Design of Operational Precipitation and Streamflow Networks for River Forecasting

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A methodology is presented for assessing the value of river forecasting to possible changes in existing precipitation and streamflow networks. This study was undertaken as a part of an effort to evaluate the expected benefit of automating all or part of the data gathering networks used by the National Weather Service. A surrogate measure of benefits, called the 'mean forecast lead time,' is related indirectly to benefits because the value of river forecasting depends on the lead time available for the flood plain dweller to take action and respond to the forecast. Presented here is the rationale for the methodology and the results of part of the research using streamflow generated by Hurricane Agnes (June 1972) and Hurricane Eloise (September 1975) for the Susquehanna River basin.

INTRODUCTION

The objective of this analysis is to analyze the trade-off between network automation, rain gage density, stream gage density, and reliable forecast lead time. The work is within the context of the river forecasting responsibilities of the National Weather Service (NWS). The detailed analysis is within the context of a systems analysis of river basin flood forecasting given network rain data.

The method of analysis is to model measurement errors in streamflow and mean areal precipitation (MAP), to simulate streamflow forecasts and to investigate user response to forecast reliability. Changes in network design are analyzed to determine changes in forecast reliability. The simulations are currently conducted using an existing, calibrated rainfall-runoff computer program used for river forecasting in the Susquehanna River basin. Thus a case study analysis is used to test the general concept.

This study is undertaken as part of an effort to evaluate in particular the expected benefits of changing network density and of automating all or part of the networks now used by the NWS. Ideally, it would be desirable to estimate the incremental benefits of network improvements directly in dollars so that comparisons might be made between these benefits and the costs of achieving them. Although some rough estimates can be made of the dollar benefits of network improvements on the basis of this study, there are so many types of flood damages such as residential, commercial, industrial, municipal, agricultural, etc., that there is a considerable amount of difficulty in making dollar benefit estimates. Nevertheless, a surrogate measure of benefits can be made that has a reasonable degree of utility. This surrogate measure called the 'mean forecast lead time' (MFLT) [*Sittner,* 1977] is strongly related to benefits because the value of river forecasts depends on the lead time available for users in an endangered area to take action and respond to the forecast. A limited amount of information exists from studies in the Susquehanna basin to relate MFLT to the damage reductions to residential properties as a percentage of the flood damages that would occur without response to a flood warning.

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A curve [*Day,* 1970] which conveys the utility of MFLT to society is shown in Figure 1. The damage reduction is related to error-free forecast lead time up to a limit corresponding to maximum practiced evacuation of flood prone areas. The situation is complicated by the fact that higher peak stages cause higher damages and by the fact that forecasts have errors in timing and peak stage. Forecast errors have a financial cost to users. While errors resulting in a low forecast result in water damage and possible loss of life, a forecast which exceeds the resulting crest may result in unneeded and expensive evacuation expenses.

The research effort involves the development of a master computer code to present equally likely rainfall traces to an existing rainfall-runoff model. This proved to be a complex but worthwhile interface to master. The master code [*Relyea,* 1968; *Richards and Strahl,* 1969] was developed to allow the rainfall traces to reflect errors associated with various network design possibilities.

As background for this systems analysis, consider the timing relationships in a NWS river stage forecast. Discounting the effects of model error and network errors, there are three time-related factors: (1) the time required for the runoff to move through the system of catchments and river forecast points in the basin, (2) the reporting delays associated with rainfall and streamflow measurements, and (3) the time required to produce and disseminate forecasts.

In greatly simplified terms the MFLT at a downstream point is item 1 less the sum of items 2 and 3 from the list above. It is the time from the issue of a warning of a given flood stage until that predicted stage is observed. However, the system is dynamic and non-linear, forecasts are issued during rising water at approximately every 6 hours corresponding to the network reporting interval and errors are part of the estimates of the subshed mean areal precipitations. Also, those affected by the forecast are located at different levels in the flood plain. As a result, different amounts of lead time are available during any event to different users. Therefore the forecast lead time is reported as a mean value to all users. This value is affected by errors associated with mean rainfall estimates, with streamflow measurement error and by the time delays to operate the entire forecast system.

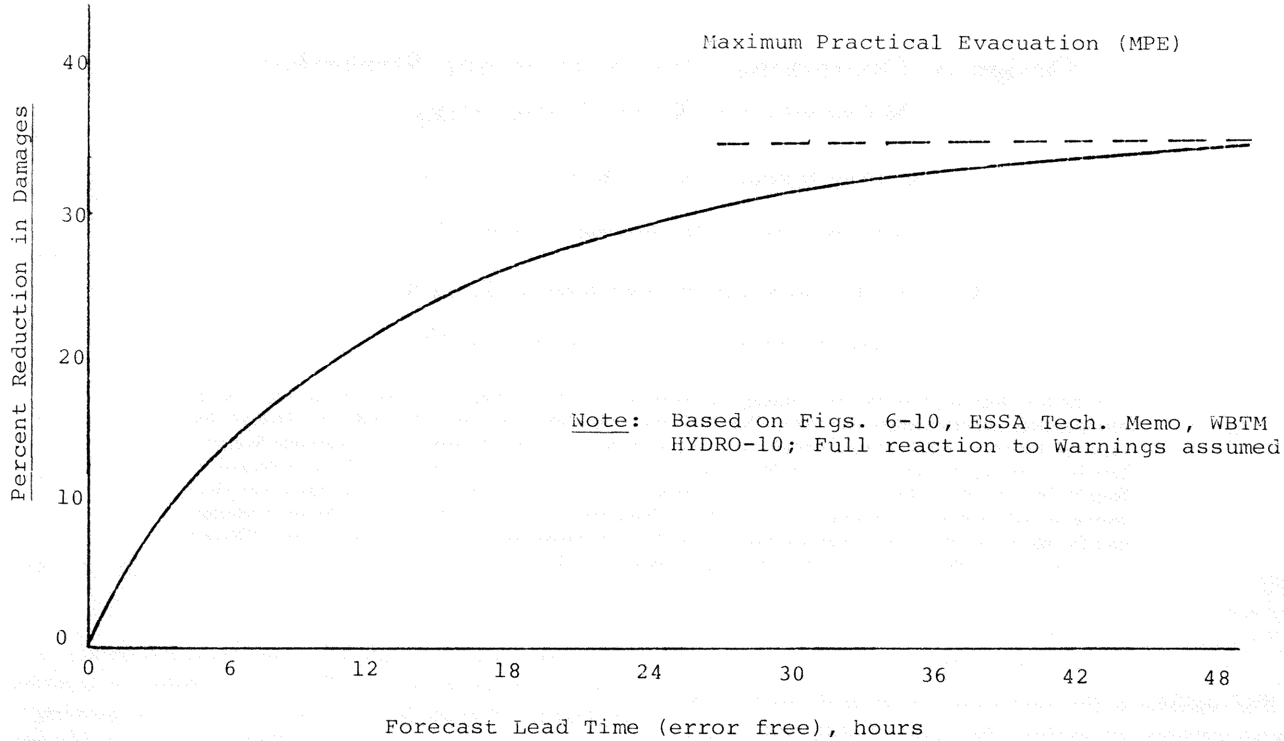

Fig. 1. Damage reduction.

