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Runoff Prediction Uncertainty for Ungauged Agricultural Watersheds

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Runoff Prediction Uncertainty for Ungauged Agricultural Watersheds

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Abstract: A physically based stochastic watershed model is used to estimate runoff prediction uncertainty for small agricultural watersheds in Hastings, Nebraska. The stochastic nature of the model results from postulating a probabilistic model for parameter estimation and input errors. The key factors assumed to contribute to prediction uncertainty are errors in estimating infiltration parameters and moisture conditions prior to a rainfall event. The error distributions for parameter estimates are inferred from soil survey information, and the error distribution for moisture conditions from a regression between antecedent precipitation indices and measured soil moisture. Comparison of model predicted and observed errors demonstrates that the model is conservative in that it is biased towards overprediction of errors.

Introduction

A common approach to deriving flood-flow-frequency curves for an ungauged watershed is to simulate a design storm with an event-oriented watershed model. As with most models, a significant problem with this approach is model parameter estimation. One approach to the problem is to estimate watershed model parameters from generally available information such as topographic maps and soil maps. Probably the most difficult part of the problem is estimating loss rates from this type of information.

Loss rate parameter estimation for an event-oriented model consists of determining both the soil moisture condition prior to the rainfall event and the soil infiltration parameters. The particular focus of this study will be on determining the uncertainty in estimating initial moisture conditions from antecedent precipitation indices and infiltration parameters from commonly available soil survey information, particle-size distribution, and porosity, as proposed by Rawls and Brakensiek (1982).

An examination of the runoff prediction uncertainty caused by estimating loss rate parameters from simple indices such as particle-size distribution will be investigated using a physically based stochastic (PBS) watershed model (Klemes 1978). The PBS model will be formulated as a typical event-oriented distributed watershed model, except that the loss rate parameters will be considered stochastic (Goldman 1987). The stochastic nature of the loss rate parameters will be represented by the loss rate parameters' probability distributions. The parameter probability distribution represents the estimation

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uncertainty when depending on typically available information such as the simple indices proposed.

The PBS model prediction uncertainty is represented by the derived probability distribution for runoff volume and peak discharge. The derived probability distribution gives the runoff exceedance probabilities for any particular runoff event. In other words, the derived probability distributions give the chance that an observed runoff volume or peak discharge will exceed a given amount for a given rainfall event and antecedent moisture condition. The usefulness of the model-estimated prediction uncertainty, and in turn the estimated uncertainty in parameter values, will be verified by comparing predicted and observed exceedance probabilities for rainfall-runoff events recorded for small agricultural watersheds in Hastings, Nebraska.

Test Watershed Description

The U.S. Department of Agriculture (USDA) maintained watersheds in Hastings, Nebraska (*The Central* no date), where rainfall-runoff, soil-moisture, and land-use data were collected from the period 1939–1967 and maintained in the REPHLEX data base (*REPHLEX* 1983). The seven watersheds used in this research were all about 4.0 acres in size with overland flow slopes ranging from 2.0 to 7.0%. The watershed soils are dominated by the Hastings silt loam and silt clay loam horizons. Although data for a number of different management practices existed, only runoff events from land surfaces with straight row contouring were considered, because this situation corresponds best to the assumptions that will be made in developing the PBS model.

There was always a rain gage within 200 ft of the border of any of the watersheds tested. Unfortunately, however, the rain gages were not shielded. The soil moisture data were obtained by analyzing fist-sized soil samples taken from field trenches. The major advantage of using the Hastings data is that they had a relatively long record, which was important for verifying the predictions of the PBS model.

Model Formulation

A single-event approach to modeling runoff was chosen to avoid the problem of simulating interstorm runoff dynamics such as evapotranspiration and long-term base flow. Assuming that overland flow will dominate the runoff process, a typical kinematic wave model will be used to model a watershed (Fig. 1). The watershed has two overland flow planes both with width W, and overland flow lengths and slopes equal to, respectively, l_1, l_2, and S_{01}, S_{02}. Rainfall excess is assumed to be uniformly distributed over each overland flow plane. The physical properties and the initial conditions for the watershed represented by the overland flow planes are assumed to be uniform both horizontally and vertically. Rainfall excess is calculated by first subtracting an initial surface loss

$$r(t) = 0 \quad \text{for } P(t) \le I_a \quad t \ge 0 \qquad (1)$$

$$r(t) = r_0(t) \quad \text{for } P(t) > I_a \quad t \ge 0 \qquad (2)$$

where $P(t)$ = the cumulative precipitation over the watershed; $r(t)$ = the

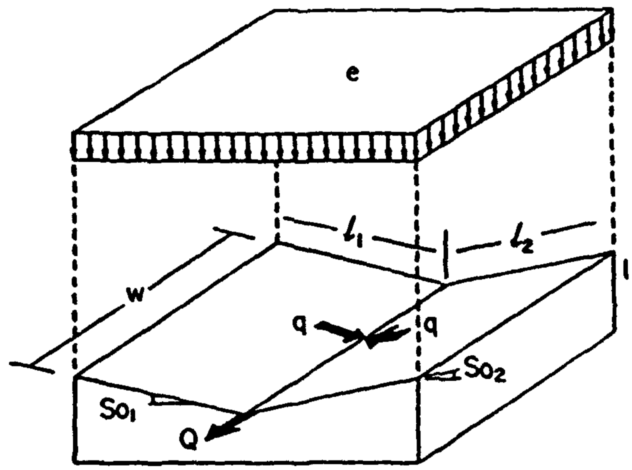

FIG. 1. Schematic of Watershed Model

rainfall intensity adjusted for surface losses; t = the time since the start of rainfall; $r_0(t)$ = the measured rainfall intensity; and I_a = the depth of surface loss assumed to be uniform over the watershed. Second, an infiltration loss is calculated by the Green and Ampt (GA) approach

$$F = \frac{\Omega}{\frac{i}{K_s} - 1} = \frac{K_s \Omega}{\frac{dF}{dt} - K_s} \qquad i > K_s \tag{3}$$

where $dF/dt = i(t)$ is equal to the infiltration rate; F = the cumulative infiltration; K_s = the soil's saturated hydraulic conductivity; Ω = the product of the wetting front suction, ψ_f, and the soil volumetric deficit at the beginning of the storm, $\Delta\theta = \phi - \theta_i$; ϕ = the soil's porosity; and θ_i = the initial volumetric water content. The GA equation, as originally developed, is only strictly applicable to a uniform moisture condition at the soil surface or, in the case of rainfall infiltration, a ponded surface condition. Modifications were made as suggested by Mein and Larson (1973) and Morel-Seytoux (1980) to use the GA equation for unponded surface conditions and variable rainfall rates.

