Nonparametric Framework for Long-Range Streamflow Forecasting

By J. A. Smith,[1] G. N. Day,[2] Member, ASCE, and M. D. Kane,[3] Associate Member, ASCE

Abstract: The extended streamflow prediction (ESP) procedure of the National Weather Service River Forecast System (NWSRFS) produces long-range forecasts of streamflow through the use of hydrologic models and historical hydrologic data. An important element of the ESP procedure is converting hydrologic-model output to estimates of a forecast random variable. In this paper, nonparametric statistical procedures are developed for combining hydrologic models and historical hydrologic data into long-range streamflow forecasts. Although these procedures are developed for use within the ESP system, they should be broadly applicable to problems of long-range streamflow forecasting. Two notable features of the procedures developed in this paper are: (1) Climate information is easily incorporated; and (2) hydrologic-model errors can be accommodated. Results are presented for a test implementation of ESP for a basin in the southeastern United States during the severe drought period of 1988. The relative importance of climate information and soil moisture information for long-range streamflow forecasting is compared and contrasted.

Introduction

Long-range streamflow forecasts are valuable for a variety of water-management activities, ranging from irrigation scheduling (Ramirez and Bras 1985) to municipal water supply operation (Smith 1989; Lettenmaier and Wood 1990). The basis for long-range streamflow forecasts is that hydrologic and meteorological processes are often characterized by significant persistence (with time scales ranging from days to months). Hydrologic persistence is associated with subsurface storage and transport of moisture, channel storage of runoff, and the accumulation and melt of snowpack. Persistence in climatic processes that determine broad features of the weather has been the subject of intensive research [see for example Namias (1980) and Rasmusson (1984)]. Research in this area is beginning to provide evidence that improvements in long-range streamflow forecasts are possible by incorporating information on climatic conditions (Redmond and Koch 1991).

Hirsch (1978) introduced the term "position analysis" to describe long-range water-resources forecasting procedures that combine current information on the hydrologic and water-resources state of a basin with historical hydrologic data to produce long-term distributional forecasts. Hirsch (1981) developed position-analysis techniques using streamflow observations and a time-series model. Position-analysis techniques utilizing hydrologic models were developed concurrently by the National Weather Service (NWS) and

[1]Asst. Prof., Dept. of Civ. Engrg., and Operations Res., Princeton Univ., Princeton, NJ 08544.

[2]Res. Hydro., Hydrologic Res. Lab., Nat. Weather Service, 1325 East-West Hwy., Silver Spring, MD 20910.

[3]Res. Hydro., Hydrologic Res. Lab., Nat. Weather Service, 1325 East-West Hwy., Silver Spring, MD.

Note. Discussion open until June 1, 1992. To extend the closing date one month, a written request must be filed with the ASCE Manager of Journals. The manuscript for this paper was submitted for review and possible publication on August 9, 1990. This paper is part of the ***Journal of Water Resources Planning and Management***, Vol. 118, No. 1, January/February, 1992. ©ASCE, ISSN 0733-9496/92/0001-0082/$1.00 + $.15 per page. Paper No. 334.

incorporated into the extended streamflow prediction (ESP) component of the National Weather Service river forecast system [see Day (1985)]. ESP uses conceptual hydrologic/hydraulic models to forecast future streamflow using the current snow, soil-moisture, and channel-storage conditions of the basin. The hydrologic modeling framework is particularly useful in situations where anthropogenic changes have affected hydrologic response of a basin and historical streamflow data are no longer representative of the basin. The hydrologic modeling framework also allows for a range of forecast variables (accumulated inflow, minimum daily flow, etc.) to be handled under one umbrella.

In this paper the hydrologic-modeling approach of ESP is developed in a nonparametric statistical framework and extended to include climatic information and the effects of hydrologic and model error. Operational implementation of ESP includes both parametric and nonparametric options. In the section headed "Estimating Conditional Distribution" we highlight the distinction between parametric and nonparametric options. An important advantage of the nonparametric framework is that it provides a consistent set of procedures for use with a range of forecast variables and forecast durations. In the parametric framework, distributional assumptions are linked to the forecast variable and duration.