Some of the technical relationships involved in the study are (1) the network density versus variance of mean areal rainfall relationship (as the number of gages increases the variance decreases), (2) the variance associated with stream gage measurements at points within the basin, and (3) the response time relationship of rainfall reporting systems. For example, for a gage operated and reported on by a person (a 'cooperator') there is a lag. It takes time to read and call in the data. The number of gages reporting tends to increase with time. Therefore there is also an effective increase in density with time after each reporting interval. The reporting interval is 6 hours in a fixed frame of 0, 600, 1200, 1800 Greenwich mean time.

To sum up, the main objective of this work is to assess the changes in mean forecast lead time, which is a surrogate benefit measure, that occurs from changes in the number of rain gages or in the number of automated gages in network. The role of automation is to eliminate time delay and increase the proportion of gages actually reporting.

The sections of this paper discuss the conceptual basis, simulation approach, the benefit measure, the network tradeoffs, typical results and the conclusions. The overall research focuses on a subbasin of the Susquehanna River and the impacts of Hurricanes Agnes (June 1972) and Eloise (September 1975). These two storms generated estimated flood damages of $4,678 million and $135 million, respectively. These two events were selected because the damages were substantial and because the hydrometeorological data were on file and available for analysis. The goal is that a damage reduction estimate can be related directly to a network design using relationships involving mean forecast lead time or similar forecast outputs.

CONCEPTUAL BASIS

The general approach is to use mathematical models to assess the effects of precipitation and stream gage network density and automation on the effectiveness of river forecasts. These mathematical models are organized to form the conceptual representation of river forecasting illustrated in Figure 2.

Base Event

Conceptually, a natural hydrometeorological event occurs and the idea of forecasting is to say how this event will evolve before and during the event. Actual historical events can never fully be observed and, therefore, are physically unknowable. Conceptually, however, it is necessary in this study to 'know' the actual event because the performance of the data networks and the forecast operations depends, in part, on what actually happens. Therefore the approach is to define a 'base event' on the basis of available historical data. In this study, historical measurements of precipitation during hurricanes Eloise and Agnes over the Susquehanna River basin are used to define the conceptually 'error free' but in reality unknowable amounts of mean areal precipitation (MAP) over each subbasin in the river forecast system for the basin. The conceptually error free streamflow for the base event is defined as the streamflow that results by inputting the previously defined MAP into the calibrated rainfall-runoff model used in the river forecast operation. Together these MAP and streamflow time series form a base event.

Network Models

Three types of network models are included. These are for precipitation, streamflow and quantitative precipitation forecasts. In each case, the output from the network involves introducing an appropriate amount of 'noise' to the base event and then transposing forward or backward in time the network output to be available in the simulation at the same time as in real-time operations.

Network noise. Network noise is introduced by multiplying the data value of the base event for a given time period by a random deviate having an appropriate mean coefficient

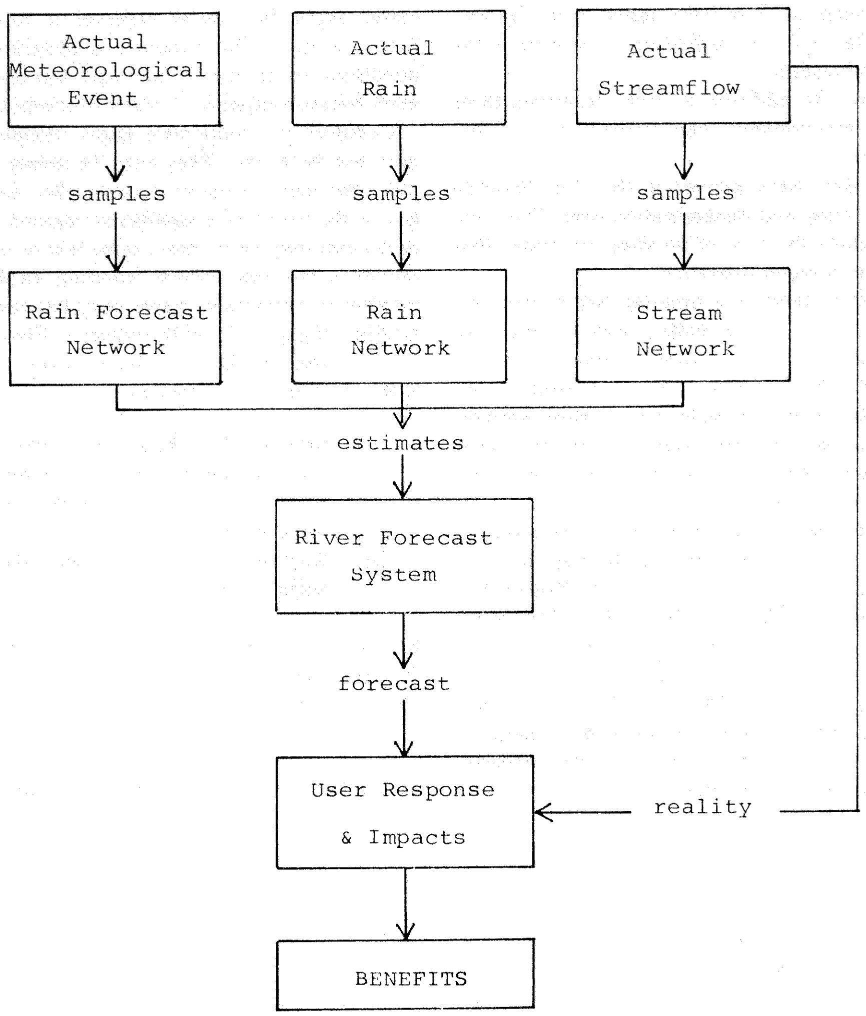

Fig. 2. Conceptual representation of river forecasting.

of variation, and serial correlation coefficient, depending on the detailed characteristics of the individual network (e.g., precipitation, streamflow or QPF). The logic is illustrated by focusing on operational estimates of MAP.