The rainfall excess is routed overland to the channel using the kinematic wave equations of motion

$$\frac{\partial q}{\partial x} + \frac{\partial y}{\partial t} = e \qquad \text{initial condition: } t = 0, y = 0$$

$$\text{boundary condition: } x = 0, y = 0 \tag{4}$$

$$q = \alpha y^m \tag{5}$$

where $q = q(x,t)$ is the flow per unit width; $\alpha = 1.49 S_0^{1/2}/N$; S_0 = the slope along the overland flow length; N = a roughness coefficient for overland flow; $m = 1.67$; $y = y(x,t)$ is the depth of flow; and x = the distance along the direction of overland flow. The equations will be solved using a finite difference scheme proposed by Leclerc and Schaake (1973).

Flow entering the channel will be concentrated immediately to the watershed outlet to obtain the total outflow, Q. Channel routing of the flow using the kinematic wave equations is a standard procedure. However, the channels of the test catchments used in this research are short and have little storage. Performing channel routing would add little in simulation capability, while adding greatly to the computational burdens in performing the uncertainty analysis. Consequently, a reasonable assumption was made that channel routing could be ignored.

Parameter Estimation

Estimating Green and Ampt Parameters from Simple Indices

Rawls et al. (1981, 1982, 1983) and Rawls and Brakensiek (1982) reported on the relationship between simple soil indices and the Green and Ampt parameters. The general procedure involved has been to relate a simple soil index such as texture class to the Brooks and Corey parameters (Rawls et al. 1982), porosity ϕ, residual saturation, θ_r, bubbling pressure ψ_b, and the pore-size distribution, λ. These parameters are used to describe the soil matric suction curve by the relationship

$$S_e = \frac{\theta - \theta_r}{\phi - \theta_r} = \frac{\psi^\lambda}{\psi_b^\lambda} \qquad (6)$$

where S_e = the effective saturation; and θ = the volumetric water content at matric suction ψ. The Brooks and Corey parameters are then used to calculate the wetting front suction, ψ_f, by

$$\psi_f = \psi_w + \frac{\psi_w^n}{1 - n}\left[\psi_i^{(1-n)} - \psi_w^{(1-n)}\right] \qquad (7)$$

where ψ_w = the water entry pressure; ψ_i = the water content corresponding to the initial soil moisture content of the soil prior to ponded infiltration; and ψ_w, the water entry pressure, and n are defined as

$$\psi_w = \frac{\psi_b}{2} \qquad (8)$$

$$n = 3\lambda + 2 \qquad (9)$$

Assuming that the initial moisture content is equal to the residual saturation, the formula finally derived by Brakensiek (1977) and applied by Rawls et al. (1982) is obtained as

$$\psi_f = \frac{n}{n - 1}\psi_w \qquad (10)$$

Since initial moisture conditions will be estimated using an API index, ψ_f will be calculated via Eq. 7 in model simulations of infiltration. The saturated hydraulic conductivity is calculated using Brutsaert's (1967) solution of the Childs and Collis-George permeability integral

$$K_s = \frac{a\theta_e^2\lambda^2}{\psi_b^2(\lambda + 1)(\lambda + 1)} \text{ (cm/s)} \qquad (11)$$

where $\theta_e = \phi - \theta_r$. The parameter a was set equal to 21.0 by fitting Eq.

11 to an average of observed saturated hydraulic conductivity values for a full range of soil texture classes (Rawls et al. 1982). Rawls and Brakensiek (1989) developed the regression relationships shown here between simple soil indices; particle size distribution and total porosity, and the Brooks and Corey parameters.

The regression equations (Rawls and Brakensiek 1989) are

$$\theta_r = -0.0182482 + 0.00087269(SA) + 0.00513488(CL) + 0.02939286(PR)$$
$$- 0.00015395(CL^2) - 0.0010827(SA)(PR) - 0.00018233(CL^2)(PR^2)$$
$$+ 0.00030703(CL^2)(PR) - 0.0023584(PR^2)(CL) \quad (12)$$

$$\lambda = \exp [-0.7842831 + 0.0177544(SA) - 1.062498(PR) - 0.00005304(SA^2)$$
$$- 0.00273493(CL^2) + 1.11134946(PR^2) - 0.03088295(SA)(PR)$$
$$+ 0.00026587(SA^2)(PR^2) - 0.0061052(CL^2)(PR^2) - 0.00000235(SA^2)(CL)$$
$$+ 0.00798746(CL^2)(PR) - 0.00674491(PR^2)(CL)] \quad (13)$$

$$\psi_b = \exp [5.3396738 + 0.1845038(CL) - 2.48394546(PR)$$
$$- 0.00213853(CL^2) - 0.04356349(SA)(PR) - 0.61745089(CL)(PR)$$
$$+ 0.00143598(SA^2)(PR^2) - 0.00855375(CL^2)(PR^2) - 0.00001282(SA^2)(CL)$$
$$+ 0.00895359(CL^2)(PR) - 0.00072472(SA^2)(PR) + 0.0000054(CL^2)(SA)$$
$$+ 0.50028060(PR^2)(CL)] \quad (14)$$

where $PR = \phi$ = total porosity (vol/vol); CL = % clay (particle size); SA = % sand (particle size); ψ_b = bubbling pressure (cm); λ = pore-size distribution; and θ_r = residual saturation (vol/vol). The data for these regressions were obtained from the numerous soil surveys performed in the United States.