Contents of the section are as follows. The forecasting problem is presented in the section headed "Formulation of Forecasting Problem." In the section headed "Estimating Conditional Distribution" the forecast procedure is developed. Application of the forecast procedure to reservoir inflow forecasting for Lake Lanier, in Georgia, is described in the section headed "Application." The application focuses on test implementation of ESP during the extreme drought year of 1988. A summary and conclusions are given in the section headed "Summary and Conclusions."

Formulation of Forecasting Problem

The long-range streamflow forecasting problem is defined with respect to a forecast variable that is a function of future streamflow. The forecast variable $X(t)$ can be represented as follows:

$$X(t) = f_t[Y(t + 1), \ldots, Y(t + J)] \quad (1)$$

where t = current day; J = duration of the forecast period in days; f_t = a function of J real-valued arguments; and $Y(1), \ldots, Y(365)$ denote daily streamflow values. The subscript t of the function f_t indicates that the forecast function can vary with time. Example forecast variables include accumulated flow

$$X(t) = \sum_{j=1}^{J} Y(t + j) \quad (2)$$

minimum flow during the period

$$X(t) = \min\{Y(t + 1), \ldots, Y(t + J)\} \quad (3)$$

and the time above a threshold y_0

$$X(t) = \sum_{j=1}^{J} 1[Y(t + j) > y_0] \quad (4)$$

where

$$1[Y(t) > y_0] = 1 \quad \text{if } Y(t) > y_0 \qquad (5)$$

$$1[Y(t) > y_0] = 0 \quad \text{otherwise} \qquad (6)$$

among others [see Day (1985)]. Daily streamflow is used throughout this paper for concreteness. Other time intervals, either shorter or longer, could be used. In the ESP framework, duration of the forecast period (J) is selected by the user and can be any multiple of 1 day.

The information available for forecasting $X(t)$ consists of hydrometeorological observations (typically of streamflow, precipitation, and temperature) prior to and including day t. The data set for day t is denoted by H_t.

Water-management decisions often require information concerning probabilities of extreme events [see Smith (1988) for an example concerning municipal water supply for the Washington, D.C., metropolitan area]. Consequently, we are interested in deriving distributional water-supply forecasts; that is, forecasts that explicitly define the probability of occurrence of events. In statistical terms, the problem is to compute the conditional distribution of the forecast variable $X(t)$ given the data available at time t, H_t

$$F_t(x) = P[X(t) \leq x | H(t)] \qquad (7)$$

where the argument x is nonnegative.

The fundamental assumption of position-analysis procedures is that the data set H_t can be condensed to a vector-valued state variable $\mathbf{B}(t)$ such that

$$F_t(x) = P[X(t) \leq x | H_t] \qquad (8)$$

$$F_t(x) = P[X(t) \leq x | \mathbf{B}(t)] \qquad (9)$$

The key feature of the position-analysis assumption is that the amount of information that needs to be incorporated into development of a forecast is greatly reduced, yet the information content of the data set remains the same. In the forecast procedures developed by Hirsch (1981) the basin state vector $\mathbf{B}(t)$ consists of lagged monthly streamflow. In the following we develop the position-analysis framework for use with hydrologic models.

The current basin state is an N-valued random vector $\mathbf{B}(t)$ representing channel, soil-moisture, and snowpack storage of water in the basin. The relationship between basin state variables and observables is represented by the model equation

$$Y(t) = g_t[R(t), T(t), \mathbf{B}(t-1)] + \varepsilon_t \qquad (10)$$

and the state equation

$$\mathbf{B}(t) = h_t[R(t), T(t), \mathbf{B}(t-1)] \qquad (11)$$

where g_t and h_t = real-valued functions of $N + 2$ arguments; $R(t)$ = mean areal precipitation for day t; $T(t)$ = surface temperature for day t; and ε_t = model error for day t. The functions g_t and h_t represent the hydrologic models that convert basin state variables describing current channel storage, soil moisture, and snowpack, and observations of temperature and rainfall into streamflow. In the section headed "Applications" for example, we use the Sacramento soil moisture accounting model and Lag/K channel-routing model. In regions where snow is an important component of the forecast

problem a snow model such as the NWS snow accumulation and melt model (Anderson 1973) would also be used. In this case temperature becomes an important observation. The models combine to form an implicit representation of the functions g_t and h_t [explicit state space representations of these models are given in Kitanidis and Bras (1980), Brazil (1988), and Day (1990)].