Mean areal precipitation for each subbasin is estimated operationally as a weighted average of data from N rain gages. The estimated MAP (i.e., $\bar{x}_N$) differs from the true MAP (i.e., $\bar{x}$) by the error

$$e_N = \bar{x}_N - \bar{x} \quad (1)$$

The variance of e_N is σ_N^2, which depends on the variance σ^2, of the point values of precipitation, on the location of the N gages, on the spatial correlation structure of the precipitation process, on the weights given to the individual gage data values, and on the size of the subbasin. The theory of how σ_N^2 depends on σ^2 is presented by *Rodriguez-Iturbe and Mehia* [1974*a*, *b*] and by *Schaake* [1979].

If point measurements of precipitation, x_i, were spatially uncorrelated and equally weighted, and if the point variance of the precipitation process, σ^2, were not a function of subbasin area, then σ_N^2 could be expressed as a function of σ^2 by

$$\sigma_N^2 = \frac{\sigma^2}{N} \quad (2)$$

In the presence of spatial correlation,

$$\sigma_N^2 = K\frac{\sigma^2}{N} \quad (3)$$

where K accounts for the effect of spatial correlation. K is a function of rain gage location, number of gages, spatial correlation structure and gage weighting and the size of the sub area.

Because σ^2 depends on $\bar{x}$, it is more convenient to work with the coefficient of variation of the point process

$$CV = \frac{\sigma}{\bar{x}} \quad (4)$$

and the error coefficient of variation

$$CV_N = \frac{\sigma_N}{\bar{x}} \quad (5)$$

In practice it has been found that this type of expression can be fitted exponentially with

$$CV_N = a_0 X_1^{a1} X_2^{a2} X_3^{a3} \quad (6)$$

where the coefficients a_0, a_1, a_2, a_3, etc., found using log transformed least squares analysis of site specific data. The X can be selected as the number of gages, size of basin, distance between gages and similar factors.

For example, data from the Muskingum, Ohio basin have yielded the empirical relationship

$$CV_N = 0.055A^{0.3}/(N^{0.602}) \quad (7)$$

where A is area in square miles and N is the number of gages.

The empirical exponent on N of 0.602 differs from the spatially independent value of 0.5 according to (2) because of the influence of spatial correlation.

Timing relationships. In addition to network errors there are network timing relationships that impact MFLT expectation and variation.

Once the network data have arrived at the river forecast center, there is a processing and dissemination time. This time reduces MFLT and limits the type of flooding situations that can benefit from a river forecast operation.

When an event occurs, there is a time lag before data are available to the forecaster. This is called network response time, τ, and is the time it takes to acquire enough data to make a forecast from the network. This is partially controllable: one can make an early forecast with a small amount of network data or one can wait and acquire more data prior to making a later forecast. Judgment and analysis, such as described herein, can be used to select τ.

Furthermore, the number of gages reporting in each watershed after each time interval is not equal to the total number of gages physically located in the watershed. This directly impacts the error relationships. Figure 3 shows this relationship for the two classes of gages: automated and cooperator. The concept of effective number of gages is illustrated.

Consider the automated gages. The reporting time is fast and depends on the operating characteristics of the communications system. Perfection is not completely possible because of gage and communication equipment down time and the possibility of blocked transmissions. The proportion of automated gages that can be expected to report after a period of time τ is $f_1(\tau)$. This function is illustrated in Figure 3. The maximum value of $f_1(\tau)$ is always less than 1.0 in a large network because gages don't work properly all of the time.

Consider the cooperator gages. People are involved. They may not be home. They may be asleep. They may not perceive the need to report because their locale is relatively dry but in the midst of a significant regional storm. Any number of reasons may cause them to be late or to completely miss reporting a rain that induces flooding. In this case, the effective number of cooperator gages may be much less than the total number of gages. Or, with respect to Figure 3, $f_{2\,max} < 1$.

To summarize the reporting situation as depicted by Figure 3, the variables are as follows:

- N total number of gages in a subwatershed;
- p fraction of gages that are automated;
- $f_1(\tau)$ fraction of automated gages reporting at the network response time;
- $f_2(\tau)$ fraction of cooperator gages reporting at the network response time.

The reporting fractions f_1 and f_2 are determined from curves that are empirically derived at river forecast centers. Thus the effective number of gages N_E is

$$N_E = [pf_1(\tau) + (1 - p)f_2(\tau)]N \tag{8}$$

It is possible to increase effective number of gages by either increasing p, by increasing N, and by increasing f_{1max} and