The data needed to apply these regressions can be conveniently obtained from the SOILS-5 data base compiled by the Soil Conservation Service and maintained by the Corps of Engineers (*SOILS-5* 1983). The relevant information provided by these data is the particle-size distribution, the percent sand, clay, and silt, and the porosity for different horizons of a soil series.

Selection of Soil Parameter Probability Distributions

In the case of the watershed model used in this research, the chosen parameters' probability distribution should describe the chance that the parameter will have a certain value for a given storm event. The random variation of a particular infiltration parameter between events might be affected by biologic (macropores), cultural (management practice), seasonal (crop growth), and meteorologic (rain-induced surface crusting) factors.

The distribution of soil properties within a given texture class or for a given particle-size distribution does not give information on the random variation of soil hydraulic properties in the field. Rather, the distribution of infiltration parameter values for a given soil property index is a measure of the uncertainty in predicting the infiltration properties of a field sample using that index. The correspondence between the probability distribution derived from a simple index and a field measurement program would be coincidental at best.

TABLE 1. Values for Watershed Model's Stochastic Parameters

	Sand		Clay		Porosity	
Watershed (1)	Mean (%) (2)	Range (%) (3)	Mean (%) (4)	Range (%) (5)	Mean (vol/vol) (6)	Coefficient of variation (7)
8	3.4	0.4–6.4	23.9	19.5–28.4	0.51	0.1
9	3.1	0.3–5.9	21.4	16.6–26.2	0.51	0.1
10	2.5	0.0–5.0	21.7	16.9–26.5	0.51	0.1
11	2.5	0.0–5.0	23.1	18.5–27.7	0.51	0.1
12	2.5	0.0–5.0	24.6	20.2–29.0	0.51	0.1
19	2.5	0.0–5.0	26.4	22.2–30.6	0.51	0.1
20	2.5	0.0–5.0	27.4	23.4–31.4	0.51	0.1

The probability distribution obtained from a simple index might be useful if the distribution of the parameter's values (e.g., the values of saturated hydraulic conductivity) bounds the range of the values for the actual field parameter. Furthermore, the parameter distribution obtained may be even more useful from an engineering perspective if it not only bounded the potential range of the field parameter, but also led to a conservative watershed model prediction of runoff. For example, the simple index probability distribution should overpredict the chance that the saturated hydraulic conductivity will be less than the true field value, which in turn will result in an overprediction of the chance that runoff will exceed a certain value. The overprediction resulting from the simple index may be considered to provide a safety factor that would be useful in design situations.

The probability distribution for the Green and Ampt infiltration parameters will be derived from assumed distributions for particle size distribution and total porosity via Eqs. 7, 11, 12, 13, and 14. The SOILS-5 data base provides the range in particle-size distribution and total porosity for the watershed soils (see Table 1). The particle-size distribution, as defined by the percentages of sand and clay, was assumed to be distributed uniformly over this range. The total porosity obtained from the SOILS-5 data base was assumed to have a normal distribution with a coefficient of variation equal to 0.1 in analogy to that found for variation within a texture class (McCuen et al. 1981).

Deriving the distributions of the Green and Ampt parameters K_s and ψ_f is an intermediate step in deriving the volume and peak discharge probability distributions. The probability distribution for K_s is independent of antecedent moisture and was derived using Monte Carlo simulation. The mean, standard deviation, skew, and kurtosis derived by Monte Carlo simulation are shown in Table 2.

The distribution of ψ_f is conditional on the antecedent moisture condition, and is not easily reported in general. However, the ψ_f corresponding to the mean infiltration parameters and initial moisture content equal to the residual saturation is shown in Table 3 for informational purposes. The derived mean values for K_s and ψ_f will not be equivalent to those calculated directly from average values of total porosity and particle distribution as can be seen, for example, by comparing the values of K_s shown in Tables 2 and 3.

No attempt will be made to assess the sensitivity of model predictions to

TABLE 2. Derived Values for Saturated Hydraulic Conductivity

Watershed (1)	Mean (in./hr) (2)	Standard deviation (in./hr) (3)	Coefficient of variation (4)	Skew (5)	Kurtosis (6)
8	0.055	0.044	0.80	1.6	6.6
9	0.061	0.045	0.74	1.6	6.5
10	0.058	0.044	0.76	1.6	6.2
11	0.055	0.042	0.76	1.6	6.4
12	0.051	0.041	0.80	1.7	6.6
19	0.047	0.039	0.83	1.7	7.0
20	0.045	0.038	0.84	1.8	7.2

Note: 1.0 in. = 2.54 cm, 1.0 in./hr = 2.54 cm/h.

the assumed probability distributions (i.e., normal or uniform) for particle-size distribution or total porosity. In verifying the model, the focus will be on comparing model predictions within one and two standard deviations about the mean prediction. Presumably, the standard deviation about the mean prediction will be most affected by the standard deviation assumed for model parameters. The tails of the assumed distributions, and consequently the shape, should be less important. Certainly, the best way to test sensitivity of model predictions to assumed parameter distributions is to try some different distributions. However, this was not possible given the computational burdens required to derive model predictions by Monte Carlo simulation.

