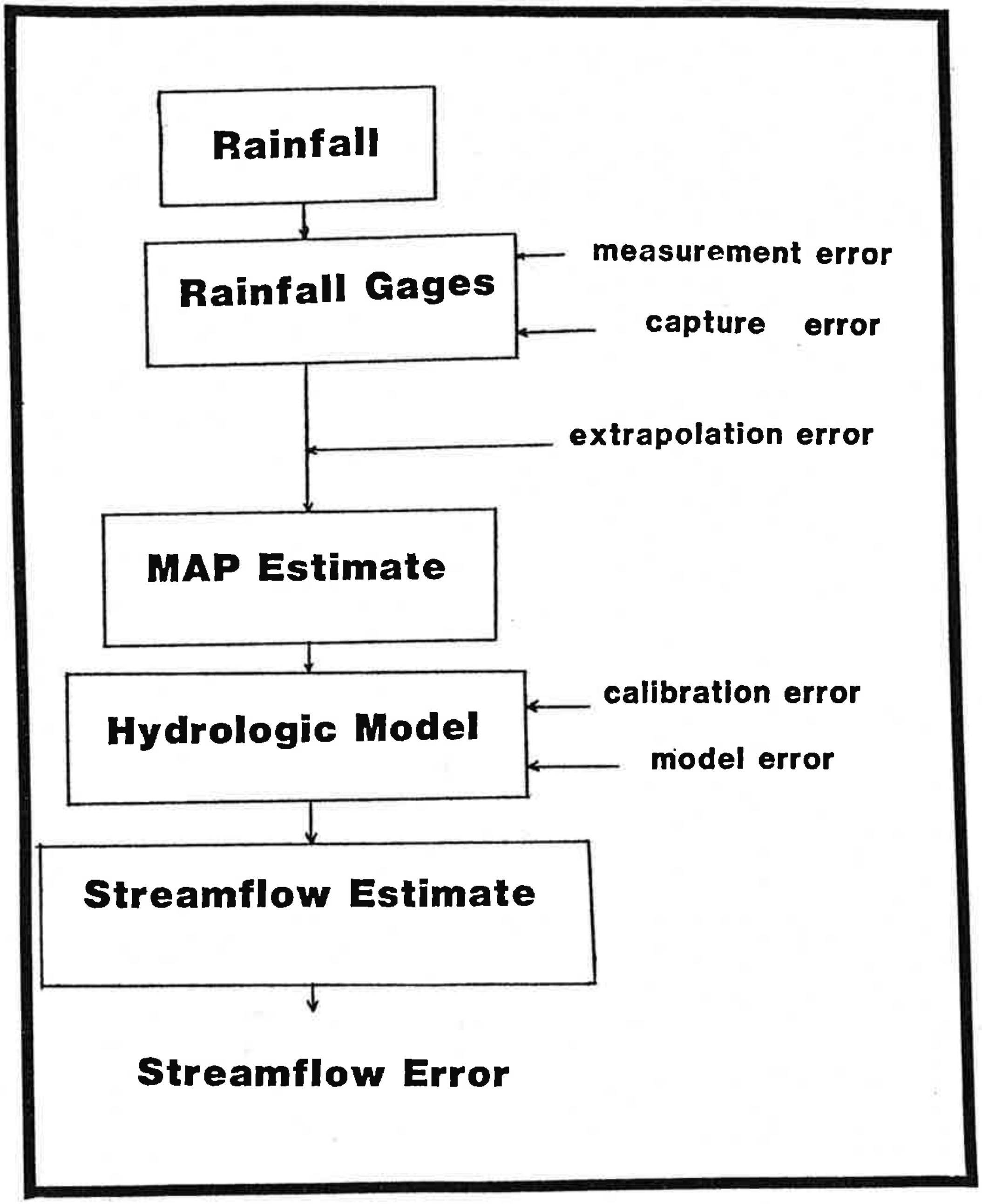


Figure 1 Components of Streamflow Estimation Error

That is,

$$MAP_t = \sum_i w_i r_{it} \qquad (1.1)$$

where: MAP_t is the mean areal precipitation estimate in time period t,

w_i is the portion of the basin represented by gage i - the ratio of the area around gage i, a_i, to the total area of the basin, A, and

r_{it} is the point estimate of rainfall at gage i in period t.

The error introduced at this step is termed extrapolation error. A larger error in the MAP estimate is expected when the area being represented by a single gage is large and, therefore, the distances over which the point estimates are being extrapolated are large.

The streamflow estimates with their associated errors are generated by routing the MAP estimates through a hydrologic model. At this point calibration error and model error are introduced; these errors are held constant in this analysis.

Capture error and extrapolation error are the errors of interest. These two types of error in addition to the number of gages are proposed as network design criteria. Different networks may be derived as the relative emphases on these two types of errors are varied and additional gages are added to a network. With this set of networks, the following questions may be answered:

1. Do networks designed to minimize capture error or networks designed to minimize extrapolation error produce better daily estimates of MAP?

2. How are the errors in MAP reduced as additional gages are added to the network?

3. How are the errors in MAP reflected in the errors in the streamflow estimates?

4. What network design criteria produce the network which results in the minimum errors in daily estimates of streamflow and in estimates of peak streamflow?

The methodology through which these questions are pursued is outlined in the next section.

2.0 Generation of "True" and Estimated Rainfall

The general methodology for examining the effect of different design criteria on errors in streamflow estimates consists of a series of models which generate rainfall, provide raingage networks, and transform precipitation estimates into streamflow estimates, see figure 2. The basis for comparison lies in the use of a rainfall simulation model which generates spatially varied rainfall and tabulates the depths, location, and areal extent of each storm in the basin. This allows the creation of a time series of "true" mean areal precipitation (MAP) and the calculation of a time series of estimates of mean areal precipitation ($\widehat{MAP}$). The estimates are obtained by applying spatial weights to the rainfall depths observed at the gages in the specified network.

Both time series, "true" and estimated, are used as input to a rainfall runoff model. This results in two time series of streamflow, a "true" streamflow (Q) series and an estimated streamflow ($\hat{Q}$) series. By generating both "true" streamflow and estimated streamflow with the same model, model bias and calibration error appear to the same extent in each series and may be ignored. Comparisons between these time series are made and presented in the next section. The rest of this section provides descriptions of the particular models used and the degree of correspondence to the North Branch basin.