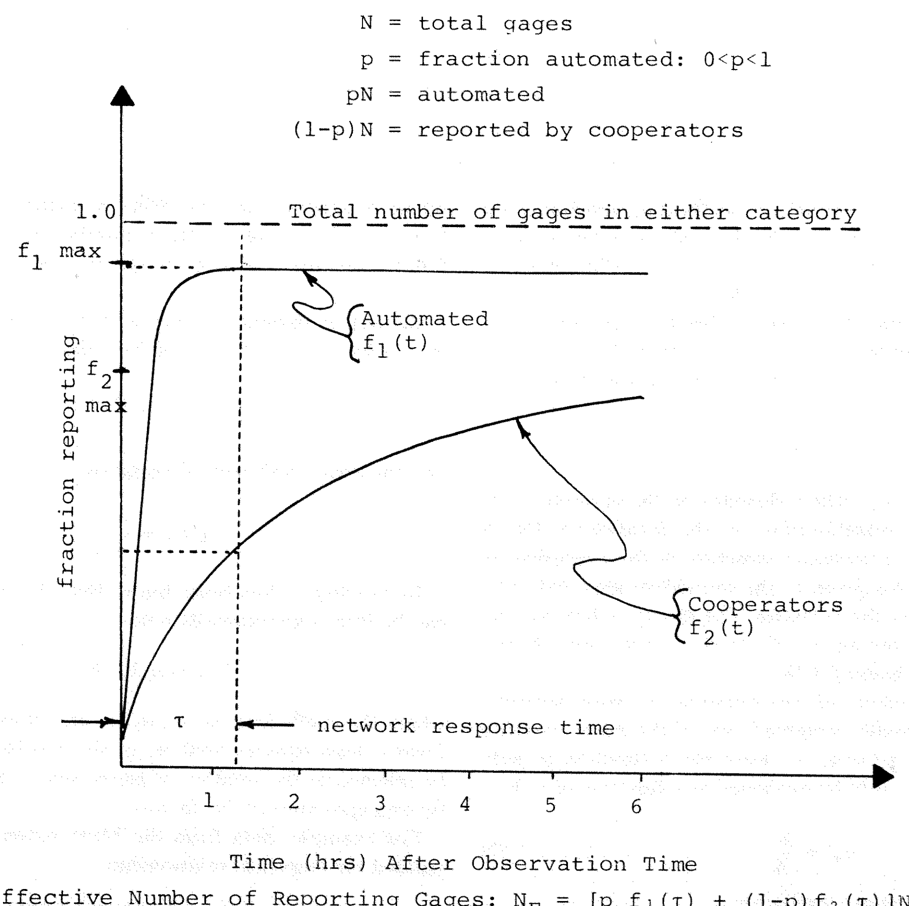

Fig. 3. Reporting network response function.

f_{2max}. The effective number of gages is then used to compute the coefficient of variation of the MAP.

The next section discusses the river forecast system used in this study. The system includes a river forecast center rainfall-runoff model that is used to generate and analyze the base hydrograph.

River Forecast System

The Susquehanna River forecast system uses an 'event' approach [*Richards and Strahl,* 1969]. The basic time interval is 6 hours. Rainfall and streamflow data from the network support a 6-hour computational interval. The data come from a mixture of automated sites and cooperators who monitor gages.

Mean areal precipitation is computed as a weighted average of gage sites for each subbasin. Direct runoff from the subbasin is calculated using an antecedent precipitation index as a surrogate for soil moisture which is corrected for time of year. At the start of a storm, the time of year, the antecedent precipitation index, and the base flow are known and define the initial state of the basin. The subbasin runoff hydrograph is a function of mean areal precipitation, storm duration and the initial state of the basin.

The subbasin hydrographs are introduced into the stream channel system and the flow is routed to the downstream forecast points using a so-called lag and K approach. This approach is typical of NWS river forecast center operations, particularly in the past. The approach is a computer application of standard hydrologic methods as they were employed in a 'hand calculation' context. The methods tend to be very situation specific and empirical. Nevertheless, it is within the context of this approach that base hydrographs and 'noisy' inputs are analyzed in this study. The technical operations of NWS are decentralized and this led to each river forecast center being individualistic in their application of hydrologic technology, a disadvantage for systematic study to obtain general network design criteria.

Currently there is a state of transition. There is a movement to 'continuous' models that are based upon soil moisture accounting. [*National Weather Service,* 1972] Their degree of empiricism is less than the event methods. This has a benefit for systems analysis of networks because the new generation of models are documented and generalized for widespread usage. The introduction of network analysis simulation procedures into the continuous simulation context is a goal of NWS.

User Response and Impacts

The evaluation of data networks should depend upon their ultimate value to society. In the case of river forecasting, much of this value derives because users have time to respond to the forecast and take action to reduce their losses. Although this study does look directly at the economic benefits of data network river forecasting, it also offers the valuable opportunity to look at forecast lead time as a surrogate measure for economic benefits. Because data networks can never provide sufficient information to determine exactly the flooding conditions for the future, there must always remain some uncertainty in the flood forecast. This uncertainty in turn can be translated into uncertainty in the amount of lead time actually available to forecast users. In other words for a given network design, there would be a distribution of possible lead times that could actually occur for a given flood event depending on the actual errors introduced by the network at that time. Because the variability in the MFLT to the network noise is indicative of economic costs of under or overestimating flood stages, a 'reliable MFLT,' that value which is expected to be exceeded 95 percent of the time, is used as a surrogate measure of benefits to forecast users of flood warning service. The reliable MFLT is decreased by uncertainty introduced into forecast operations by any source, including network noise and model error.

SIMULATION METHOD

Figure 4 shows the overall scheme. Historical records are used to produce a base event. Mean areal precipitation data in the base event are error free. These error-free MAP data are processed by the rainfall-runoff model to produce hydrographs or flood state histories that are assumed error free. These hydrographs are termed the base hydrographs.

Then network parameters are used to generate measurement noise to be added to the historical mean rain record. The noise is a function of the network density; density varies with time during each reporting interval in accordance with empirical data on cooperator performance.

As Figure 4 shows, replicate, equally likely traces of noisy data are presented to the rainfall-runoff simulation. The noisy forecasts are compared with the base hydrograph forecast to obtain samples of the mean forecast lead time. These samples are thus Monte Carlo data from which to compute the reliability of the mean forecast lead time.

The simulations provide the ability to relate the forecast reliability to network density and to the number of automated gages in the network. Practically speaking, the approach is 'messy' for the following reasons:

1. The rainfall-runoff model is exceedingly complex in its file structure and logic. The Susquehanna computer model has evolved from the earliest computers. It is very situation specific and tedious in its management of the hydrologic computations.
2. The model must be initialized to a common set of starting conditions prior to each replicate simulation.
3. There are many forecast points in a basin. Therefore there is an MFLT for every point in the river basin for which NWS issues forecasts. In the Susquehanna, for example, there are approximately 40 forecast points.

The simulation approach uses various error relationships as follows:

1. The population mean of the mean areal precipitation, $\overline{\mathrm{MAP}}_{(i,j)}$ for each time interval i for each subwatershed j is assumed to be the same as was measured during a significant historical event.
2. For each subwatershed a coefficient of variation of MAP error $CV_N(i, j)$ is calculated based on the subwatershed effective number of rain gages N_E. Note that one can parametically study the number of gages N and fraction automated p by varying these parameters at this point in the analysis.
3. Replicate simulations of rainfall measurements are obtained by adding noise to the population mean of the mean areal precipitation. For the kth replication, the ith interval and the j watershed,

$$\mathrm{MAP}_{\mathrm{measured}} = \mathrm{MAP}_{\mathrm{historical}} \exp\,(\mathrm{avg} + V_{i,2}) \qquad (9)$$