Estimation of Initial Abstraction

The initial abstraction is defined as the water that is not free to flow overland to a stream. These losses are due to the interception of rain by crops and the depression storage due to the microrelief of the surface. Viessman et al. (1977) summarize studies that could be used to estimate interception loss. However, estimation of the depression storage from soil survey information is extremely difficult. Linden (1979) estimated depression storage for cultivated soils using a microrelief model. The key parameters in this model are random roughness and land surface slope (random roughness is essentially a measure of the variation of soil heights from the plane that would

TABLE 3. Deterministic Values for Watershed Green and Ampt and Brooks and Corey Parameters

Watershed (1)	Sand (%) (2)	Clay (%) (3)	Porosity ϕ (vol/vol) (4)	Residual saturation, θ_r (vol/vol) (5)	Effective saturation θ_e (vol/vol) (6)	Wetting front suction ψ_f (in.) (7)	Saturated hydraulic conductivity K_s (in./hr) (8)	Bubbling pressure ψ_b (in.) (9)	Pore size distribution λ (10)
8	3.4	23.9	0.51	0.080	0.430	18.62	0.0430	24.19	0.296
9	3.1	21.4	0.51	0.074	0.436	18.14	0.0487	23.67	0.306
10	2.5	21.7	0.51	0.075	0.435	18.41	0.0468	24.03	0.305
11	2.5	23.1	0.51	0.078	0.432	18.69	0.0435	24.35	0.299
12	2.5	24.6	0.51	0.082	0.428	19.02	0.0400	24.72	0.293
19	2.5	26.4	0.51	0.086	0.424	19.45	0.0364	25.19	0.286
20	2.5	27.4	0.51	0.088	0.422	19.69	0.0342	25.48	0.281

Note: 1.0 in. = 2.54 cm, 1.0 in./hr = 2.54 cm/h.

define zero cut and fill). Application of Linden's results are hampered because, as Allmaras et al. (1966) found, random roughness in an agricultural soil is a function of the plowing tool, initial water content prior to plowing, and soil preparation. Consequently, random roughness and, correspondingly, depression storage are very difficult to estimate from soil survey information.

Linden's results indicated that for the surface slopes of the test watersheds, 3–7%, the depression storage could vary between 0.08 and 0.40 in. (0.20 and 1.05 cm), corresponding to random roughness values between 0.3 and 1.6 in. (0.8 and 4.0 cm) (Linden 1979). Combining this depression storage with potential interception loss would lead to a surface loss that at the high end could account for the observed losses in 80% of the observed events.

Given that there are no simple indices for estimating random roughness from soil survey information and the large impact that assumptions about this parameter can have on predicted runoff, the assumption was made that the initial loss is zero. This assumption should lead to a model bias towards overprediction on the average. The actual bias can be observed by comparing mean predicted runoff with observed runoff values. Whether the bias is in a range reasonably attributed to surface loss can be judged in the context of future research. The advantage of this assumption is that the surface loss does not end up being a "fudge factor" that is varied to account for model bias.

Kinematic Wave Parameter Estimates

The estimates of overland flow lengths and slopes for overland flow planes were obtained from 2-ft contour interval topographic maps. The roughness values for overland flow were estimated as a best average value for all runoff events based on published values [summary given by Hjemfelt (1986)]. The values for these parameters are given in Table 4 for each test watershed.

Estimating Initial Moisture Content

An estimate of the average moisture conditions prior to a rainfall event is needed to implement the Green and Ampt method. The moisture condition was estimated by developing regression relationships between an antecedent precipitation index (API) and essentially point measurements of soil moisture. The regression relationships will then be used to predict the average moisture condition prior to a rainfall event given the API.

There are a number of difficulties with this approach. First, the use of soil moisture data to develop this relationship is a departure from the ungauged analysis procedure. However, soil moisture measurements are rarely available, and it was felt that investigating their usefulness was an important opportunity. Second, the assumption is made that the estimates of soil moisture obtained from grab samples (point measurements) are indicative of the general watershed moisture condition. Certainly, there will be spatial variation of soil moisture across a watershed. However, the point soil moisture is the best indicator of the average watershed moisture condition available, although it has drawbacks.

Third and finally, the assumption that an API can be used to assess average watershed conditions ignores the effect of evapotranspiration between storm events on available moisture. Again, API is not an ideal proxy for

TABLE 4. Kinematic Wave Parameters for Test Watersheds

Watershed (1)	Area[a] (acre) (2)	Overland flow length l (ft) (3)	Overland slope S_o (4)	Roughness coefficient N (5)	Initial abstraction I_a (in.) (6)
8	3.84	280	0.07	0.1	0
8	3.64	220	0.07	0.1	0
9	3.93	280	0.04	0.1	0
9	4.02	220	0.05	0.1	0
10	4.16	250	0.03	0.1	0
10	4.01	200	0.05	0.1	0
11	4.16	210	0.04	0.1	0
11	4.26	200	0.03	0.1	0
12	3.93	280	0.03	0.1	0
12	3.97	270	0.02	0.1	0
19	3.62	390	0.07	0.1	0
19	3.62	280	0.04	0.1	0
20	2.48	500	0.05	0.1	0
20	2.48	220	0.05	0.1	0

[a]Area after 1959.
Note: 1.0 acre = 0.405 ha; 1.0 ft = 3.28 m, 1.0 in. = 2.54 cm.

soil moisture; but for ungauged analysis with a single-event model, it is probably the only one available.

The soil moisture data were obtained at various unreported locations within the test watersheds (*The Central* no date). The data were obtained by making gravimetric measurements of soil moisture for specimens taken from fist-sized field samples. The sampling interval was unevenly spaced over about 30 years of the measurement program. The volumetric water content was calculated from the reported gravimetric values, θ_D (fraction of dry unit weight), by applying the following formula:

$$\theta = \frac{\theta_D \gamma_{SD}}{\gamma_w} = 1.36228\theta_D \qquad (15)$$

where θ = the volumetric water content; γ_w = the unit weight of water; and γ_{SD} = the dry unit weight of soil, taken as 85 lb/cu ft for all soils in the study area.