Estimating Conditional Distribution

In this section we develop procedures for estimating the conditional distribution F_t using the hydrologic modeling approach of ESP. The statistical framework we develop in this section for estimating the conditional distributions F_t is nonparametric. This does not mean that the underlying models are free of parameters, but rather that we do not characterize the distribution function F_t by a finite vector-valued parameter. The principal consequence of working in a nonparametric framework is that we attempt to estimate F_t from "sample" distribution functions. We develop forecasts of F_t for increasingly complex forecast situations, including: (1) Basin information is of no value in long-term forecasts; (2) basin information is used in long-term forecasts; (3) basin information and climate information are used; and (4) basin information and climate information are used and hydrologic model error is accommodated. Throughout this section it is assumed that an n-year historical data base of streamflow, precipitation, and surface temperature is available. The historical observations are denoted $[Y_i(s), R_i(s), T_i(s);\ i = 1, \ldots, n;\ s = 1, \ldots, 365]$.

The condition under which current basin information is not useful for forecasting corresponds to the following condition:

$$P[X(t) \leq x | \mathbf{B}(t)] = P[X(t) \leq x] \qquad (12)$$

Eq. (12) is simply a mathematical representation of the situation in which the forecast variable does not depend on the basin state variable.

In this case a simple procedure for estimating the distribution of $X(t)$ is to compute a sample distribution based solely on the historical streamflow values. The sample estimator is given by

$$\hat{F}_t(x) = n^{-1} \sum_{i=1}^{n} 1[X_i(t) \leq x] \qquad (13)$$

where

$$X_i(t) = f_t[Y_i(t+1), \ldots, Y_i(t+J)] \qquad (14)$$

In (13) we have used the indicator function notation again [as in (4)] with the interpretation

$$1[X_i(t) \leq x] = 1; \quad \text{if } X_i(t) \leq x \qquad (15)$$

$$1[X_i(t) \leq x] = 0; \quad \text{if } X_i(t) > x \qquad (16)$$

In (13) and in subsequent development the sample estimator of the distribution function is used. More sophisticated nonparametric estimators may be appropriate in certain situations [notably, when sample size is small; see Serfling (1980)].

If basin information is useful in forecasting $X(t)$, that is, if the simplification of equation (12) does not hold, then the estimator of (13) is inappropriate. A sample distribution approach to computing the conditional distribution utilizing the hydrologic modeling framework is outlined in the following. A data set of conditional discharge is obtained from rainfall and temperature data as follows:

$$\hat{Y}_i(t+1) = g_t[R_i(t+1), T_i(t+1), \mathbf{B}(t)] \quad (17)$$

$$\hat{B}_i(t+1) = h_t[R_i(t+1), T_i(t+1), \mathbf{B}(t)] \quad (18)$$

For $j > 1$

$$\hat{Y}_i(t+j) = g_{t+j}[R_i(t+j), T_i(t+j), \hat{B}_i(t+j-1)] \quad (19)$$

$$\hat{B}_i(t+j) = h_{t+j}[R_i(t+j), T_i(t+j), \hat{B}_i(t+j-1)] \quad (20)$$

The interpretation is that the random variable $\hat{Y}_i(t+j)$ represents conditional discharge on day $t+j$ of year i, given that the initial basin state is $B(t)$. The procedure can be described in simulation terms: Hydrologic models are executed for days $t+1, \ldots, t+J$ of each historical year. The initial state variables (describing soil moisture, channel storage, and snowpack) are the same for each year and represent basin state variables on the forecast day. The sequence of state vectors $\hat{\mathbf{B}}_i(t+j)$ represent the state variables that would have occurred in year i if the initial state variables on day t were those of the current year, $\mathbf{B}(t)$.