where

$$\mathrm{avg} = \ln\,(CV_1{}^2 - 1) \qquad (10)$$

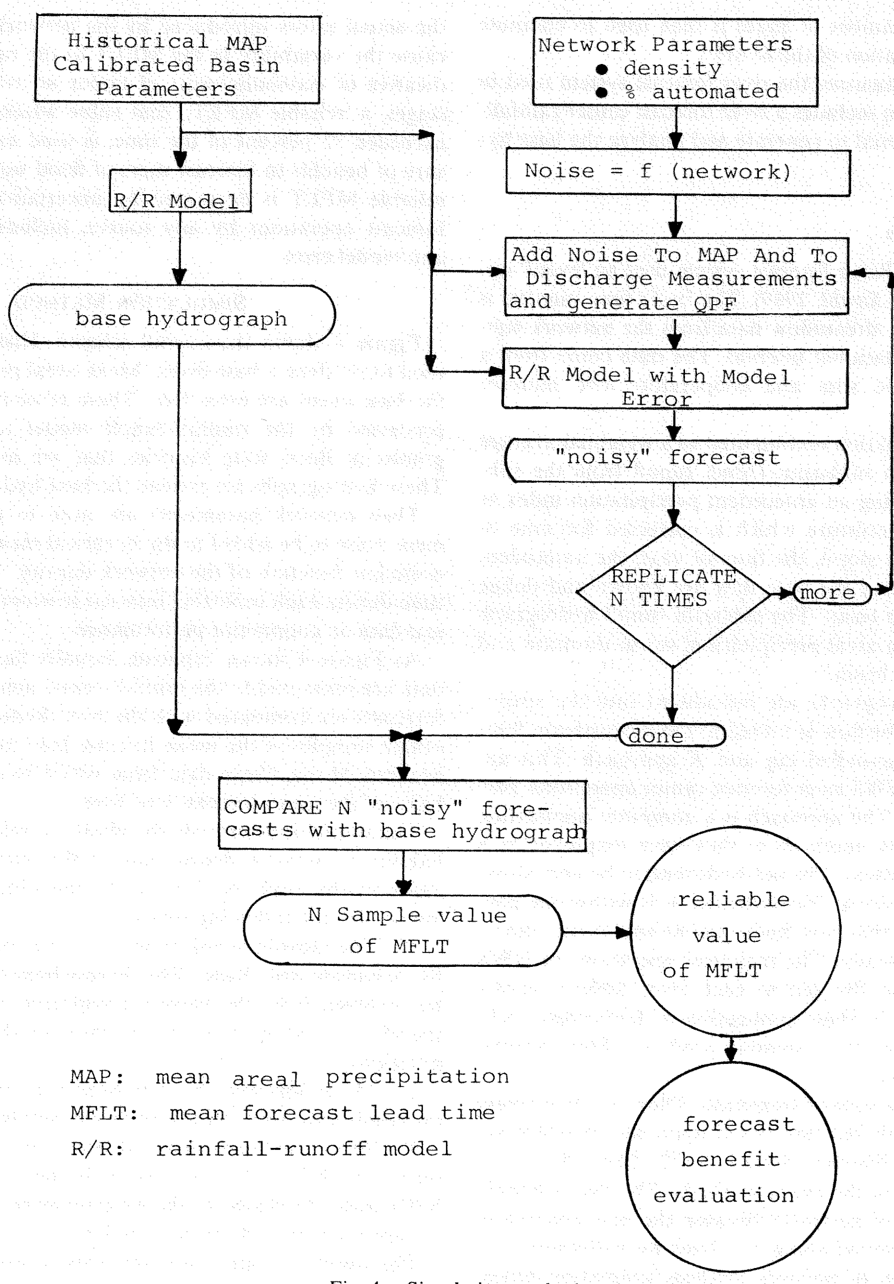

Fig. 4. Simulation method.

and $V_{i,2}$ is a random variable having a zero mean and a standard deviation that depends on the network density, size of MAP area, sampling interval and storm characteristics.

4. Each simulated rainfall measurement series is processed with the rainfall-runoff model to obtain simulated runoff forecasts. Simulated model error sequences can be added to account for limitations inherent in the rainfall-runoff model.

5. The NWS measures river stage at upstream points as well as point rainfall. This introduced another gaging network, the stage gages, into the analysis. In fact this network, in the past, was the primary early warning system on floods. The pressures for more forecast lead time led to the rain gage networks. This older, stage network, is used in the rainfall-runoff modeling for base flow initialization and for continuing adjustments to upstream routing errors in a manner analogous to Bayesian updating in a real-time context. Measurement and reporting noise is introduced into the simulation method to represent the stage errors and more importantly, to represent uncertainty in the stage-discharge relationship.

6. The stage forecasting process can theoretically utilize a forecasted rain to secure additional lead time. As it stands now, typically the stage forecasts are made based on rain that has already fallen. Research is being conducted to understand the effects of uncertainty in forecasts of rain for future 6-hour increments corresponding to the rainfall-runoff model timing conventions. Such rain forecasts and their standard errors are included in the simulation method. In principle, quantitative precipitation forecasts should tend to increase the overall stage forecast lead time but the effect of uncertainty will also increase the forecast variance and thereby decrease the reliable MFLT.

7. Each runoff forecast is compared with the base hydrograph forecast to analyze mean forecast lead time and its variance.

To sum up, the overall method permits study of improvement of reliable mean forecast lead time attributable to automation (increasing p) to increasing the number of gages (increasing N) to changing the mix of rain gages and stream gages and to reducing uncertainty in the QPF through improved meteorological methods. This is done by selecting N and p for each watershed and then by generating the Monte Carlo model outputs of noisy forecast data which are analyzed for variance. Model error is assumed to be of second-order importance. It is also assumed that the nature of model errors would be similar from model to model but that the parameters would change. The precise impact of model errors on this study is left for future work.

The simulation of forecast lead times is a research project and is being viewed in the broadest possible manner. Future versions of the method may consider refinements or other errors in a production model for network analysis. In terms of pinning down the method's exact configuration, it represents a 'moving target.' The underlying computer program is being improved and updated very frequently.

RELIABLE LEAD TIMES AND BENEFITS

The mean forecast lead time (MFLT) computation is illus trated in Figure 5. In this example a sequence of forecasts is issued as the rain continues. This leads to a sequence of forecast stages that are successively higher. Each forecast hydrograph is compared to the base hydrograph. The time from the time of forecast issuance to the time the forecast stage occurs in the base hydrograph is the lead time for that forecast. Thus, MFLT is the average over the forecast sequence of warning times until actual stages match the forecast stage.