The soil measurements are most plentiful for the months during the growing season, April–October. The measurements were taken at depths between 0.0 and 6.0 ft. For the purposes of calculating infiltration, soil moisture measurements from 0.0 to 1.0 ft were considered most important. These soil moisture measurements covered a full range of soil moisture conditions. A linear regression relationship was established between the 5-, 15-, and 30-day API and the estimated soil moisture to explore the effects of short-, medium-, and long-term antecedent rainfall. Both multiple regression and simple regressions were explored, as can be seen from the results shown in Fig. 2. The multiple coefficient of determination, R^2, is not tremendously impressive for any of the months examined. The results indicate that the best simple regression was not significantly poorer than the multiple regres-

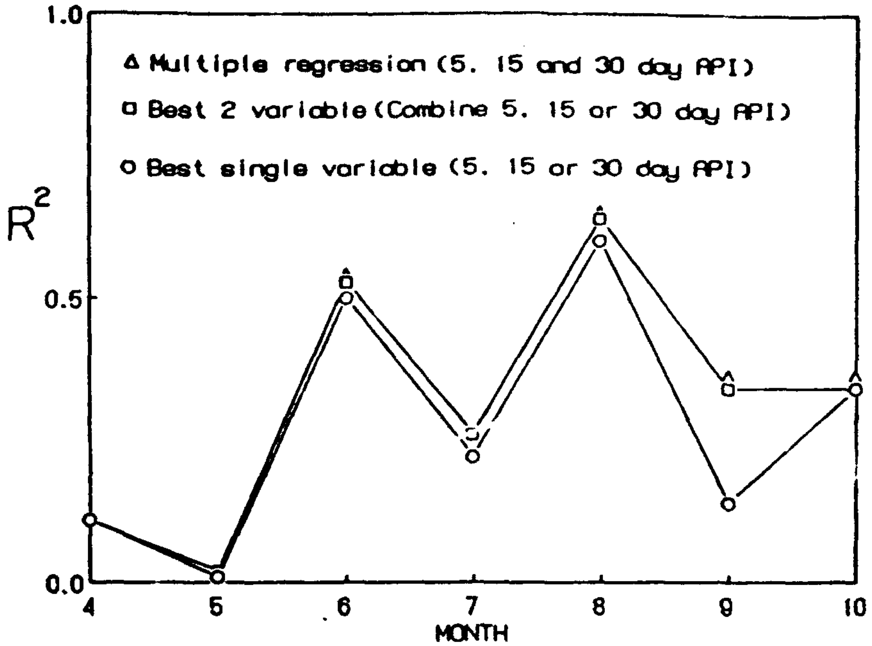

FIG. 2. Multiple Linear Regression between 5-, 15-, and 30-Day API and Soil Moisture at 0–1 ft Depth

sion relationships. Consequently, the best simple regression relationship was used for predicting average watershed moisture conditions.

The error made in estimating the average moisture condition via API is computed by using the final regression results shown in Table 5. The estimated error is modeled by a normal distribution whose mean value is given by the regression for each month and standard deviation is estimated by the standard error of the regression. Technically, the error distribution should be proportional to the product of the standard error and the student's t-distribution. However, the number of degrees of freedom available for the regression makes the difference between the normal and t-distribution small enough to be ignored.

TABLE 5. Simple Regression Equations for API and Soil Moisture Using Best Index

Month (1)	Abscissa intercept a (2)	Slope b (3)	Simple correlation, R (4)	Number of API days[a] (5)	Mean predicted moisture content (vol/vol) (6)	Standard error (vol/vol) (7)	Number of observations (8)
4	0.32	0.022	0.33	15	0.35	0.07	230
5	0.34	0.004	0.04	5	0.34	0.07	189
6	0.26	0.046	0.71	15	0.40	0.11	227
7	0.14	0.020	0.58	30	0.21	0.07	171
8	0.23	0.064	0.38	15	0.33	0.13	199
9	0.16	0.043	0.77	30	0.32	0.12	212
10	0.23	0.036	0.47	30	0.30	0.10	188

[a] $\theta_i = a + b(P)$, where P is the antecedent precipitation for days designated in column 5.

STOCHASTIC ANALYSIS RESULTS

Stochastic model predictions were made by using Monte Carlo simulation to derive the probability of runoff volumes, peak discharge, and time-to-peak discharge for a given rainfall event. The distributions were estimated by performing sufficient Monte Carlo simulations to obtain stable estimates of the distribution's mean, standard deviation, skew, and kurtosis. The distributions were estimated for 101 events observed for the test watersheds. Other rainfall events were available from the test watershed records, but various observation errors excluded their use.

The statistics for the predicted volume and peak discharge stabilized in a reasonable number of simulations (5,000). However, the derived standard deviation, skew, and kurtosis for the time-to-peak discharge did not stabilize as readily, requiring at least 50,000 simulations. Since the estimation of time-to-peak discharge statistics led to onerous computer time, only the mean time-to-peak discharge was calculated.

The model was verified by comparing both model mean runoff predictions and predicted exceedance probabilities as determined from derived distributions with corresponding runoff observations and exceedance probabilities estimated from observations. A comparison of mean predicted and observed runoff resulted in a bias towards overprediction for runoff volumes of 0.20 in. and for peak discharge an overprediction of about 1.3 cfs. The prediction of time-to-peak discharge waas biased towards an underprediction of about 24 minutes on the average. However, any individual prediction of volume, peak discharge, or time-to-peak discharge can differ from the observed value by a much larger amount than the average bias, as can be seen from Figs. 3–5.