Sample values of the forecast variables are obtained as follows:

$$\hat{X}_i(t) = f_t[\hat{Y}_i(t+1), \ldots, \hat{Y}_i(t+J)] \qquad i = 1, \ldots, n \quad (21)$$

The sample estimator of the conditional distribution F_t is given by

$$\hat{F}_t(x) = \left(\frac{1}{n}\right) \sum_{i=1}^{n} 1[\hat{X}_i(t) \le x] \quad (22)$$

A useful role for climate information is to indicate the representativeness of individual years of the historical record. We assume that this information can be converted to weights $\theta_1, \ldots, \theta_n$ which are nonnegative and sum to 1. In an extreme case a weight θ_i might equal 0, indicating that current climatic conditions are incompatible with the climatological development during the forecast period of year i. In general, the ratio θ_i/θ_j indicates the likelihood of climatic conditions during year i occurring during the forecast period, relative to those of year j. A sample distribution function can be obtained for a weighted sample as follows. Denote the order statistics of the sample of (21) by

$$\hat{X}_{(1)}(t) \le \hat{X}_{(2)}(t) \le \cdots \le \hat{X}_{(n)}(t) \quad (23)$$

The corresponding weights are $\theta_{(1)}, \ldots, \theta_{(n)}$; that is, $\theta_{(j)}$ = weight corresponding to the jth order statistic $\hat{X}_{(j)}(t)$. The sample distribution is defined by

$$\hat{F}_t(x) = 0; \qquad \hat{X}_{(1)}(t) > x \quad (24)$$

$$\hat{F}_t(x) = \sum_{i=1}^{j} \theta_{(i)}; \qquad \hat{X}_{(j)}(t) < x \le \hat{X}_{(j+1)}(t) \quad (25)$$

$$\hat{F}_t(x) = 1; \qquad \hat{X}_{(n)}(t) < x \quad (26)$$

A range of scenarios can be accommodated using weights. First it should

be noted that the estimator of (24)–(26) reduces to the estimator of (22) if θ_i equals $1/n$ for all i. Information from a quantitative climate index, such as the southern oscillation index, can be objectively incorporated into determination of weights through a kernel of the form

$$\theta_i = \frac{K(|A - A_i|)}{\sum_{j=1}^{n} K(|A - A_j|)} \quad (27)$$

where A_i = index value for the ith historical year; A = index value for the current year; and K = a univariate distribution function [see also Kelman et al. (1990) and Karlson and Yakowitz (1987a,b)]. If climatic trends are present in the historical record it may be desirable to weight recent years more heavily than past years, for example by

$$\theta_i = a(n - i + 1)^b \quad (28)$$

where b is negative; and

$$a = \left[\sum_{i=1}^{n} (n - i + 1)^b\right]^{-1} \quad (29)$$

Thus far we have implicitly assumed that hydrologic model error is small. This assumption will certainly not hold in many situations. It is, however, straightforward to develop an adjusted sample distribution utilizing the historical record. A historical model time series of streamflow is defined by

$$\tilde{Y}_i(t+j) = g_{t+j}[R_i(t+j), T_i(t+j), B_i(t+j-1)] \quad (30)$$

$$B_i(t+j) = h_{t+j}[R_i(t+j), T_i(t+j), B_i(t+j-1)] \quad (31)$$

Note that in contrast with (17)–(20) we use the state variables $B_i(t+j-1)$, which represents conditions in year i. The procedure can be described in simulation terms as follows. Hydrologic models are executed continuously over the n-year period of record. We extract the simulated model streamflow values for days $t+1, \ldots, t+J$ of each historical year. The streamflow series produced by (30) and (31) are estimates of the actual streamflow.

Sample values corresponding to the streamflow series obtained from (30)–(31) are given by

$$\tilde{X}_i(t) = f_t[\tilde{Y}_i(t+1), \ldots, \tilde{Y}_i(t+J)] \quad (32)$$

Define a bias-corrected forecast sample by

$$Z_i(t) = [X_i(t)\tilde{X}_i(t)^{-1}]\hat{X}_i(t) \quad (33)$$

and denote their order statistics by

$$Z_{(1)}(t) \le Z_{(2)}(t) \le \cdots \le Z_{(n)}(t) \quad (34)$$

The sample distribution function for the forecast problem with weights and hydrologic model error is given by