Notice by inspection of Figure 5 that a computational timing difference can occur between the forecast hydrograph and the base hydrograph. In the example the shift is positive. It could also be negative. This shift does not affect the MFLT definition. Thus, the definition represents the interval from the time of the notice of the possibility of a future flood stage till the time of the actual flood stage.

One can deduce, during rising stage, that successive forecast lead times exist, but that the last forecast may be in error. Typically, the issue time of last forecast corresponds to the end of the rain. The last forecast can under or overshoot the peak of the actual flood. The convention used to weight this case, allowing for some tolerance interval, is to assign a zero lead time if the last forecast(s) misses its mark.

One can further deduce, that rainfall and streamflow measurement errors will add noise and decrease the lead times of forecasts. Logic indicates that input noise will contribute to

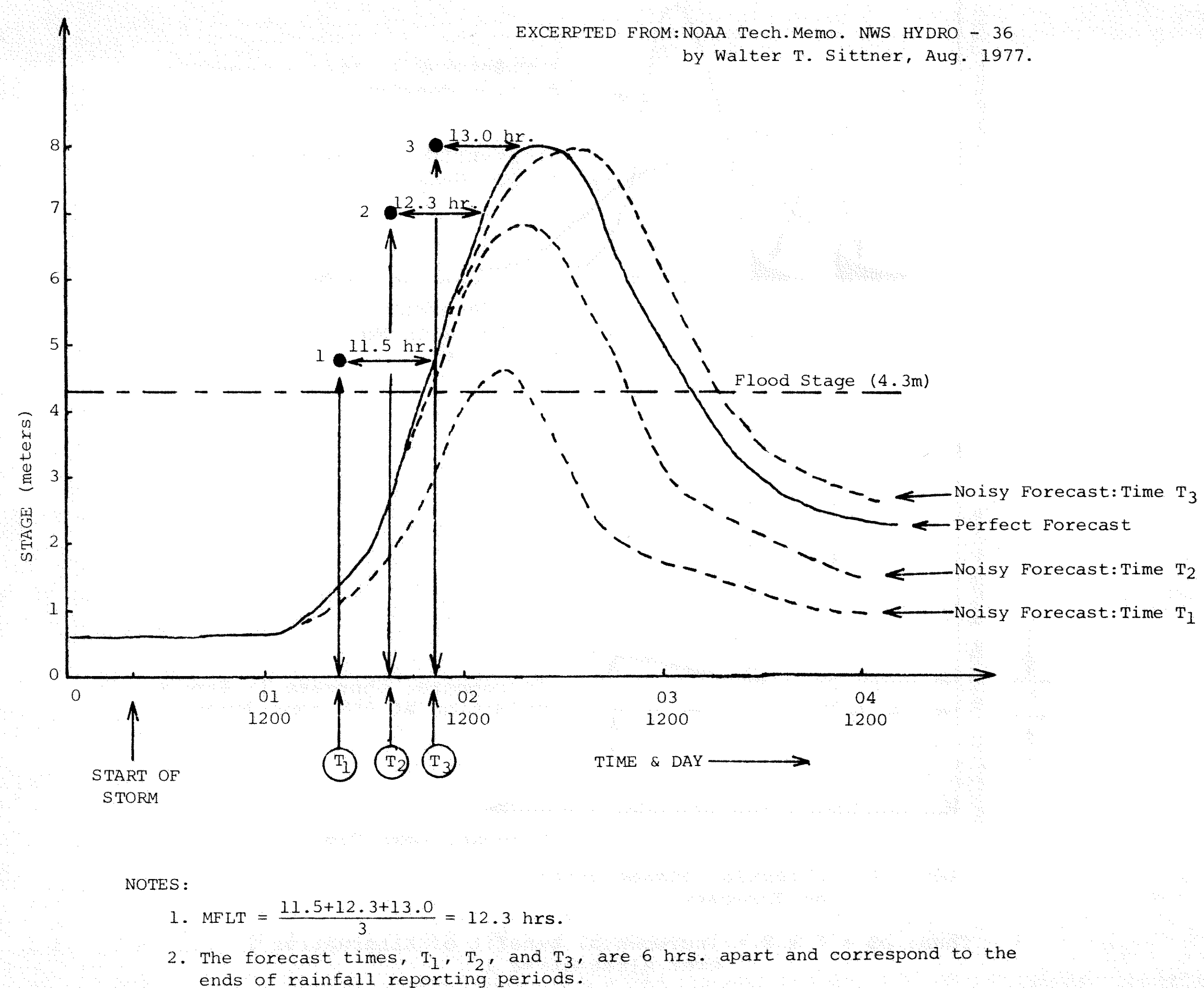

Fig. 5. Mean forecast lead time.

output noise. Input noise decreasing output expectation is a fact deriving from the penalties associated with missing the last forecast during a forecast sequence.

Let us further examine the linkage of MFLT to benefits. The Monte Carlo simulation approach used herein develops the sampling distribution of MFLT. If the input rain data have low noise the MFLT distribution will have low variance and cluster at its mean. High noise will spread the distribution. The central tendency of the MFLT varies inversely with high or low noise in the inputs because of the penalty potential of a miss on the last forecast of a sequence of forecasts during rising stage. Thus, MFLT variance reduction and expectation increase is the impact of an improved network. How does this tie in with benefit estimation?

The answer must be phased in probabilistic terms coupled with incremental benefits. Consider Figure 6 which shows hypothetical MFLT distributions for two alternatives. Alternative 1 has noisy inputs associated with low gage density or low automation. Alternative 2 has lower variance inputs associated with high gage density or high automation. The MFLT distributions for these cases can be derived by Monte Carlo simulations using the rainfall-runoff model.

The left-hand tails of these distributions give probabilistic lead times T_1 and T_2, for which the probability is 95% that the actual lead time is greater. One would be 95% confident of these lead times; the level of confidence that we used earlier to define our reliable lead time. These reliable lead times link to the damage reduction curve, with 95% confidence, to give the incremental increases or damage reduction associated with improved networks. The benefit is thus the incremental damage reduction of alternative 2 over alternative 1 as depicted in Figure 6.