The exceedance probability comparisons were made at plus or minus one or two standard deviations for the derived distributions (see Fig. 6). The observed exceedance or nonexceedance probabilities are defined as, respec-

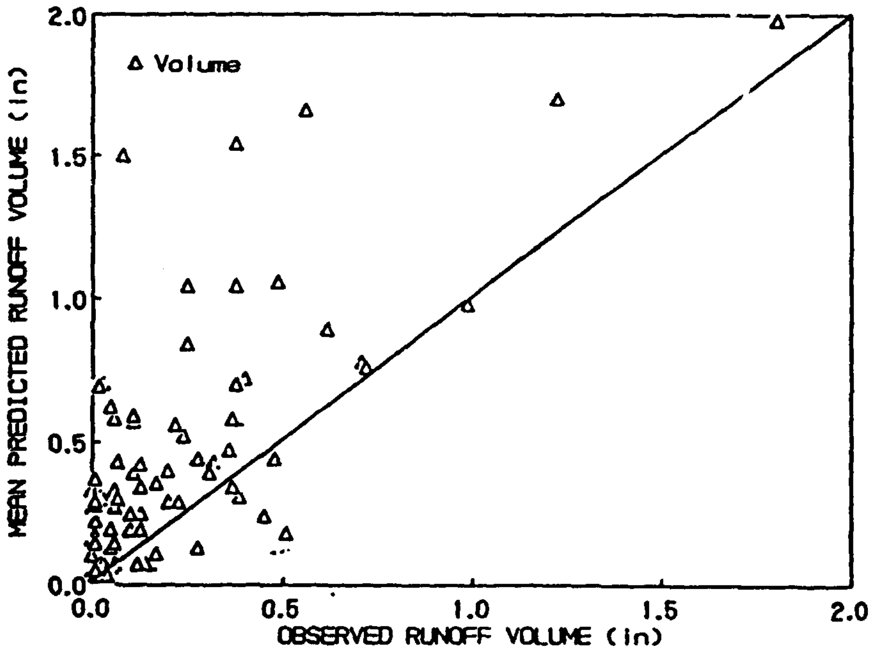

FIG. 3. Predicted Mean Volumes versus Observed Volumes

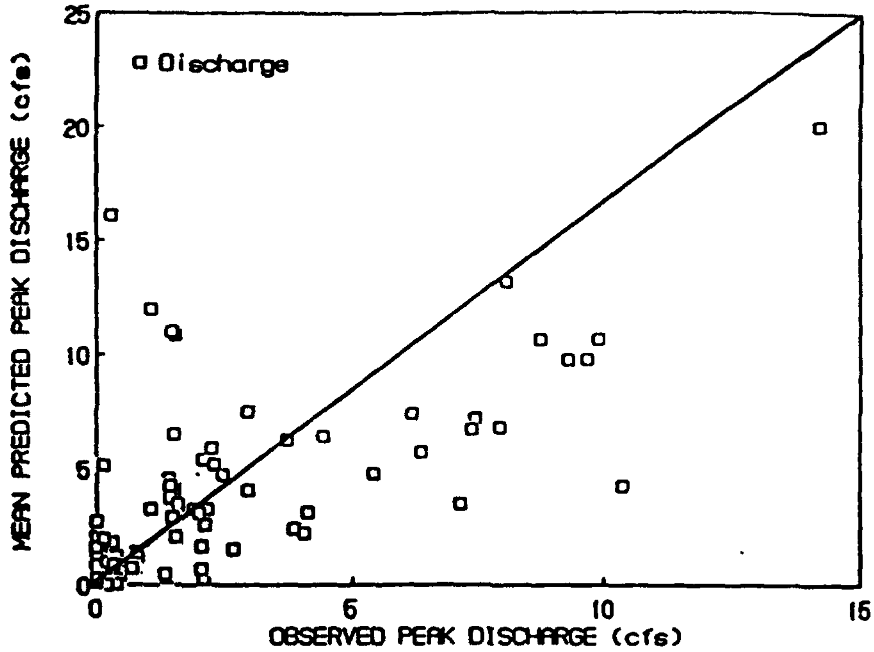

FIG. 4. Predicted Mean Peak Discharge versus Observed Volumes

tively, the fraction of observed occurrences that are greater than the mean prediction plus one or two standard deviations, and/or less than the mean prediction minus one or two standard deviations.

To estimate the predicted exceedance probability, a functional form for the derived distributions was determined by comparing the relationship of the coefficient of variation of the skew or kurtosis for the derived runoff distributions with that of the normal and lognormal distributions, as shown