$$\hat{F}_t(x) = 0; \qquad Z_{(1)}(t) > x \quad (35)$$

$$\hat{F}_t(x) = \sum_{i=1}^{j} \theta_{(i)}; \qquad Z_{(j)}(t) < x \le Z_{(j+1)}(t) \quad (36)$$

$$\hat{F}_t(x) = 1; \qquad Z_{(n)}(t) < x \quad (37)$$

Note that if model error is negligible, that is if $\tilde{X}_i(t) = X_i(t)$, then (35)–(37) reduces to (24)–(26). If there is no useful information in the basin state variable, that is if $\hat{X}_i(t) = \tilde{X}_i(t)$, then (35) reduces to (13).

Application

In this section we apply the procedures developed in the preceding sections to reservoir inflow forecasting for Lake Lanier, in Georgia, during the severe drought of 1988. Lake Lanier is a principal source of municipal water supply for the city of Atlanta. A test implementation of ESP was conducted in the Chattahoochee River basin, which contains Lake Lanier. As part of this test the NWS River Forecast Center (RFC) in Atlanta was able to provide long-term forecasts of Lake Lanier inflow to the water managers responsible for water supply for the city of Atlanta.

Implementation of ESP for Lake Lanier inflow was based on the Sacramento soil moisture accounting model (Burnash et al. 1973) and the Lag/*K* routing model. Snow is not a significant component of the hydrology of the basin, so the snow-accumulation model was not used. Historical inflow time series are not available for Lake Lanier. Calibration of hydrologic models was carried out by RFC staff and based on data from nearby basins. Fig. 1 shows the distribution of the June 1 soil moisture state variable for the Lake Lanier basin using the Sacramento soil moisture accounting model and a historical record of 26 years (1949–84). Notably, the June 1, 1988 soil moisture state variable is the lowest during the period of record. This result is consistent with drought assessments produced during 1988 [see Changnon (1989)]. This type of information is clearly useful in characterizing the drought, but it does not provide quantitative information on water-supply reliability.

Fig. 2 shows the sample distribution of $\hat{X}_i(t)$ for Lake Lanier inflow over the 30-day period from June 1, 1988 to June 30, 1988. Because observed streamflow values are not available for inflow to Lake Lanier, we compare the conditional model distribution, based on $\hat{X}_i(t)$, with the historical model distribution, based on $\tilde{X}_i(t)$. Recall that the sample values of the conditional model distribution are obtained by using the June 1, 1988 soil moisture state variable for June 1 of each historical year. The sample values of the historical