The damage reduction curves are probability valid but their estimation is difficult. Therefore, the focus of the network

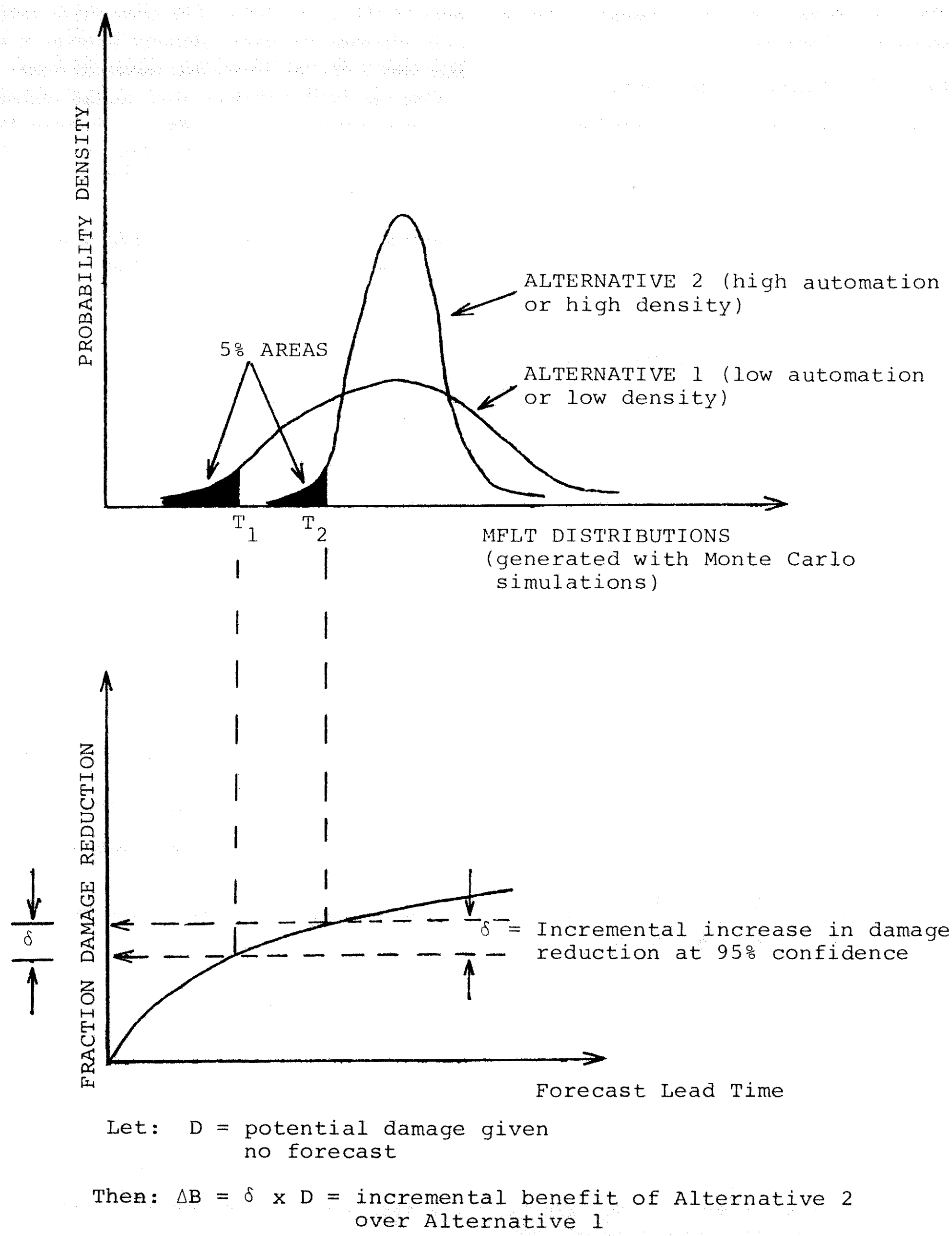

Fig. 6. Probabilistic incremental benefits.

evaluation is on investigating the impact of measurement noise upon the distribution of MFLT. The discussion in this section is intended to rationalize the selection of the 95% confidence MFLT value as a surrogate for benefit. Reduction in reliable lead time is taken to be directly related to the benefit measure. Future efforts can move closer toward direct benefit evaluation. Also the 95 percent level could be further analyzed for appropriateness.

To sum up, the calculation of reliable lead times is the pay off of this research. This section illustrates how reliable lead times may be related to benefits. The next section discusses typical reliable lead time results.

TYPICAL RESULTS

An upland subbasin of the Susquehanna River basin in Pennsylvania was isolated for preliminary study. The purpose of this initial work was to debug the simulation program and test the logic on real data.

The real data consisted of (1) all the detailed hydrologic overland flow and channel routing coefficients calibrated by the NWS staff, (2) stage versus flow curves, (3) a collection of six subbasins and six river forecast points, and (4) mean areal rainfall data from past hurricanes (Agnes and Eloise) to use as inputs to generate the base hydrographs.

These data are a subset of the model and data used to forecast floods in the Susquehanna basin. The future modeling will address this larger basin as the testing progresses.

The preliminary testing was successful in that the behavior of typical reliable lead time forecasts was as expected. Figure 7 shows such typical results.

The curves in Figure 7 are representative of different levels of automation. The effects of automation are to increase the effective rain gage density and to drive the input uncertainty lead times. Each curve in Figure 7 is calculated using 20 Monte Carlo computer runs simulating forecasts in the testing subarea.

The results demonstrated that as automation increases; (1) the mean lead time increases, (2) the standard deviation of the lead time decreases, and (3) the reliable lead time increases.

These effects were expected and the testing confirms the rationale for conducting the research. Future efforts will move to larger systerms and new data sets to quantify the network tradeoffs. The research, to date, has shown the feasibility of the approach and had confirmed the logic.

NETWORK ANALYSIS POSSIBILITIES

The rain and stream gage network simulator as described herein can be used to analyze the effects of the following.