2.1 The Gage Location Models

The raingage networks were obtained through the solution of one of two models. Each model is a constrained optimization model with linear objective functions and linear constraints. The first model is a multiobjective gage location model in which the two objectives were formulated to represent capture error and extrapolation error. The first objective may be stated as minimizing the sum of distances between every point in the basin and its closest gage and may be viewed as a surrogate measure of extrapolation error. The second objective is to minimize the sum of precipitation weighted distances between each point in the basin and its closest gage. This objective may be viewed as a surrogate for capture error since its effect is to locate gages in areas experiencing higher precipitation and thereby reduce the likelihood of missing large precipitation events. The major constraint of the model is the number of gages to be included in the network. The multiobjective model which provides raingage networks (locations of a prescribed number of gages) is stated mathematically as follows:

$$\text{Minimize} \quad z_1 = \sum_i \sum_j d_{ij} x_{ij} \qquad (2.1)$$

$$z_2 = \sum_i \sum_j r_i d_{ij} x_{ij} \qquad (2.2)$$

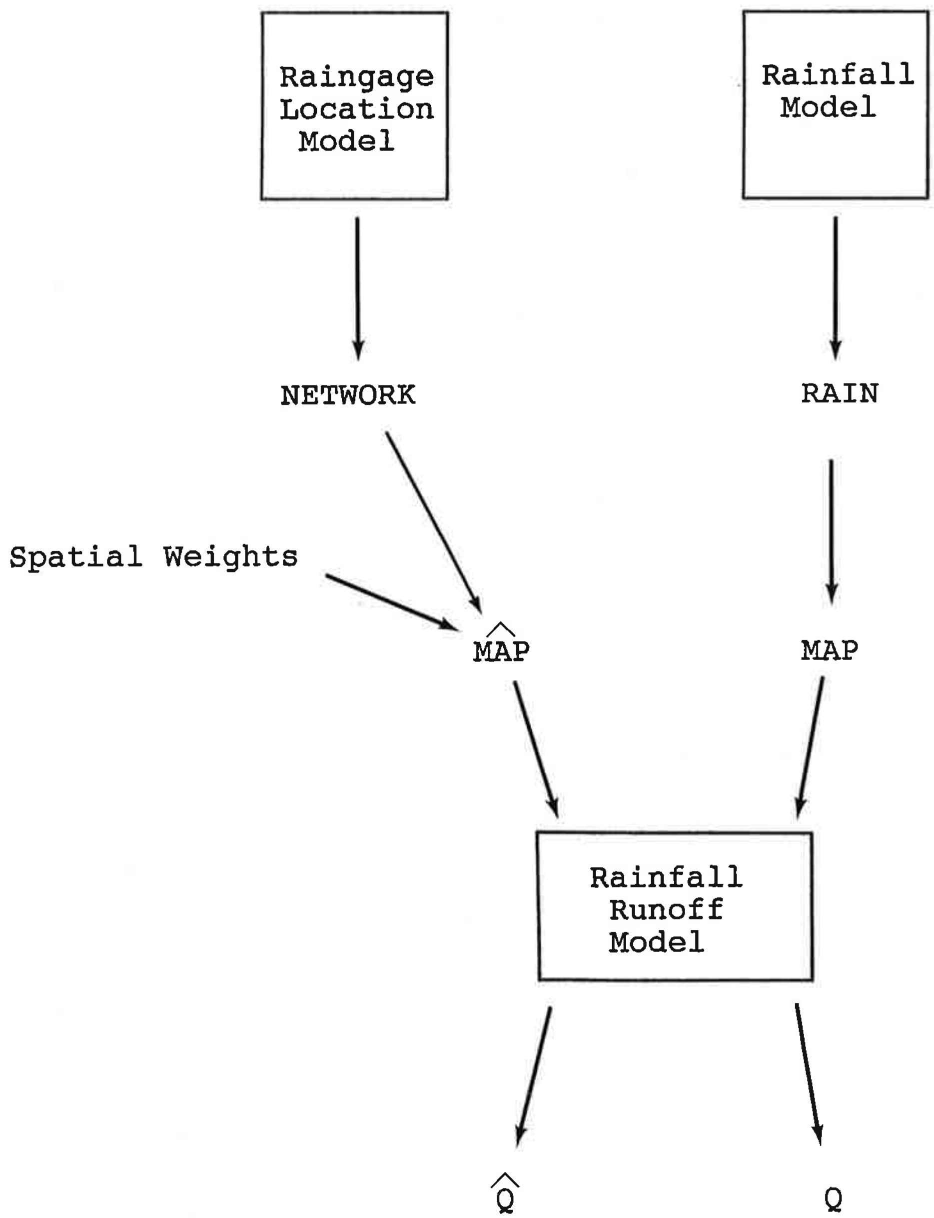


Figure 2 The process of generating "true" and estimated precipitation and streamflow

subject to

$$\sum_j x_{ij} = 1 \qquad \forall\ i \qquad (2.3)$$

$$\sum_j x_{jj} = p \qquad (2.4)$$

$$x_{ij} \leq x_{jj} \qquad \forall\ i,j \qquad (2.5)$$

where:

x_{ij} = 1, if point i is closest to gage j
0, otherwise,

x_{jj} = 1, if a gage is located at point j
0, otherwise,

d_{ij} = distance from point i to point j,

r_i = mean intensity at point i, and

p = number of gages.

This model with one objective is known in the facility location literature as the p-median problem (Hakimi(1964)). Equations (2.1) and (2.2) are the objectives which minimize the sum of distances and the sum of precipitation weighted distances, respectively. The first set of constraints (2.3) ensure that each point in the basin is assigned to a gage (the solution technique ensures the gage is the closest gage). Equation (2.4) limits the number of gages to p, and the final set of constraints (2.5) ensure that a point is not assigned to an ungaged site.

When this problem is solved, a new objective function is obtained by forming a weighted combination of z_1 and z_2. That is,

$$Z = W z_1 + (1-W) z_2 \qquad (2.6)$$

where $0 \leq W \leq 1$. The weight, W, is varied between zero and one to change the emphases placed on the minimization of extrapolation error and the minimization of capture error. For each value of W, the model is solved and a network is obtained. Any network derived with this model, therefore, may be characterized by the parameters p and W.

The second location model has one objective function which is designed to minimize capture error. The distinguishing feature of this model is that it incorporates characteristics of the average storm within the basin. Using this information, the model seeks to locate gages in the areas with the most intense rainfall while simultaneously spacing the gages sufficiently far apart so as to eliminate the opportunity for the same storm to be measured by two gages. Specifically, storm cells are assumed to be circular with an expected radius (this is compatible with the assumptions of the rainfall model described in the next section). Therefore, a storm will not be observed if its center is farther than a cell radius from a gage. The intent is to place a gage within a cell radius of the high precipitation areas while also placing subsequent gages at least the diameter of a cell apart, so the storm is not measured twice. The following model provides networks with the desired spacings. The model is called the covering model and is formulated as follows:

$$\text{Maximize} \quad Z = \sum r_i \, y_i \qquad (2.7)$$

Subject to:

$$\sum_{j \in N_i} x_j \geq y_i \qquad \forall \; i \qquad (2.8)$$

$$\sum_{j} x_j = p \qquad (2.9)$$

where:

y_i = 1 if the point i is within a cell radius of a gage and 0 otherwise,

x_j = 1 if a gage is placed at point j and 0 otherwise,

N_i = the set of all points i within a cell radius of j,

and the other parameters are as defined above. This formulation is known as the Maximal Covering Location Problem (Church and ReVelle(1974)) in the literature. The objective function (2.7) weights the covered nodes by the associated rainfall intensity. This drives the model to cover the areas with the highest rainfall intensities first. The first constraint set (2.8) ensures that a node is not covered unless there is a raingage within a cell's radius of the node. The second constraint (2.9) limits the number of gages to p. The important feature is that since y_i can not be greater than one, the objective function is not increased by the multiple covering of points in the basin. Therefore, the likelihood of observing the same localized storm by two gages is reduced.