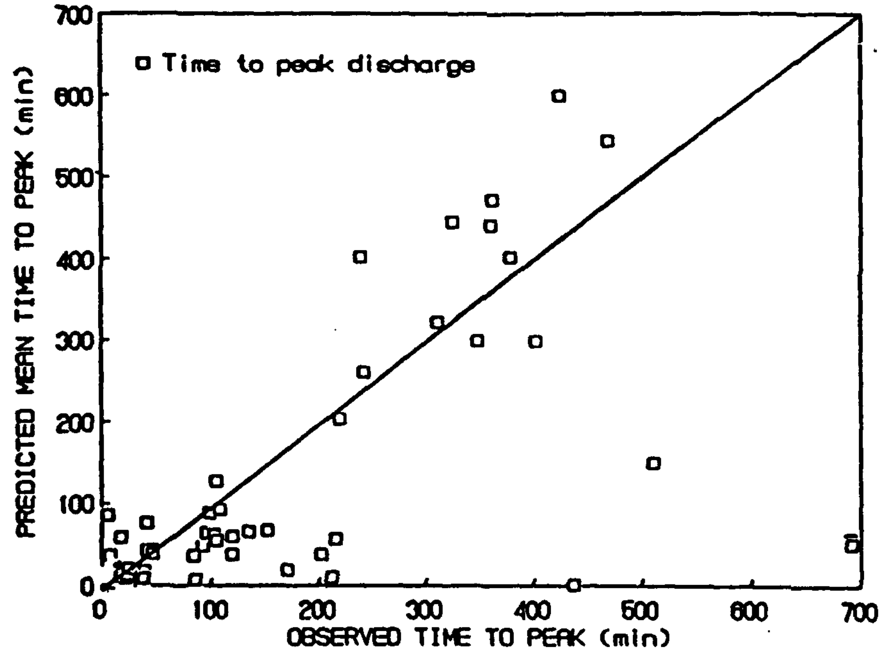

FIG. 5. Predicted Mean Time to Peak Discharge versus Observed Peak Discharge

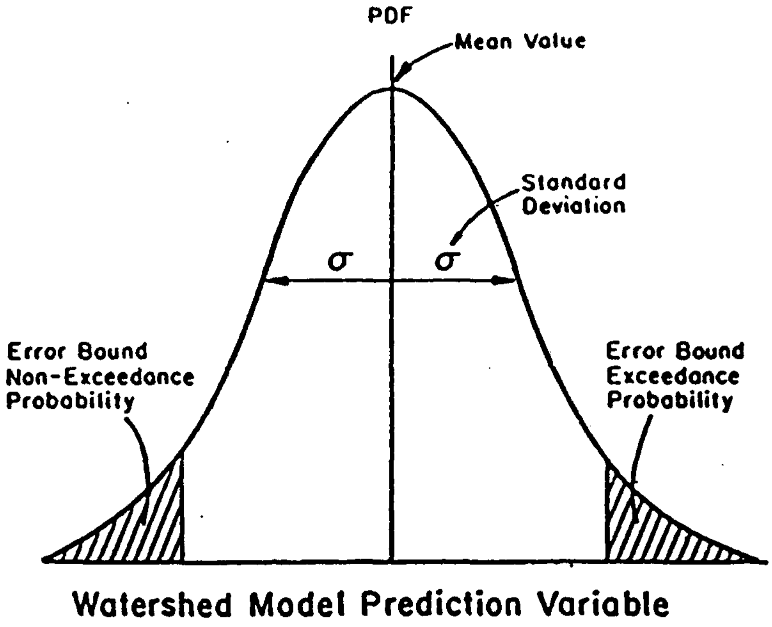

FIG. 6. Definition of Error Bounds and Corresponding Error Exceedance Probabilities

in Figs. 7 and 8. A comparison of the simulation results shows that the derived distributions for both runoff volume and peak discharge are better represented by a normal distribution than a lognormal distribution.

Assuming that the derived distributions are normal, model-predicted exceedance probabilities at plus or minus one and two standard deviations about the mean are equal to 16% and 2.5%, respectively. The estimated observed exceedance probabilities for the volume and peak discharge analysis are

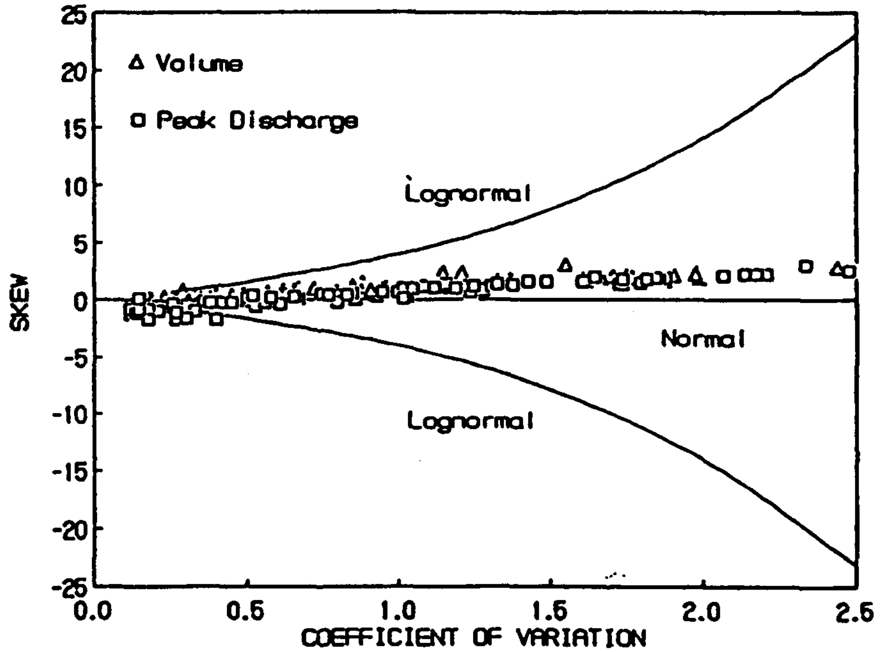

FIG. 7. Comparison of Derived Skew for Runoff Volumes and Peak Discharges with Those for Normal and Two-Parameter Lognormal Distributions

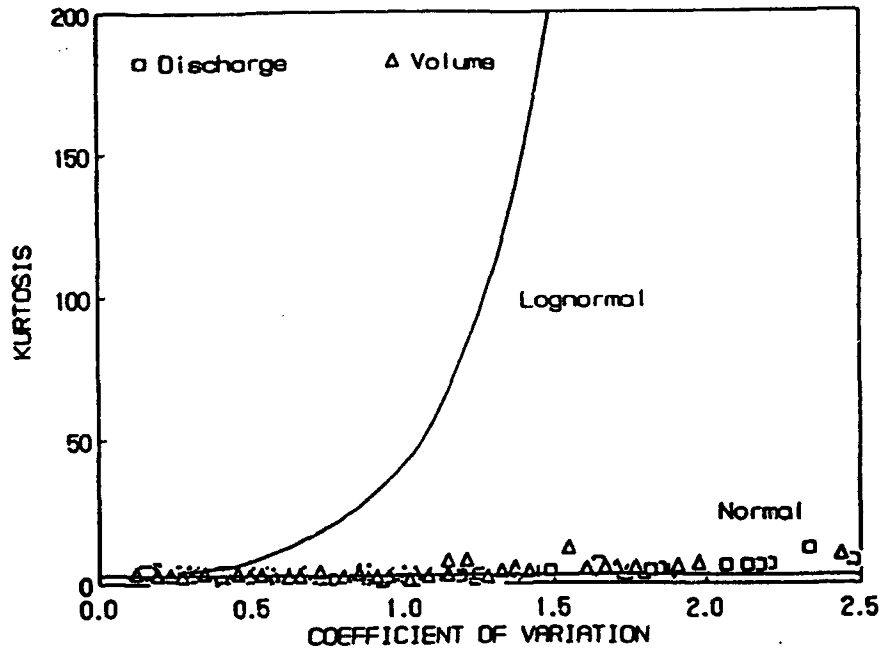

FIG. 8. Comparison of Derived Kurtosis for Runoff Volumes and Peak Discharges with Those for Normal and Two-Parameter Lognormal Distributions

