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# USING CURVE NUMBERS TO DETERMINE BASELINE VALUES OF GREEN-AMPT EFFECTIVE HYDRAULIC CONDUCTIVITIES<sup>1</sup>

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ABSTRACT: Since the trend in infiltration modeling is currently toward process-based approaches such as the Green-Ampt equation, more emphasis is being placed on methods of determining appropriate parameters for this approach. The SCS curve number method is an accepted and commonly used empirical approach for estimating surface runoff, and is based on numerous data from a variety of sources. The time and expense of calibrating processbased infiltration parameters to measured data are often prohibitive. This study uses curve number predictions of runoff to develop equations to estimate the "baseline" hydraulic conductivities  $(K_b)$  for use in the Green-Ampt equation. Curve number predictions of runoff were made for 43 soils.  $K_b$  values in the Water Erosion Prediction Project (WEPP) model were then calibrated so that the annual runoff predicted by WEPP was equal to the curve number predictions. These calibrated values were used to derive an equation that estimated Kb based on the percent sand, percent clay, and cation exchange capacity of the soil. Estimated values of K<sub>b</sub> from this equation compared favorably with measured values and values calibrated to measured natural runoff plot data. WEPP predictions of runoff using both optimized and estimated values of K<sub>b</sub> were compared to curve number predictions of runoff and the measured values. The WEPP predictions using the optimized values of K<sub>b</sub> were the best in terms of both average error and model efficiency. WEPP predictions using estimated values of K<sub>b</sub> were shown to be superior to predictions obtained from the curve number method. The runoff predictions all tended to be biased high for small events and low for larger events when compared to the measured data. Confidence intervals for runoff predictions on both an annual and event basis were also developed for the WEPP model.

(KEY TERMS: infiltration; hydrologic modeling; WEPP; hydraulic conductivity; Green-Ampt equation; SCS curve number.)

## INTRODUCTION

Accurate infiltration components are essential to process-based hydrologic or soil erosion models. Many current hydrologic models use some form of the

Green-Ampt equation (Green and Ampt, 1911) to partition rainfall between runoff and infiltration. While decades of use have confirmed the validity of this equation, as with all models, accurate parameter estimates are required to obtain reliable results. To apply models to ungaged areas, a procedure for estimating the key parameters of the model must be developed. This is usually accomplished by estimation based on theoretical considerations or through calibration to measured data. Calibration is often required for most current hydrologic models to account for spatial variations not represented in the model formulation or model inadequacies; functional dependencies between model parameters; and to extrapolate laboratory measurements of parameters to field conditions.

In 1985, the USDA initiated the Water Erosion Prediction Project (WEPP) to "develop a new generation of water erosion prediction technology . . ." (Nearing et al., 1989). This new process-based model offers several advantages over existing erosion prediction technology. It has capabilities of predicting spatial and temporal distributions of net soil loss and net soil loss or gain for the entire hillslope for single storm or continuous simulations. It also has a wider range of applicability as it contains its own process-based hydrology, water balance, plant growth, residue decomposition, and soil consolidation models as well as a climate generator and many other components that broaden its range of usefulness. A complete explanation of each of these components may be found in Lane and Nearing (1989).

Infiltration in WEPP is calculated using a solution of the Green-Ampt equation for unsteady rainfall developed by Chu (1978). It is essentially a two-stage

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process. Initially, the infiltration rate is equal to the rainfall application rate. After ponding occurs, the infiltration rate is calculated using the equation:

$$f = K_e \left[ 1 + \frac{N_s}{F} \right] \tag{1}$$

where f is the infiltration rate in mm/h,  $N_s$  is the effective matric potential in mm, F is the cumulative infiltration in mm, and  $K_e$  is the effective hydraulic conductivity for the given event in mm/h. The effective matric potential in mm is given by:

$$N_s = (\eta_e - \Theta_i) \Psi \tag{2}$$

where  $\eta_e$  is the effective porosity,  $\Theta_i$  is the soil water content, and  $\Psi$  is the average wetting front capillary potential in mm. The effective porosity is defined as the difference between the total porosity corrected for entrapped air and the antecedent water content. The average wetting front capillary potential is calculated from the Brook and Corey's pore size index and bubbling pressure and can be further related to effective porosity and the sand and clay content of the soil (Brakensiek, 1977; Rawls and Brakensiek, 1983). While WEPP allows the user to enter up to ten soil layers and uses these layers in the water balance component of the model, the infiltration routine uses a single layer approach. The harmonic mean of the soil properties in the upper 20 cm is used to represent the effects of multilayer systems. The effective porosity, the soil water content, and the wetting front capillary potential are all calculated based on the mean of these soil properties.