2.2 The Rainfall Model

The precipitation model used in this study generates convective thunderstorm cells over a basin. The timing and placement of the storms is obtained from the combination of three stochastic processes, see figure 3. First, as the timeline at the top of

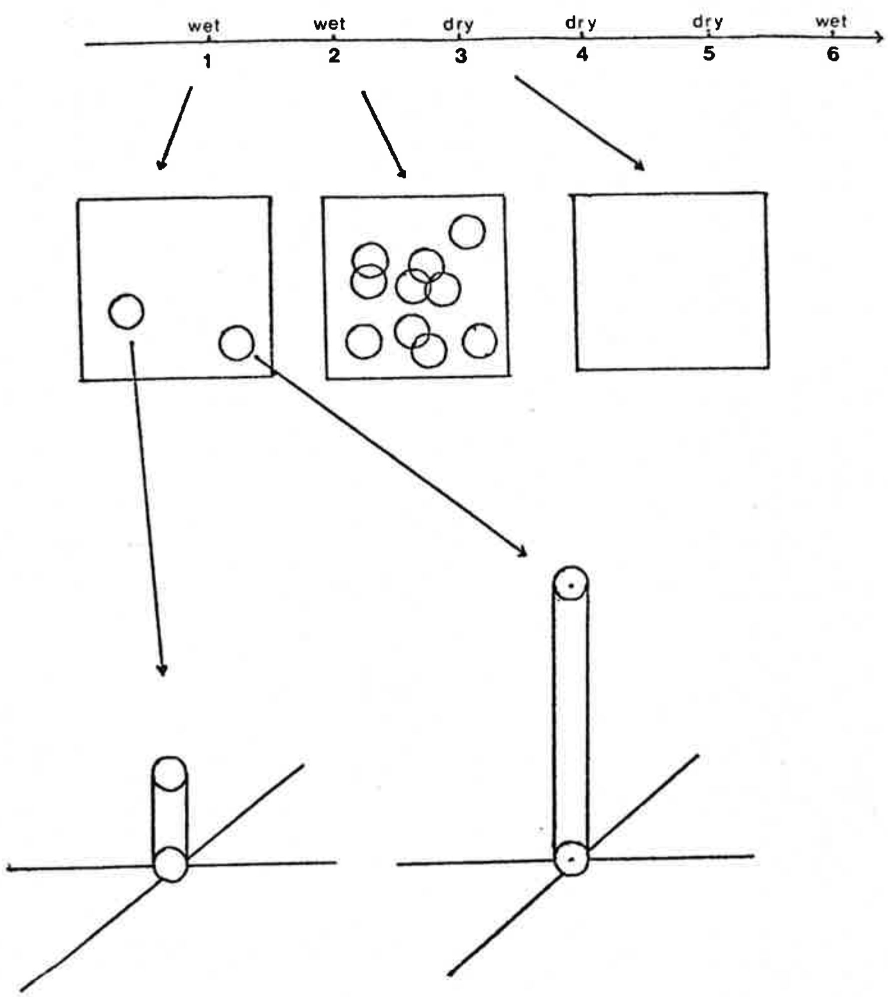


Figure 3 The rainfall model

the figure depicts, a day is determined to be either wet or dry. This is modeled as a first order markov chain with fixed transition probabilities. Second, on a wet day a random number of rainfall cells are generated based on the mean spatial intensity of storms within the basin. Third, the intensity of each storm is modeled as an exponential distribution where the mean intensity of the storm is a function of the location of the storm within the basin. The first two processes of this model have been calibrated for the North Branch basin by Smith and Karr(1985) and the resulting parameters are used in this study. The third process represents a modification of the model, one by which spatial variability in rainfall intensities is generated.

2.3 The Rainfall-Runoff Model

The rainfall-runoff model used in this analysis is the Sacramento model. Of existing techniques, this model best represents the physical processes involved in overland and subsurface routing of precipitation. The model takes observed rainfall and distributes it between a number of storage zones. The flow from these zones into the stream channel represent the traditional components of the hydrograph; overland flow, sub-surface flow, and baseflow. A schematic of the storage zones, the routing of flow between zones, and the discharge of flow into the stream channel is provided in figure 4. A complete description of the model may be found in Burnash and Ferral(1972) and Peck(1976).

There exists a strong correspondence between the structure of the Sacramento model and the structure of the physical system of the North Branch. The primary parameters of the model are water seepage rates and soil moisture capacities. These parameters reflect the underlying structure and for a water basin contained with in a fairly homogeneous region are descriptive of the region as a whole. This is the case for the North Branch basin which is set in the Appalachian Plateau, a region comprised of thin clayey soils which exhibit low seepage rates and low storage potentials (Smith et al.(1982)). Parameters derived for the North Branch basin by the National Weather Service are used in this analysis.

3.0 The Precipitation and Streamflow Estimates

3.1 The Hypothetical Basin

The sequence of modeling procedures was employed on a rectangular basin representing 300 mi^2. The basin was discretized into a 48 node grid (8 X 6). This creates a 2.5 mile spacing between adjacent nodes and since every node is a potential site for a raingage allows for a fairly dense network. A mean storm intensity is associated with each node to incorporate the spatial variability in rainfall. The rectangular basin and the isohyetal contours are shown in figure 5.