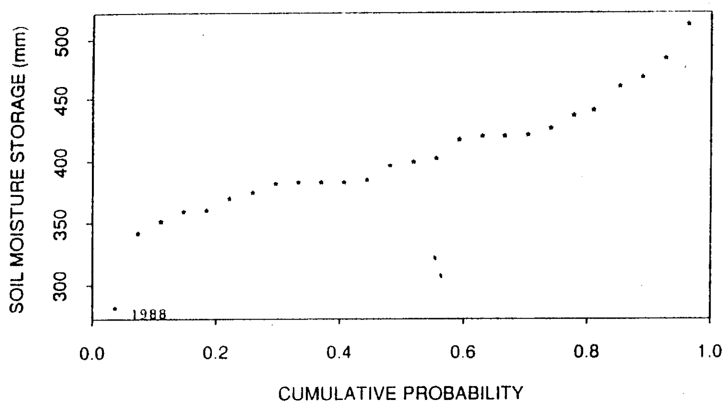

FIG. 1. June 1 Soil Moisture Distribution for Lake Lanier Basin

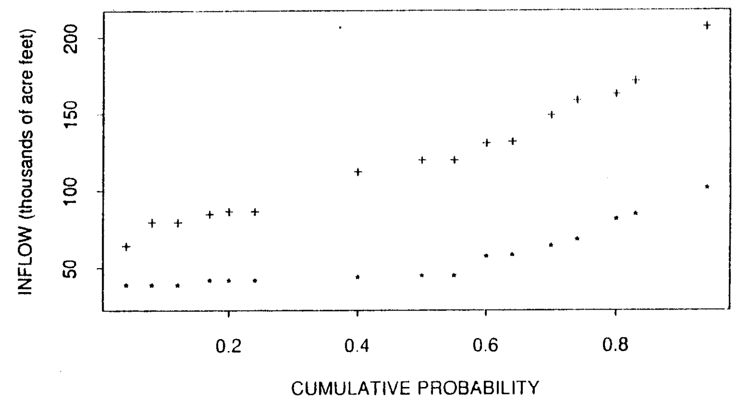

FIG. 2. Estimated Inflow Probabilities for Lake Lanier during period May 31–June 29, 1988 (+ = Historical Inflow Distribution; * = Estimated Inflow Distribution Derived Utilizing Soil-Moisture Information)

model distribution are obtained using the historical June 1 soil moisture state variables. Note that the flow with 90% reliability (that is the inflow that has a cumulative probability of 0.1, or 0.9 probability of being exceeded) drops by a half from a historical value of approximately 76,000 acre ft (9.4×10^7 m^3) to a conditional model value of 38,000 acre ft (4.7×10^7 m^3).

As part of the test implementation of ESP in the Chattahoochee River basin, the Long-Range Forecast Branch of the Climate Analysis Center (CAC) developed a data set of analog values for testing the utility of climate information in long-range forecasting. The information provided by CAC was interpreted as relative likelihoods $\gamma_1, \ldots, \gamma_n$, which take three possible values: 1, 2, and 5 and are related to the historical weights defined in the section headed "Estimating Conditional Distribution" by

$$\theta_i = \frac{\gamma_i}{\sum_{j=1}^{n} \gamma_j} \quad \text{(38)}$$

Note that the weights $\theta_1, \ldots, \theta_n$ are positive and sum to 1.

The interpretation for $\gamma_i = 1$ is that the climatic conditions for year *i* are dissimilar to the current year. For $\gamma_i = 5$, the interpretation is that climate conditions for year *i* are similar to the current year. For $\gamma_i = 2$, the interpretation is that climate conditions are neither similar nor dissimilar.

The analog values are available for a five-year period extending from 1982 to 1986. Table 1 shows a summary of forecast results for mean inflow. For each year shown in Table 1, the other four years were used to develop expected value forecasts under two scenarios: (1) Only hydrologic state variables are used; and (2) climate information, as described before, is used. Table 2 presents similar results for minimum daily flow. The short period of record precludes detailed inferences. Two features are suggested, however: (1) Basin information on soil moisture condition is significantly more useful than climate information; and (2) climate information is more useful for water-balance variables like mean inflow than for base-flow variables like minimum daily flow.

TABLE 1. Mean Inflow Forecast to Lake Lanier, January 1–February 28

Forecast year (1)	Historical mean (1,000 acre ft) (2)	Conditional mean[a] (1,000 acre ft) (3)	Conditional mean[b] (1,000 acre ft) (4)
1982	336	277	265
1983	336	411	390
1984	336	508	497
1985	336	224	216
1986	336	241	265

[a]Equal weights.
[b]Weights conditioned on climate state.
Note: 1 acre ft = 1,233 m^3.

TABLE 2. Minimum Daily Flow Forecast to Lake Lanier, January 1–February 28

Forecast year (1)	Historical mean (cfs) (2)	Conditional mean[a] (cfs) (3)	Conditional mean[b] (cfs) (4)
1982	1,400	890	890
1983	1,400	2,080	2,040
1984	1,400	2,880	2,800
1985	1,400	540	530
1986	1,400	450	470

[a]Equal weights.
[b]Weights conditioned on climate state.
Note: 1 cfs = 0.0283 m^3/s.

Summary and Conclusions

A nonparametric framework was developed for constructing distributional forecasts of long-range streamflow variables using conceptual hydrologic models. The procedures can account for climate information through weighting of historical years and the effects of hydrologic model error. Utility of the procedures is illustrated for inflow forecasting at Lake Lanier, in north Georgia, during the drought of 1988. Implementation results suggest that soil-moisture information is significantly more valuable than climate information and that climate information is more useful for long-range forecasting of water-balance variables (such as accumulated reservoir inflow) than for baseflow variables (such as minimum daily flow).