Sensitivity analysis on the hydrologic component of WEPP has indicated that the predicted runoff amounts are most sensitive to the rainfall parameters (depth, duration, and intensity) and the hydraulic conductivity (Nearing et al., 1990). Several other studies have concluded that proper determination of the hydraulic conductivity parameter is critical to obtaining reliable estimates of runoff from the WEPP model (Van der Zweep, 1992 and Risse, 1994).

Two approaches of hydraulic conductivity input have been used for the WEPP model. In the first method, the user enters an average effective value of hydraulic conductivity that remains constant throughout the simulation. Nearing et al. (1995) developed a procedure for estimating these average effective values based on soil properties and Risse (1994) showed that this method produced reliable event estimates of runoff on natural runoff plots at eleven different locations. The second method allows for the temporal variation of the hydraulic conductivity. In it, the user enters a "baseline" value of hydraulic conductivity that is then adjusted to

account for temporal changes in the effective hydraulic conductivity. On fallow plots, the effective hydraulic conductivity at any time is calculated using the equations given in Risse *et al.* (1995) which state:

$$K_e = K_b \left( CF + (1 - CF)e^{-C*Ea*\left(1 - \frac{rr}{4}\right)} \right)$$
 (3)

where CF is a crust factor ranging from zero to one that is calculated based on soil properties using the equations of Rawls et al. (1990), Ea is the cumulative rainfall kinetic energy since last tillage  $(J/m^2)$ , rr is the random roughness of the soil surface (cm), and C is a soil stability factor that represents the rapidity that the effective conductivity declines from  $K_b$  to a fully crusted condition. Risse (1994) showed that C could be related to soil properties using the equation:

$$C = -0.0028 + 0.000113 Sa + 0.00125 \frac{Cl}{CEC}$$
 (4)

where Sa and Cl are the percent sand and clay, and CEC is the cation exchange capacity. In Equation (3), the "baseline hydraulic conductivity,"  $K_b$ , is defined as the maximum infiltration rate (mm/h). In agricultural areas, the hydraulic conductivity that occurs under freshly tilled conditions should be most representative of this value since the reduction in infiltration due to crusting has been removed. Under cropped conditions, the effective hydraulic conductivity is further adjusted to account for the effects of canopy cover and residue using the equations presented in Zhang et al. (1994). Risse (1994) and Zhang et al. (1995) showed that the use of temporally varying values of  $K_e$  produced better estimates of runoff than those obtained using a constant value of  $K_e$  in the WEPP model.

While the methods described above provide a method for allowing for variation in the Green-Ampt effective hydraulic conductivity, the accuracy of the runoff predictions obtained from the model will still be highly dependent on the baseline values of hydraulic conductivity that the user must enter. Risse (1994) compared calibrated and measured values of  $K_b$  to hydraulic conductivities estimated by a variety of equations and found that none of the methods tested could consistently produce reliable estimates of  $K_b$ . Since reliable values of  $K_b$  for a wide range of soil types under natural rainfall conditions are extremely limited, a method for determining the appropriate baseline values of conductivity,  $K_b$ , for a given soil needed to be developed.

#### **OBJECTIVE**

The objective of this study was to develop a set of equations to estimate "baseline" values of hydraulic conductivity to be used in the Green-Ampt equation in the WEPP model. Once this method was developed, it was compared to both calibrated values and measured values. To obtain some measure of the accuracy of runoff predictions obtained using these estimated values, they were used in the WEPP model to predict runoff and the runoff estimates were compared to measured natural runoff plot data from eleven different locations.