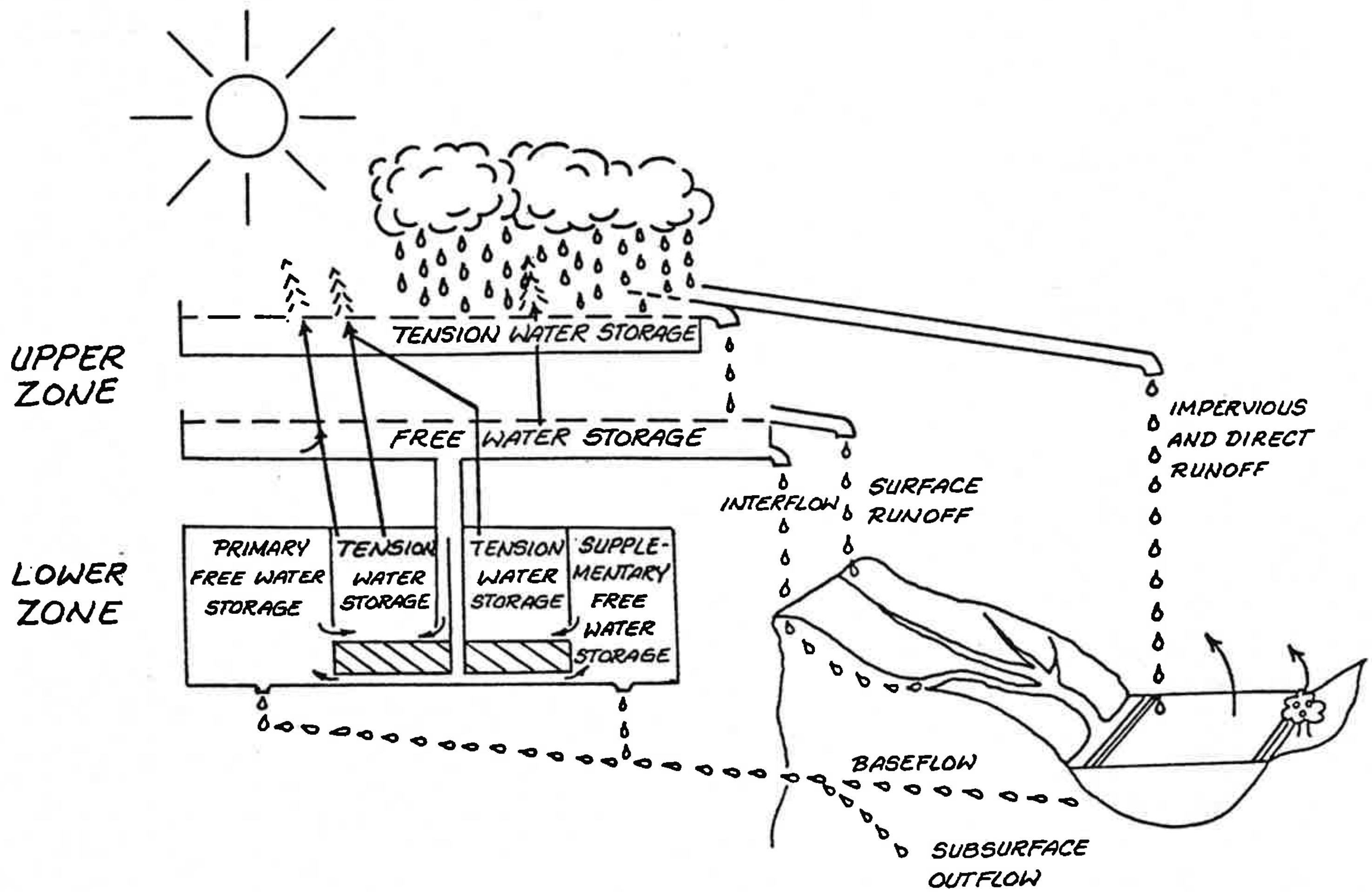


Figure 4 The rainfall-runoff model

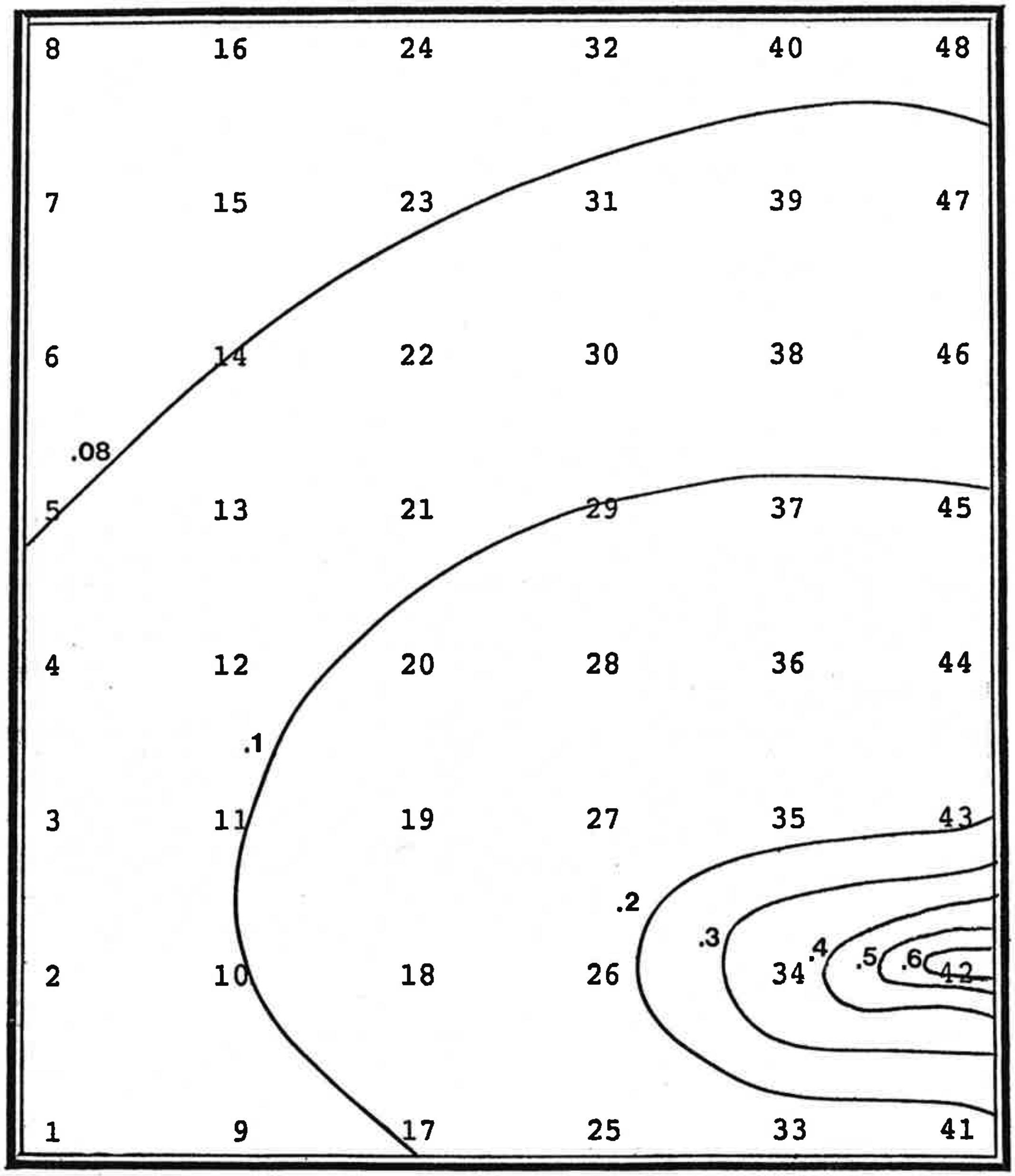


Figure 5 The hypothetical basin

3.2 The Networks

The Multiobjective model was solved for four different values of W. These were

$$W = 1$$
$$W = .9$$
$$W = .2$$
$$W = 0$$

Decreasing the value of W corresponds to increasing the weight on the reduction of capture error. For each value of W, the number of raingages, p, was varied between 3 and 10. The same range of p was used to solve the covering model. The networks generated using the two location models are provided in Table 1. Examination of the networks reveals that as the weight on capture error is increased, the raingages tend to be located in the areas with greater storm intensities. The networks obtained with the covering model, which does not include an extrapolation component, show even higher densities of gages in the areas with greater storm intensities.

3.3 Errors in MAP Estimates

Rainfall (storm centers and depths) was generated for this basin for 665 days, 500 of which were wet days (days with at least one storm). The simulated storms were analyzed to verify that a period of this length was sufficient to reflect the long term spatial variability in rainfall. Figure 6 shows the results of this analysis with the plus signs (+) representing the specified mean storm intensity for a node and the squares (□) representing the mean storm intensity for a node from the simulation. Using visual inspection, this time horizon was judged to be sufficient.

Daily precipitation estimates were calculated for a network by tabulating which storms occurred within a cell's radius of a raingage and then by applying areal weights to the daily depth totals at each gage. To determine the error associated with each network, the root mean squared error between the series of estimates and the series of "true" rainfall in the basin was calculated. That is,

$$RMSE_k = \left(\sum_t (MAP_{kt} - MAP_t)^2 \right)^{1/2} \qquad (3.1)$$

where:

$RMSE_k$ is the root mean squared error associated with network k,

MAP_{kt} is the estimate of mean areal precipitation for network k on day t, and

MAP_t is the "true" value of mean areal precipitation on day t.