compared to the predicted ones in Table 6. The comparisons indicate that the model conservatively predicts exceedance probability at plus one standard deviation for both prediction variables and at two standard deviations for runoff volume. However, the model prediction of discharge is not conservative at two standard deviations in that the estimated observed exceedance probability is 3.0%, whereas the predicted one is 2.5%. Consequently, the results demonstrate that the model is conservative at one standard deviation, but not necessarily at two standard deviations. A corresponding comparison of nonexceedance probabilities also shown in Table 6 indicates

TABLE 6. Comparison of Observed and Predicted Exceedance Probabilities (Based on 101 Events)

Number of standard deviations (1)	Exceedance (%)[a]		Nonexceedance (%)[b]	
	Predicted (2)	Observed (3)	Predicted (4)	Observed (5)
(a) Volume				
1.0	16.0	1.0	16.0	44.6
2.0	2.5	0.0	2.5	12.9
(b) Peak Discharge				
1.0	16.0	9.9	16.0	31.7
2.0	2.5	3.0	2.5	9.9

[a]Exceedance probability = the chance that runoff volume or peak discharge will exceed the mean prediction by the given number of standard deviations.

[b]Nonexceedance probability = the chance that runoff volume or peak discharge will be less than the mean minus the given number of standard deviations.

that the model underpredicts the chance that the runoff will be less than one or two standard deviations. Thus, the model is conservative in this respect.

Conclusions

The uncertainty in model predictions was conservatively estimated, for the most part, by considering the error resulting from using simple indices to estimate infiltration parameters. In other words, the assumed error model for infiltration parameter estimates resulted in estimated model prediction errors that were somewhat greater than the observed prediction error. This conservatism may be useful in that it could be used to obtain a safety factor in a design situation.

The conservatism of the estimated prediction uncertainty might be attributed to the assumptions made in choosing parameter probability distributions and in assuming zero surface loss. The conservatism in the estimated prediction uncertainty would be lessened if some type of peaked distribution were used instead of the uniform distribution assumed for particle-size distribution. Estimation of a surface loss may have helped in reducing the bias towards overprediction of runoff. However, further research in quantifying surface losses for ungauged watersheds would be helpful in attempts to estimate this parameter for the model. Additionally, the infiltration estimation procedure could be improved by finding a better indicator of soil moisture than an antecedent precipitation index.

The estimation procedure used for infiltration parameters could be useful when applying a PBS type model to derive flow-frequency curves (Eagleson 1972). However, application of this estimation procedure to more gauged basins would be necessary to determine whether it is consistently conservative and to determine the degree of conservatism.

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Appendix II. Notation

The following symbols are used in this paper:

F = cumulative infiltration (in.);
I_a = initial abstraction (in.);
i = infiltration rate (in./hr);
K_s = saturated hydraulic conductivity (in./hr);
l = length along overland flow plane (ft);
P = cumulative precipitation (in.);
Q = total watershed outflow (cfs);
q = flow per unit width of channel (cfs/ft);
m = kinematic wave discharge exponent = 1.67;
N = roughness coefficient for overland flow;
n = $3\lambda + 2$;
r = rainfall intensity adjusted for surface loss (in./hr);
r_0 = rainfall intensity (in./hr);
S_0 = slope along overland flow plane (ft/ft);
S_e = effective saturation;
t = time (sec);

W = width of overland flow plane (ft);
x = distance along overland flow plane (ft);
y = flow depth along overland flow plane (ft);
α = $1.49S_0^{1/2}/N$;
γ_{Sd} = soil dry unit weight (lb/cu ft);
γ_W = unit weight of water (lb/cu ft);
$\Delta\theta$ = volumetric water deficit (vol/vol);
θ = volumetric water content (vol/vol);
θ_D = gravimetric water content (fraction of dry unit weight);
θ_e = $\phi - \theta_r$ (vol/vol);
θ_i = initial water content (vol/vol);
θ_r = residual saturation (vol/vol);
λ = pore-size distribution;
σ = standard deviation;
ϕ = porosity (vol/vol);
ψ = matric suction (in.);
ψ_b = bubbling pressure (in.);
ψ_f = wetting front suction (in.);
ψ_w = water entry pressure (in.); and
Ω = $\psi_f\Delta\theta$ (in.).

Appendix III. Conversion to SI Units

To convert	To	Multiply by
acre	ha	0.405
ft	cm	30.48
in.	cm	2.54
lb/cu ft	N/m^3	157.05
cu ft/sec	m^3/s	0.0283

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A physically based stochastic watershed model is used to estimate runoff prediction uncertainty for small agricultural watersheds in Hastings, Nebraska. The stochastic nature of the model results from postulating a probabilistic model for parameter estimation and input errors. The key factors assumed to contribute to prediction uncertainty are errors in estimating infiltration parameters and moisture conditions prior to a rainfall event. The error distributions for parameter estimates are inferred from soil survey information, and the error distribution for moisture conditions from a regression between antecedent precipitation indices and measured soil moisture. Comparison of model predicted and observed errors demonstrates that the model is conservative in that it is biased towards overprediction of errors.

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