Acknowledgments

The writers are indebted to the Climate Analysis Center for providing climate forecast information and to the Atlanta River Forecast Center for providing calibrated models and historical precipitation data.

Appendix I. References

Anderson, E. (1973). "National Weather Service river forecast system—snow accumulation and ablation model." *NOAA Tech. Memorandum NWS HYDRO-17,* U.S. Department of Commerce, Silver Spring, Md.

Brazil, L. (1988). "Multilevel calibration strategy for complex hydrologic models." *NOAA Tech. Report NWS 42,* U.S. Department of Commerce, NOAA/NWS, Silver Spring, Md.
Burnash, R. J., Ferral, R. L., and McGuire, R. A. (1973). "A generalized streamflow simulation system—conceptual modeling for digital computers." State of California Department of Water Resources, Sacramento, Calif.
Changnon, S. (1989). "Drought and climate change." *Res. Report 89-02,* Midwest Climate Center, Champaign, Ill.
Day, G. N. (1985). "Extended streamflow forecasting using NWSRFS." *J. of Water Resour. Planning and Mgmt.,* ASCE, 111(2), 157–170.
Day, G. N. (1990). "A methodology for updating a conceptual snow model with snow measurements." *NOAA Tech. Report NWS 43,* U.S. Department of Commerce, NOAA/NWS, Silver Spring, Md.
Hirsch, R. (1978). "Risk analyses for a water supply system—Occoquan Reservoir, Fairfax and Prince William Counties, Virginia." *Open File Report 78-452,* U.S. Geological Survey, Reston, Va.
Hirsch, R. (1981). "A stochastic hydrologic model for drought management." *J. Water Resour. Planning and Mgmt. Div.,* ASCE, 107(2), 303–313.
Karlsson, M., and Yakowitz, S. (1987). "Nearest-neighbor methods for nonparametric rainfall-runoff forecasting." *Water Resour. Res.,* 23(7), 1300–1308.
Karlsson, M., and Yakowitz, S. (1987). "Rainfall-runoff forecasting methods, old and new." *Stochastic Hydro. and Hydr.,* 1, 303–318.
Kelman, J., Stedinger, J., Cooper, L., Hsu, E., and Yuan, S.-Q. (1990). "Sampling stochastic dynamic programming applied to reservoir operation." *Water Resour. Res.,* 26(3), 447–454.
Lettenmaier, D., Wood, E., and Parkinson, D. (1990). "Operating the Seattle water system during the 1987 drought." *Mgmt. and Operations J. of AWWA,* (May), 55–60.
Namias, J. (1986). "Persistence of flow patterns over North America and adjacent ocean sectors." *Monthly Weather Review,* 114, 1368–1383.
Ramirez, J., and Bras, R. (1985). "Conditional distributions of Neyman-Scott models for storm arrivals and their use in irrigation scheduling." *Water Resour. Res.,* 21(3), 317–330.
Rassmusson, E. (1984). "El Nino: The ocean/atmosphere connection. *Oceanus,* 27(2), 4–12.
Ropelewski, C. F., and Halpert, M. S. (1986). "North American precipitation and temperature patterns associated with the El Nino/southern oscillation (ENSO)." *Monthly Weather Review,* 114 (Dec.), 2352–2362.
Redmond, K., and Koch, R. (1991). "Surface climate variability in the western U.S. and its relationship to large scale circulation indices." *Water Resour. Res.,* 27(9), 2381–2399.
Serfling, R. (1980). *Limit theorems of mathematical statistics.* John Wiley and Sons, New York, N.Y.
Smith, J. A. (1988). "A model of daily municipal water use for short-term forecasting." *Water Resour. Res.,* 24(2), 201–206.
Smith, J. A. (1989). "Water supply yield analysis for the Washington metropolitan area." *J. Water Resour. Planning and Mgmt.,* ASCE, 115(2), 230–242.