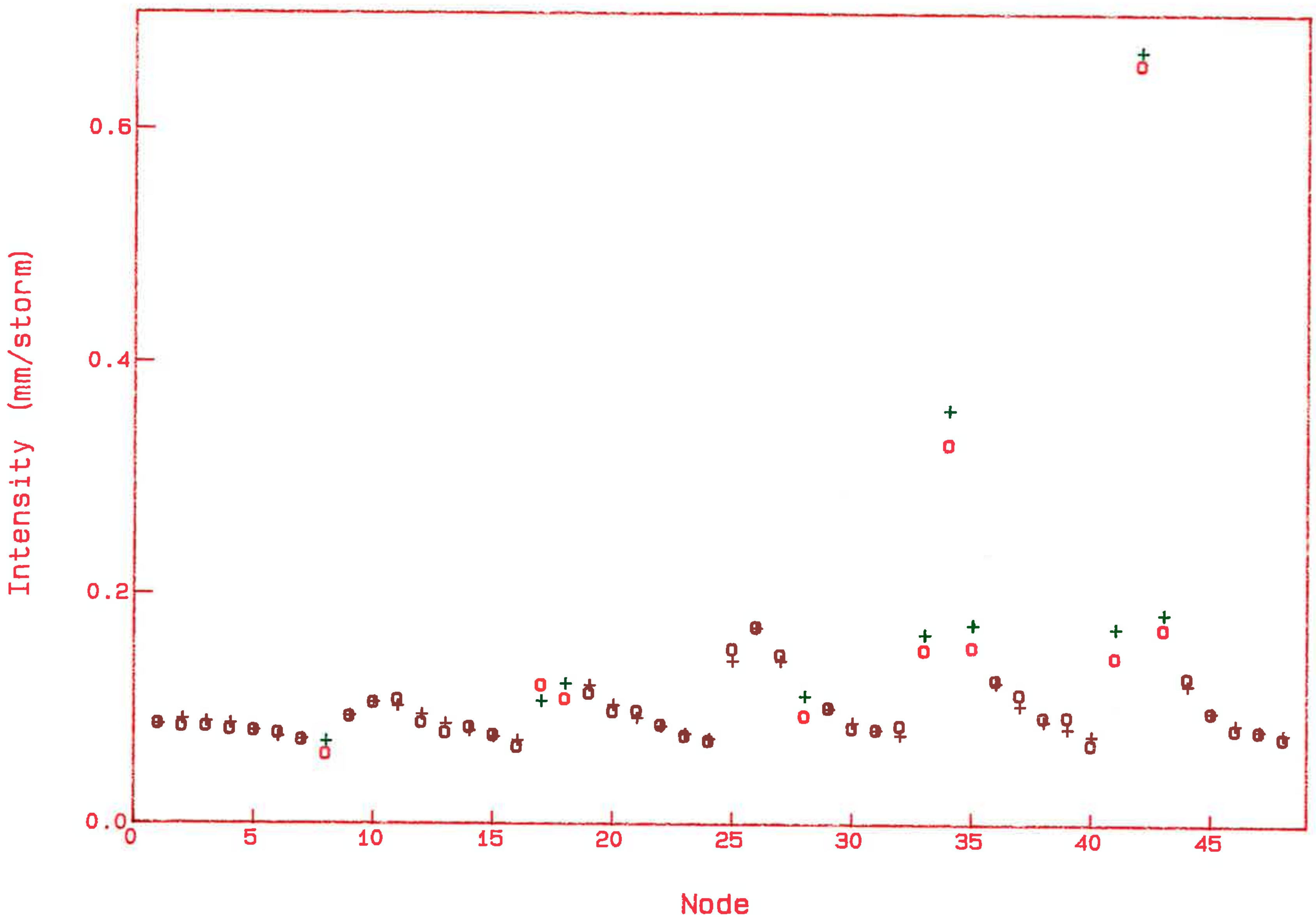
Table 1 The raingage networks

Number of Gages - p	Weight W	Raingage Locations							
3	1.0	14	18	38					
	.9	11	31	35					
	.2	11	31	34					
	.0	11	30	34					
	-	19	34	37					
4	1.0	11	15	34	38				
	.9	10	14	34	38				
	.2	10	14	34	38				
	.0	14	18	38	42				
	-	13	19	34	37				
5	1.0	10	15	20	34	39			
	.9	10	15	28	34	39			
	.2	10	15	28	34	39			
	.0	14	18	36	39	42			
	-	10	13	28	34	38			
6	1.0	9	12	15	34	37	39		
	.9	10	12	15	34	36	39		
	.2	12	15	18	36	39	42		
	.0	12	15	18	36	39	42		
	-	10	13	23	28	34	38		
7	1.0	4	10	15	29	34	39	44	
	.9	10	12	15	29	34	39	44	
	.2	9	12	15	26	36	39	42	
	.0	10	12	15	34	36	39	42	
	-	13	18	23	28	33	38	43	
8	1.0	4	9	15	19	29	34	39	44
	.9	4	9	15	19	29	34	39	44
	.2	2	13	15	19	25	36	39	42
	.0	10	13	15	28	34	39	42	45
	-	3	13	18	23	28	33	38	43

Table 1 The raingage networks (cont.)

Number of Gages - p	Weight W	Raingage Locations									
9	1.0	4	9	14	15	19	29	34	39	44	
	.9	5	10	15	20	25	32	37	42	47	
	.2	5	10	16	22	28	34	39	42	45	
	.0	9	12	15	26	29	34	39	42	44	
	-	4	9	14	19	24	29	34	39	44	
10	1.0	2	7	12	17	24	29	35	39	41	45
	.9	4	10	14	16	25	27	31	37	42	47
	.2	2	5	11	15	17	28	34	39	42	45
	.0	5	9	11	15	26	29	34	39	42	44
	-	2	7	13	19	24	25	30	36	42	47

Figure 6 Specified and Simulated Mean Storm Intensities at Each Node -- period = 665 days



The RMSE's are shown in table 2 for each of the derived networks. The same values are presented graphically in figure 7 where the following colors and symbols are used to represent the sets of networks derived from the multiobjective model with various values of W and the covering model:

o	--	red	--	Multiobjective model with W = 1.
+	--	green	--	Multiobjective model with W = .9
□	--	blue	--	Multiobjective model with W = .2
#	--	purple	--	Multiobjective model with W = 0
*	--	black	--	Covering model

The following observations may be made:

1. The error in MAP estimates generally decreases with increased raingage density; significant reductions are observed when additional gages are added to sparse networks.

2. As increased weights are placed on reducing the capture error, errors in MAP estimates are reduced with the networks obtained with a weight of one on capture error (#) and the networks obtained from the covering model (*) performing well for all values of p.

3. The networks resulting from the covering model are generally one of the two best networks for every value of p.

4. The networks resulting from W = 1 (o) (minimizing extrapolation error only) are out performed by the networks resulting from W = .9 (+). This is of interest because this second set of networks are alternate optima to the first set. That is, with the second curve, capture error was reduced without increasing the distances over which the point estimates would be extrapolated.