#### LITERATURE REVIEW

In their discussion of determination of Green-Ampt parameters, Skaggs and Khaleel (1982) state that it will usually be advantageous to determine equation parameters from measured infiltration data as these measurements tend to lump the effects of heterogeneity's, worm holes, crusting, etc. While the use of measured data would be ideal, the time and expense of obtaining measurements for every location to which the model will be applied is prohibitive. Calibrating values of  $K_b$  to measured data at a large variety of locations would also be difficult due to the large cost of data. Additionally, very few databases exist which would be large enough to develop equations to predict  $K_b$  based on soil properties using calibrated values.

The curve number technique was derived based on an extensive database and is commonly used for predicting runoff from daily rainfall amounts. It has been used extensively in various hydrologic, erosion, and water quality models including CREAMS (Knisel, 1980), EPIC (Sharpley and Williams, 1990), SWRRB (Williams et al., 1985), and AGNPS (Young et al., 1989). The method has been calibrated and evaluated for many sets of measured runoff data and is generally reliable over a wide range of geographic, soil, and land management conditions. Details of the curve number method are given in the USDA-SCS National Engineering Handbook (USDA-SCS, 1985). Essentially, the method estimates runoff depth, Q (mm), as a function of rainfall depth, P (mm), and a storage term, S, which depends on the curve number, CN. Curve number values are assigned based on the soil type (one of four hydrologic soil groups) and land use, and are modified depending on the soil moisture content at the time of rainfall.

Since the curve number method for predicting runoff is accepted technology and most of the soils in the United States have been assigned to one of the four hydrologic soil groups, this method may be used to determine infiltration parameters for other models. Rawls and Brakensiek (1986) compared runoff predictions obtained from the Green-Ampt infiltration model to SCS curve number runoff predictions for 330 events from 17 watersheds. They concluded that the Green-Ampt infiltration model produced better predictions of runoff volumes. Nearing et al. (1994) calibrated constant values of Green-Ampt effective hydraulic conductivity to curve number predictions of runoff on 43 soils. Based on these calibrated values, they presented equations for estimating the constant Green-Ampt effective conductivities based on the hydrologic soil group and sand content of the soil. Using estimated values of K<sub>e</sub> obtained from these equations, they showed that runoff volumes predicted by the Green-Ampt infiltration model were closer to the distribution of measured values than runoff predicted by the curve number method. This paper proposes a similar approach, however, it will focus on calibrating baseline values of hydraulic conductivity rather than constant effective values.

### MATERIALS AND METHODS

Description of Data Sets

Two different data sets were used in this study. The first data set, the calibration data, consisted of 43 measured soils files and management, topographic, and climate files that were generated using assumed conditions. Curve number predictions of runoff were generated for each of these soils. The Kb value in the WEPP model was then calibrated to minimize the difference between the WEPP predictions of runoff and the curve number estimations at each of these sites. The second set of data, the validation data, consisted of eleven sites of fallow natural runoff plot data (Table 1). This data consisted of measured values of runoff on an event basis as well as measured soil, topographic, management, and climate inputs. It was primarily used to validate the relationships developed in the first phase of this study.

The measured soils data for both of the data sets came from a variety of sources. Thirty of the soils were part of the WEPP Cropland Field Erodibility Study (Elliot et al., 1989). These sites were sampled and analyzed by the USDA-SCS Soil Survey Laboratory and complete pedon descriptions were available. Data for the 11 soils in the validation set were obtained from a literature review, experiment station bulletins, and the repository of soil erosion data located at the National Soil Erosion Research Laboratory.

TABLE 1. Selected Natural Runoff Plots Used in This Study.

Site	Soil*	Years	Slope (percent)	Replicates	Number of Selected Events**
Bethany, Missouri	Shelby sil	1931-40	8.0	1	109
Castana, Iowa	Monona sil	1960-71	14.0	2	90
Geneva, New York	Ontario 1	1937-46	8.0	1	97
Guthrie, Oklahoma	Stephensville fsl	1940-56	7.7	1	170
Holly Springs, Mississippi	Providence sil	1961-68	5.0	2	208
Madison, South Dakota	Egan sicl	1961-70	5.8	2	60
Morris, Minnesota	Barnes 1	1961-71	5.9	3	72
Pendleton, Oregon	Thatuna sil	1979-89	16.0	2	82
Presque Isle, Maine	Caribou gr sil	1961-69	8.0	3	99
Tifton, Georgia	Tifton sl	1959-66	3.0	2	72
Watkinsville, Georgia	Cecil scl	1961-66	7.0	2	110

<sup>\*</sup>sil = silt loam; sicl = silty clay loam; gr = gravelly; l = loam; sl = sandy loam; fsl = fine sandy loam; scl = sandy clay loam.