Appendix II. Notation

The following symbols are used in this paper:

a = multiplicative parameter in trend model for annual weights;
$\mathbf{B}(s)$ = basin state vector for day s of forecast year;
$\hat{B}_i(t)$ = conditional model estimator of basin state vector for year i of historical record;
b = exponent in trend model for annual weights;

$F_t(x)$ = probability that forecast variable $X(t)$ is less than or equal to x;
$\hat{F}_t(x)$ = estimator of $F_t(t)$;
f_t = function specifying dependence of forecast variable on future streamflow, with t current day;
g_t = function specifying dependence of streamflow on current basin state vector, precipitation, and temperature for day t of year;
H_t = observations of precipitation, temperature, and streamflow prior to forecast day t;
h_t = function specifying dependence of basin state vector for day t on basin state vector for preceding time period and current precipitation and temperature;
J = forecast duration in days;
n = number of years of historical data;
$R(s)$ = precipitation on day s;
$T(s)$ = temperature on day s;
t = current day, from which forecast is computed;
$X(t)$ = forecast variable for day t;
$\hat{X}_i(t)$ = conditional model estimator of forecast variable for year i conditions;
$\tilde{X}_i(t)$ = historical model estimator of forecast variable for conditions during year i;
$Y_i(s)$ = observed streamflow for day s of year i;
$\hat{Y}_i(s)$ = conditional model estimator of streamflow on day s for year i conditions;
$\tilde{Y}_i(s)$ = historical model estimator of streamflow on day s for year i conditions;
$Z_i(t)$ = bias adjustment for sample forecast variable of year i;
γ_i = weight factor for historical year i;
ε_s = hydrologic model error for day s; and
θ_i = weight for historical year i.

TECHNICAL NOTES

Technical notes provide a way of publishing: (1) original, practical information, (2) preliminary or partial results of research, (3) concisely presented research results, and (4) innovative techniques to accomplish design objectives. The technical note should follow all the basic requirements for papers but should not exceed 3,500 word-equivalents in length. An abstract, which will be published if length permits, and key words should be submitted with the technical note. (This definition and increase in length was approved by the ASCE Publication Committee on July 15, 1991.)

1. Five copies of an original manuscript are to be submitted to the Journals Department, ASCE, 345 East 47th Street, New York, NY, 10017-2398, along with a request by the author that it be considered as a technical note.
2. Four of the copies will be sent to an appropriate technical division or council for review.
3. If the division or council approves the contribution for publication, it will be returned to Society Headquarters with appropriate comments.
4. The journal staff will prepare the material for use in the earliest possible issue of the journal, after proper coordination with the author.
5. Each technical note is not to exceed 3,500 words. (This includes word-equivalents for figures and tables.)
6. The technical notes are grouped in a special section of the journal.
7. A 175-word information retrieval abstract and key words are necessary for technical notes.
8. The final date on which a discussion should reach the Society is given as a footnote with each technical note.
9. Technical notes will be included in *Transactions*.
10. Technical notes will be included in ASCE's annual and cumulative subject and author indexes.

The manuscripts for technical notes must meet the following requirements:

1. Titles must have a length not exceeding 70 characters and spaces.
2. The manuscript should be typed double-spaced on one side of 220 mm by 280 mm paper. Five copies of all figures and tables must be included.
3. The author's full name, Society membership grade (if applicable), and a footnote stating present employment must appear on the first page of the note. Authors need not be Society members.
4. All mathematics must be typewritten and special symbols must be properly identified. The letter symbols used must be defined where they first appear, in figures, tables, or text.
5. Standard definitions and symbols must be used. Reference must be made to the lists published by the American National Standards Institute and to the *ASCE Authors' Guide to Journals, Books, and Reference Publications.*
6. Figures must be drawn in black ink on one side of 220 mm by 280 mm paper. Because figures will be reproduced with a width of between 76 mm to 110 mm, the lettering must be large enough to be legible at this width. Photographs must be submitted as glossy prints. Explanations and descriptions must be made within the text for each figure.
7. Tables must be typed on one side of 220 mm by 280 mm paper. An explanation of each table must appear in the text.
8. References cited in text must be typed double-spaced at the end of the technical note in alphabetical order in an Appendix. References.
9. Each author is encouraged to use the International System of Units (SI), and units acceptable in SI, though other units may be used at this time. The primary use of SI units will be mandatory after January 1, 1993. When SI units are used, no other units are required. When other units are used, the SI units shall be given in parentheses; in a supplementary or dual-unit table; or an appendix.