5. Different raingage locations, produced by varying the weights on the measures of error, are important for p = 3 through p = 7.

The next graph, figure 8, shows the RMSE for the five largest overestimates and the five largest underestimates of "true" daily MAP during the 665 day simulation period for each network (same color and symbol codes). Visual inspection reveals a general trend of decreasing error in overestimation with the denser networks and a very slight trend in decreasing errors in underestimation with the denser networks. Again, it appears that raingage location is more important with the less dense networks since the range in errors for a specific number of raingages decreases when more raingages are present.

Table 2 RMSE for the MAP estimates of different Networks

# of Gages	Root Mean Squared Error (mm)				
	Multiobjective Model with W =				Capture Model
	1.0	0.9	0.2	0.0	
3	2.35	2.47	2.64	2.48	2.39
4	2.27	2.28	2.25	1.69	1.80
5	1.82	1.64	1.64	1.35	1.57
6	1.59	1.38	1.19	1.19	1.40
7	1.39	1.33	1.17	1.23	1.12
8	1.18	1.18	1.12	1.15	1.06
9	1.14	1.05	1.11	1.08	1.12
10	1.44	0.94	1.07	1.06	1.04

Figure 7 Root mean error for daily MAP estimates
period = 665 days

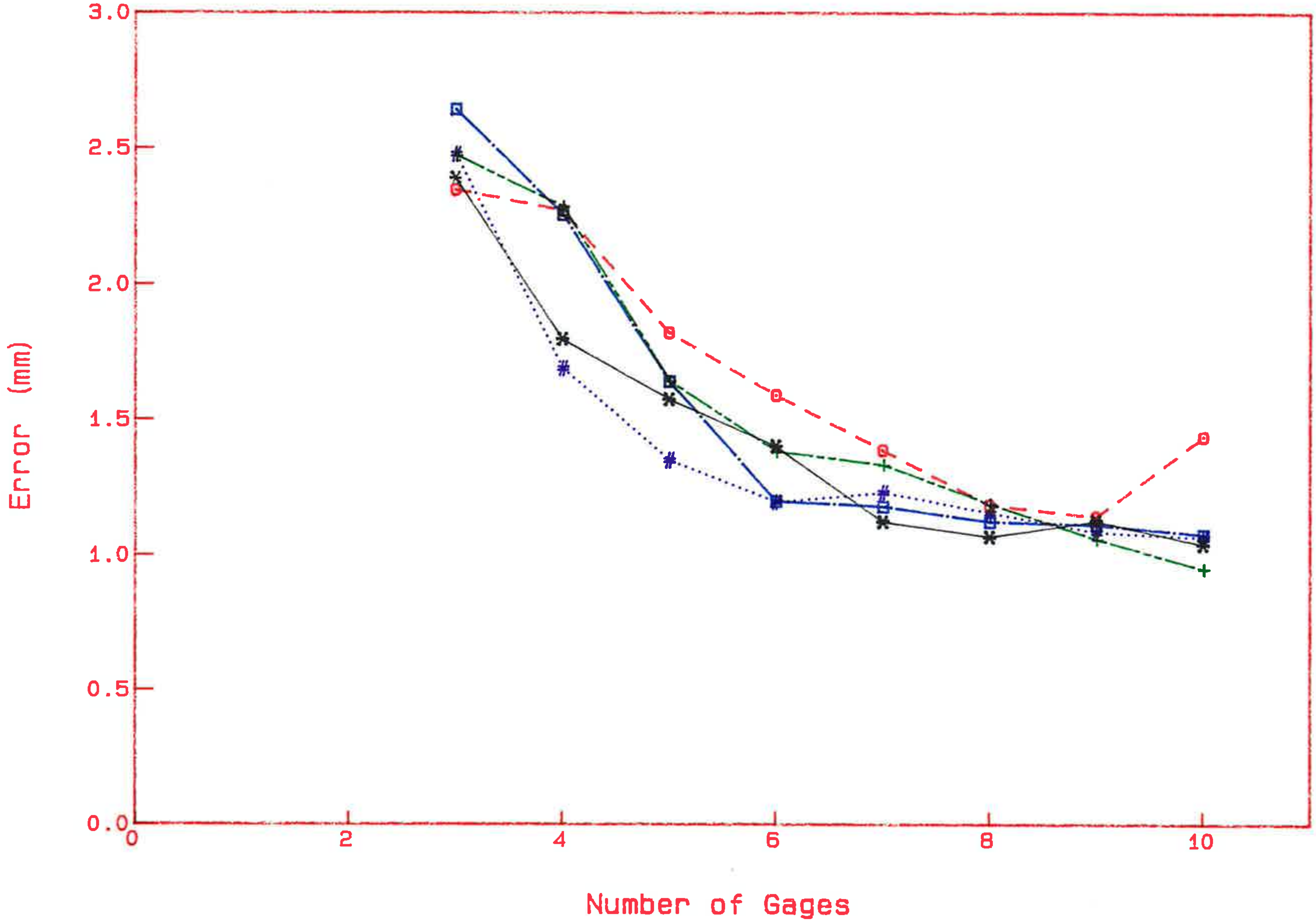
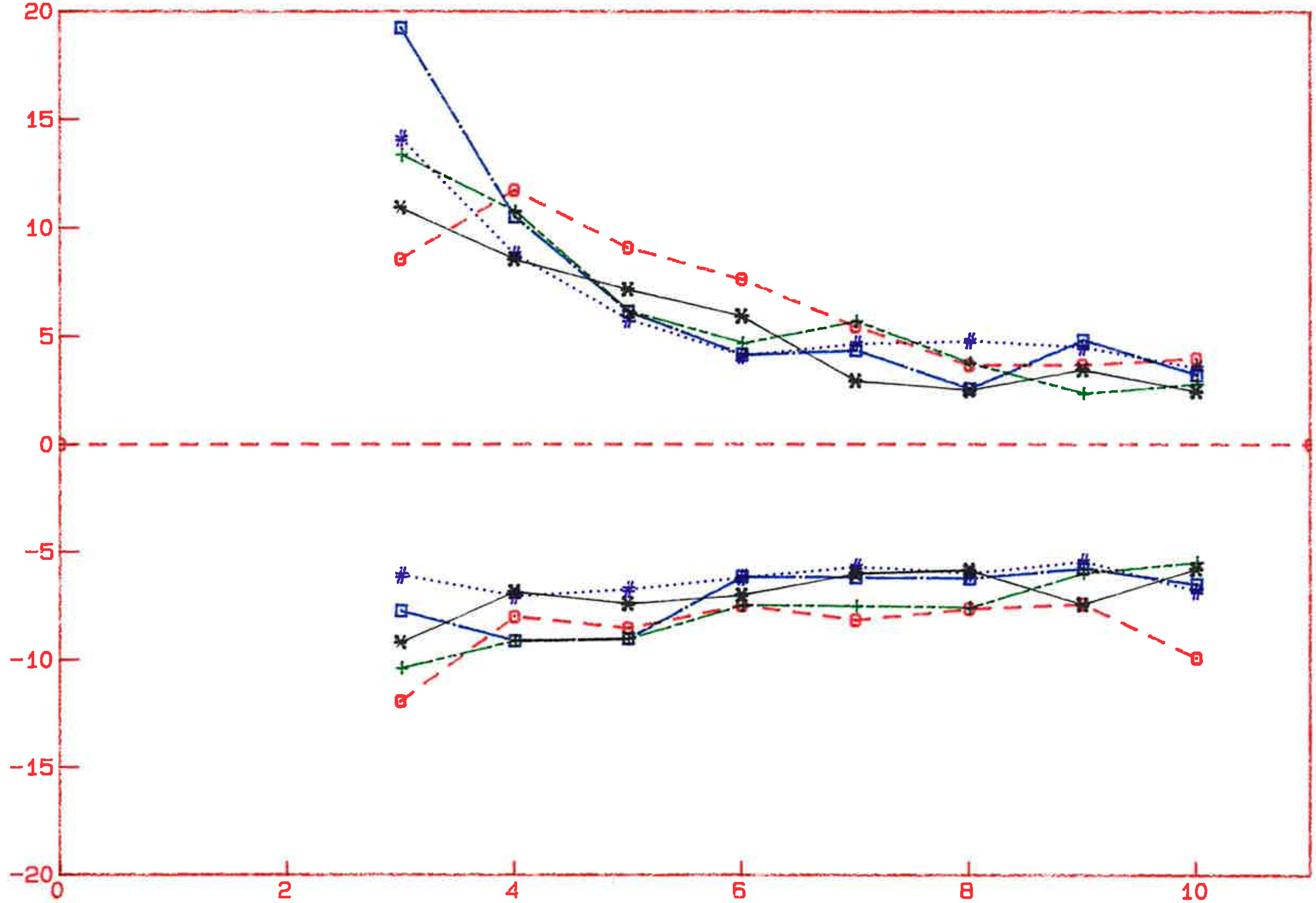