While these 11 soils were used in both the validation and calibration data set, the validation was accomplished independently as the measured values of runoff were not used in the calibration phase of the study. Since only one soil from hydrologic soil group A was included in the first two data sources, two additional A group soils were selected. Data for these soils was taken from the SCS soil survey results. The required soils data for the WEPP input files included erodibilities and albedo for the upper soil layer as well as percent sand, clay, organic matter, rock fragments and the cation exchange capacity for all of the soil layers. The hydraulic conductivities of the soil sublayers (those below 20 cm) were calculated internally in the WEPP model using the equations developed for the Erosion Productivity Impact Calculator (EPIC) model (Sharpley and Williams, 1990). These hydraulic conductivities do not directly affect the Green-Ampt infiltration as only the hydraulic conductivity in the infiltration zone is used in the infiltration calculations. However, they do influence percolation and thus the estimated soil moisture throughout the simulation. Table 2 lists the input soil properties for the upper soil horizon for each soil. Curve numbers for each soil in the calibration data set were taken from the SCS handbook (USDA-SCS, 1985). Since all the plots were assumed to be fallow, these values were only adjusted to account for antecedent moisture conditions.

For the 11 locations in the validation study, the measured climate data consisted of maximum and minimum temperatures and daily rainfall amounts. In addition, most of the storms which produced runoff also had detailed breakpoint data from tipping bucket rain gages. This data was used to calculate the rainfall durations, time to maximum intensity, and

relative peak intensity. CLIGEN version 2.3, the stochastic weather generator included with WEPP, was used to generate the remaining climate parameters including solar radiation, wind velocity and direction, and dew point temperature. For the calibration data set, CLIGEN was used to generate a 20-year climate file for Jefferson City, Missouri. This file was used for all of the calibration runs. Nearing et al. (1995) showed that the differences in climate had relatively small effects on calibrated hydraulic conductivities on fallow plots. Jefferson City was selected as it could be considered representative of the major rain-fed crop producing areas of the U.S.

All of the plots in the validation data set were of nearly uniform slope with constant widths and could be represented with a single overland flow element. They were all of standard USLE natural runoff plot dimensions (4.05 x 22.13 m) except Tifton (8.10 x 44.26 m) and Pendleton (4.05 x 33.50 m) and were on the slopes given in Table 1. A standard USLE natural runoff plot was also assumed for the topographic file used in the calibration runs.

All of the plots in the validation data set and the management file for the calibration runs were for fallow conditions. Information on the dates and types of tillage were given in the data. The tillage data base included in WEPP documentation was used to estimate tillage parameters including the tillage depth, random roughness, tillage intensity, ridge height, and ridge spacing for the construction of management files. Weed and residue cover were assumed to be insignificant as each of these plots had been in continuous cultivated fallow condition for at least a year prior to the first simulation.

<sup>\*\*</sup>Number of events used in statistical analysis.

TABLE 2. Soil Properties and Measured, Calibrated, and Estimated Baseline Conductivities.