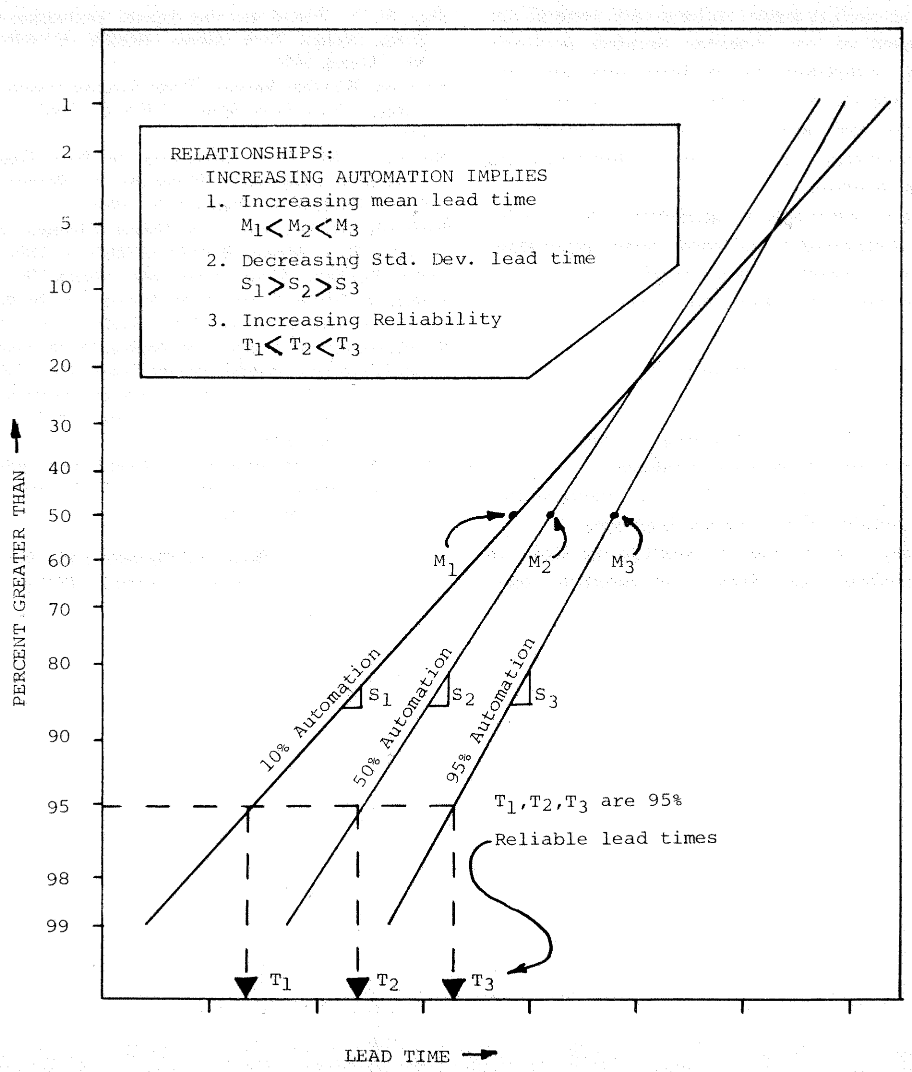

Fig. 7. Typical results.

Automation of reporting networks. Higher automation should cut down on network response time and increase effective number of reporting sites. Both effects should increase MFLT.

Increased numbers of gages. This will decrease the variance of weighted inputs to simulation models.

Gage down time. The model can consider the maximum number of reporting gages to follow a random distribution to simulate the effects of gage down time. This will permit the review of in-house or contract agreements for gage maintenance.

Varying the network response time τ. Various levels of τ imply a trade-off between information on hand and versus additional delay to acquire more information.

Introducing quantitative precipitation forecasts (QPF) into MFLT estimation. QPF will increase mean lead time but will also add significant noise which tends to reduce reliable lead time. The necessary improvement in QPF to increase reliable lead time can be determined.

Model error. At present we do not have an estimate of the magnitude of model error. Future work may provide estimates which can be used to relate to MFLT.

Various components and sources of error. The individual component error impacts on MFLT can be used as a guide to priorities for modeling and network improvements.

In general, the approach is meant to be a very general network analyzer focused on user-oriented network products. Any error generating component can be introduced and analyzed. Furthermore, the use of the network analyzer in a sensitivity analysis context can pinpoint the effects on forecast reliability of any error sources in the network configuration and rainfall-runoff model structure.

The models are also amenable to application to snowfall networks involving temperature and snow water equivalent. This use of the network simulator is a straightforward application of the concepts and networks of this paper.

CONCLUSIONS AND RECOMMENDATIONS

The following conclusions can be drawn:

1. The network simulation methodology is feasible and flexible and preliminary results meet expectations.
2. The methodology relates directly to a measure that links to benefits, the reliable mean forecast lead time.
3. The methodology can be used to analyze the issues of network design including gage density, automation, gage down time, network timing relationships, effects of rain forecasts, and model and other sources of error.
4. The methodology is expected to meet a significant number of management needs of the NWS for network design and the investigation of various river forecast operations.
5. Future work will be guided by specific management needs and hypotheses geared toward improving reliable forecasts.
6. The method can be used to evaluate existing networks.
7. Given network and modeling automation, the method can be used to automatically select the network response time.

The following recommendations can be made:

1. A more detailed analysis and investigation of the Susquehanna data base should be undertaken.
2. The linkage to benefits should be extended and pinned down with an objective of direct benefit estimates being generated as functions of network design parameters.
3. The methodology should be generalized to the current generation of state-of-the-art conceptual rainfall-runoff models being introduced within NWS.
4. An analysis should be conducted with the methodology on sufficiently general data sets to enable the generation of network design guidelines and criteria.

REFERENCES

Day, H. T., Flood warning benefit evaluation–Susquehanna River Basin, *NOAA Tech. Memo. WBTM HYDRO-10,* Silver Spring, Md., March 1970.

National Weather Service, River forecast system and forecast procedures, *NOAA Tech. Memo. NWS HYDRO-14,* Silver Spring, Md., Dec. 1972.

Relyea, C. M., River forecasting, in *Proceedings of IBM Scientific Computing Symposium: Water and Air Resources Management,* pp. 63–79, IBM, White Plains, N.Y., 1968.

Richards, M. M., and J. A. Strahl, Elements of river forecasting, *ESSA Tech. Memo. WBTM HYDRO-9,* Office of Hydrol., World Weather Serv., Silver Spring, Md., March 1969.

Rodriguez-Iturbe, I., and J. M. Mehia, On the design of rainfall networks in time and space, *Water Resour. Res., 10*(4), 713–728, 1974*a*.

Rodriguez-Iturbe, I., and J. M. Mehia, On the transformation of point rainfall to areal rainfall, *Water Resour. Res., 10*(4), 729–735, 1974*b*.

Schaake, J. C., Jr., Accuracy of point and mean areal precipitation estimates from point precipitation data, *NOAA Tech. Memo. NWS HYDRO,* in preparation, 1979.

Sittner, W. T., Determination of flood forecast effectiveness by the use of mean forecast lead time, *NOAA Tech. Memo. NWS HYDRO-36,* Silver Spring, Md., Aug. 1977.

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