Figure 8 Root mean error of extreme daily MAP estimates period = 665 days, 5 most extreme estimates



3.4 Errors in the Streamflow Estimates

The MAP estimates described above were routed through the Sacramento model with initial conditions representing an average May. Evapotranspiration was held at a constant level so that the timing of large events during the simulation period would not act to attenuate the errors in streamflow (evapotranspiration increases over the summer months and can reduce the effective runoff).

The analogous RMSE's were calculated for the daily streamflow estimates resulting from each raingage network. The RMSE values for the entire simulation period are provided in table 3 and presented graphically in figure 9 with the same color and symbol codes as above. The following observations may be made:

1. With sparse raingage networks, the addition of a raingage reduces the errors in streamflow estimates.

2. The networks designed to reduce capture error perform well for p = 4 through p = 8.

3. Significant gains in the reduction of errors in streamflow estimates are not observed for values of p greater than 6.

The RMSE for the five largest daily overestimates and the five largest daily underestimates are shown in figure 10 (same color and symbol codes). Here, a decreasing trend in errors in overestimates with more dense networks is observed. Conversely, the errors in the underestimates tend to worsen with the more dense networks.

From examining these two figures, it appears that the consistent reduction in the errors in the MAP estimates as additional gages were added to the networks are not carried over to the errors in streamflow estimates. While this may be a significant result, it may also be a result of the structure of the hydrologic model and may require further investigation. Streamflow estimates, unlike precipitation estimates, depend not only on current rainfall but also on the preceding rainfall to fill the storage zones to the appropriate levels. If a storm event is missed, storage zones are not replenished and the subsequent contributions from the subsurface zones to streamflow are underestimated. This underestimation may persist for days or weeks. This explanation is supported by figure 10 in which the underestimation of events is observed to worsen with the addition of raingages. Also, re-examination of figure 8 shows that overestimation of the "true" MAP is reduced to a greater degree than underestimation. Therefore, the cumulative water volume provided by the MAP estimates may be viewed as continually diverging from the actual volume of water the basin has seen. This problem may be remedied by updating past

Table 3 RMSE for the daily streamflow estimates of different networks

# of Gages	Multiobjective Model with W = 1.0	0.9	0.2	0.0	Capture Model
3	123.4	136.8	265.4	175.6	172.2
4	125.5	145.2	140.9	88.1	111.4
5	91.7	74.1	74.1	76.7	74.7
6	69.9	67.8	75.8	75.8	62.5
7	63.9	61.2	85.3	58.3	60.7
8	68.4	68.1	87.6	47.2	72.6
9	67.6	83.8	52.4	60.4	72.1
10	115.8	61.0	71.0	76.6	94.8

Root Mean Squared Error (cfs)

Figure 9 Root mean error for estimated streamflow
period = 665 days

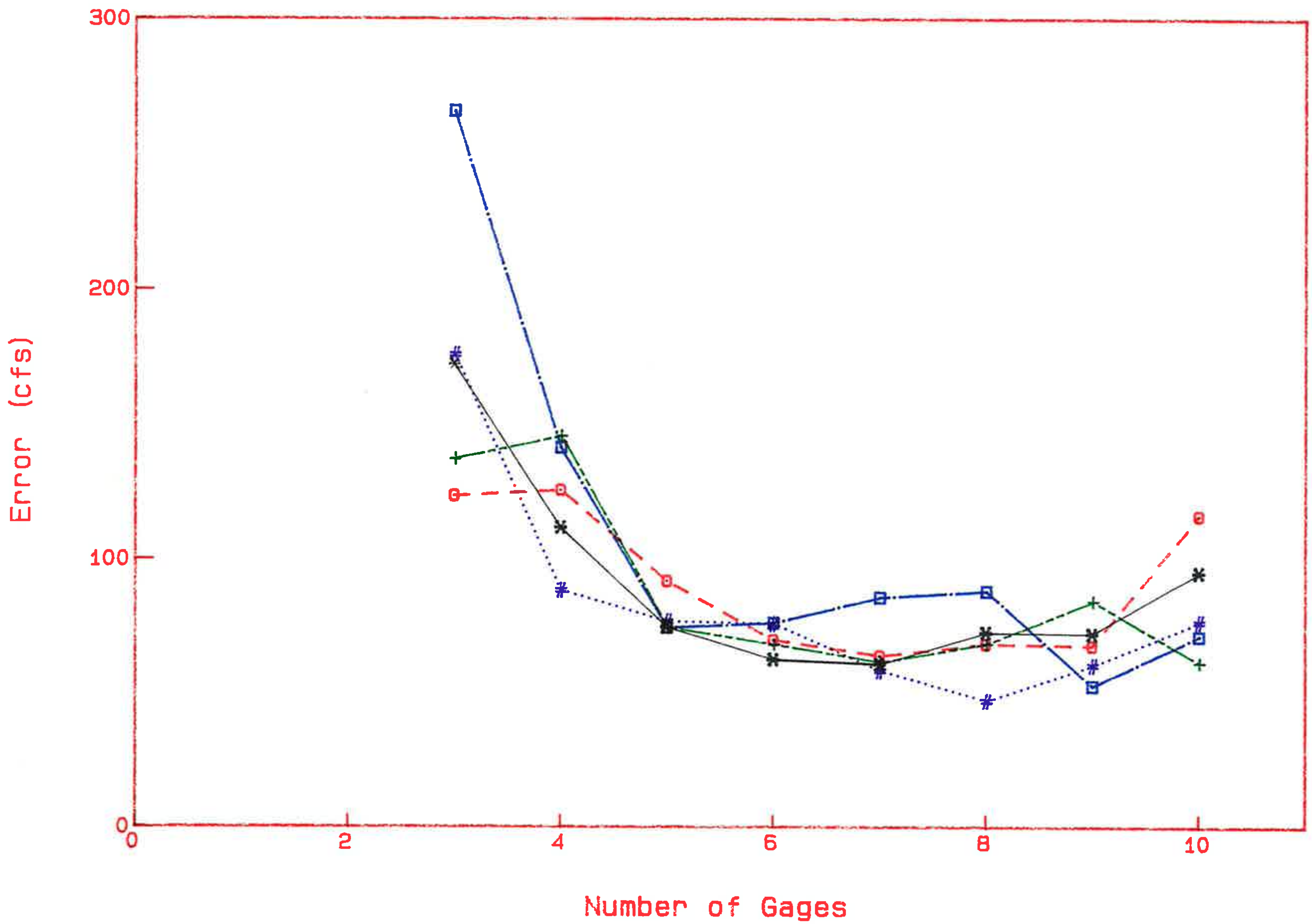
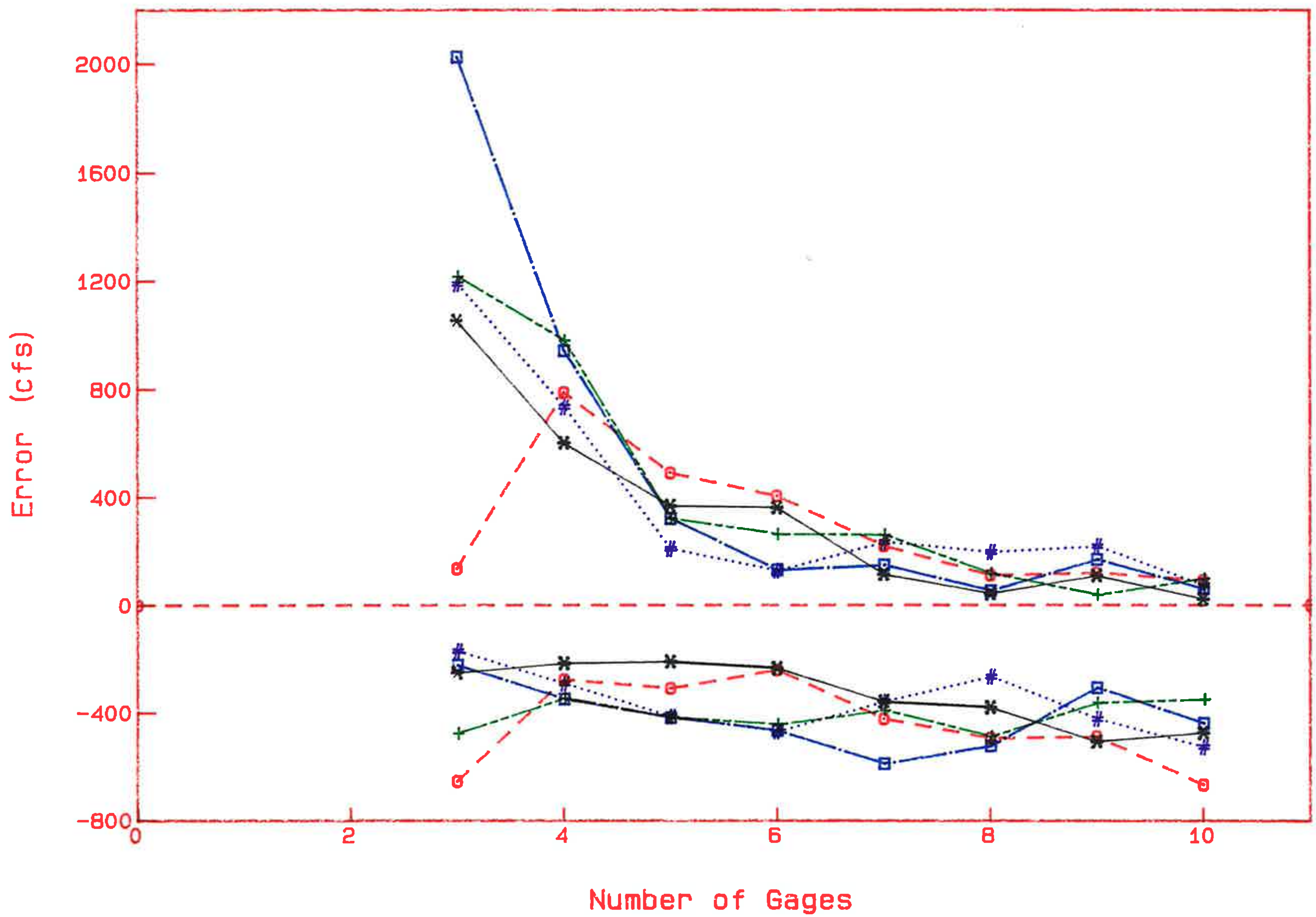


Figure 10 Root mean error for extreme daily streamflow estimates
period = 665 days, 5 most extreme estimates



streamflows with actual observed streamflows, a practice which is easily implemented in real-time application.

4.0 Conclusions and Further Work for the North Branch Basin

Raingage network design criteria which incorporate spatially varying rainfall have been proposed with the objective of reducing the errors in daily precipitation and daily streamflow estimates. The criteria have been applied to a hypothetical basin which resembles the North Branch basin. The results show that the design criteria are effective in generating raingage networks which reduce the errors in precipitation estimates. Both the location of the raingages and the density of the network are important factors. These reductions in errors are not consistently carried over to the errors observed in streamflow estimates. However, this last result requires further investigation to discern how the errors in streamflow estimates are affected when the cumulative error of underestimation is removed (see section 3.4).

The next step is to apply the network design criteria to a more accurate representation of the North Branch basin. The North Branch basin is a desirable site for two primary reasons. First, it is the site of the only major multipurpose impoundment in the Potomac River basin and therefore provides the only situation in which better streamflow estimates could be used enhance flood control operations. Second, there exists a large opportunity to generate better streamflow estimates. The current operational raingage network is sparse, consisting of the six gages shown in table 4. These gages are used to represent 225 mi^2 of basin which experience large variations in rainfall; average annual rainfall varies between 50 inches and 30 inches as one proceeds down the basin.

Further modeling of the North Branch system, in this multiyear project, will proceed by developing mean rainfall intensities for many locations within the basin, not just where raingages are currently located. This will be accomplished by exploring the relationship between topographic factors (elevation, orientation, etc.) and rainfall in a densely gaged, high relief experimental watershed in Pennsylvania. This watershed is also located in the Appalachian Plateau, so the derived relationships will be easily transferable to the North Branch basin. Developing these relationships for the subsequent application of network design in the North Branch constitutes the direction of further work.

Table 4 Gages in the North Branch Basin

Gage Location	Elevation (ft)
Kitzmiller	1580
Oakland	2500
Pinto	660
Bayard	2400
Mt. Storm	2600
Savage River Dam	1500

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