Soil	Hydrologic Soil Group	Sand (percent)	Clay (percent)	CEC (meq/100g)	Measured K <sub>b</sub> <sup>1</sup> (mm/h)	Calibrated K <sub>b</sub> <sup>2</sup> (mm/h)	Estimated K <sub>b</sub> <sup>3</sup> (mm/h)
Amarillo	b	85.0	7.3	5.1	15.0	26.6	28.7
Barnes*	ь	39.0	23.2	18.4		9.9	7.4
Barnes, MN	b	48.6	17	19.5	19.1	10.4	10.3
Barnes, ND	ь	39.3	26.5	23.2	16.7	11.7	7.2
Bonifay	a	91.2	3.3	1.7	34.8	60.2	36.4
Caribou*	b	38.8	13.7	13.2		8.2	7.6
Cecil	b ·	69.9	11.5	2.9	13.3	17.2	24.4
Cecil*	ь	66.5	19.6	4.8		29.7	22.8
Collamer	c	6.0	15.0	9.2	3.6	0.7	2.1
Colonie	а	90.5	2.1	10.0		38.3	30.4
Egan*	b	7.0	32.2	25.1		1.8	1.0
Frederick	ь	25.1	16.6	8.2	2.9	5.9	4.9
Gaston	С	37.2	37.9	9.2	3.6	6.3	7.7
Grenada	c	1.8	20.2	11.8	3.4	0.7	1.6
Heiden	d	8.6	53.1	33.3	4.7	0.3	0.4
Hersh	Ъ	72.3	10.9	7.7	15.8	17.6	21.3
Hiwassee	ь	63.7	14.7	4.4	13.6	17.2	18.7
Keith	b	48.9	19.3	18.3	3.5	11.5	10.5
Lewisburg	c	38.5	29.3	12.5	3.7	5.5	7.6
LosBanos	c	15.5	43.7	39.1	3.9	1.1	1.1
Manor	ь	44.0	25.2	13.2	10.0	14.0	9.2
Mexico	d	5.5	25.3	21.3	6.2	0.4	1.1
Miami	b	4.2	23.1	13.3	0.9	1.7	1.5
Miamian	c	31.3	25.9	14.9	4.4	3.3	5.5
Monona*	ь	7.1	23.5	20.1		1.9	1.2
Nansene	Ъ	20.1	12.8	16.6	5.3	2.8	3.0
Ontario*	ь	44.2	14.9	11.8		8.6	9.4
Opequon	С	37.7	31.1	12.9	7.6	6.3	7.3
Palouse	b	9.8	20.1	19.6	2.6	1.9	1.5
Pier <del>r</del> e	d	16.9	49.5	35.7	2.4	0.7	0.6
Portneuf	b	18.2	11.1	12.6	7.9	2.7	3.0
Pratt	а	89.0	2.2	3.1		32.8	32.4
Providence*	c	2.0	19.8	9.3		0.7	1.9
Sharpsburg	Ъ	5.2	40.1	29.4	7.3	1.8	1.8
Shelby*	b	27.8	29.0	16.5		7.8	4.6
Stephensville*	b	73.2	7.9	7.2		13.7	21.9
Sverdrup	b	75.3	7.9	11.0	20.3	14.5	22.2
Thatuna*	c	28.0	23.0	16.2		2.6	4.6
Tifton	b	86.4	2.8	2.1	14.9	14.8	32.6
Tifton*	b	87.0	5.7	4.1	2	26.6	30.4
Williams	b	40.8	26.9	22.7	8.3	12.9	7.7
Woodward	b	51.7	13.0	11.6	12.0	9.2	12.0
Zahl	b	46.3	24.0	19.5	5.7	14.1	9.5

<sup>\*</sup>Indicates one of the 11 soils with measured runoff data.

# Calibration Algorithm

A calibration algorithm was required to determine the optimum baseline hydraulic conductivity based on the curve number predicted runoff. For each soil, curve number predictions were made based on the 20-year climate file. The WEPP model (Version 94.305) was then run iteratively until the value of  $K_b$  that made the average annual runoff predicted by WEPP

<sup>&</sup>lt;sup>1</sup>Measured under simulated rainfall in study of Elliot et al. (1989).

 $<sup>^2\</sup>mbox{WEPP}$   $\mbox{K}_b$  calibrated to SCS curve number predictions.

<sup>&</sup>lt;sup>3</sup>K<sub>b</sub> estimated by Equation (7).

equal that predicted by the curve number method was found. To eliminate the influence of snowmelt runoff and frozen soils, events that occurred under winter conditions were not included in this analysis. It should be stressed that the calibrated values are calibrated to curve number predictions and not measured data.

The calibrated values of K<sub>b</sub> for the 43 soils were tabulated and statistically analyzed. Equations were developed to relate these calibrated Kb values to soil properties. The 11 validation data sets were then used to compare runoff predictions from WEPP using estimated values of Kb to curve number predictions and measured data. Additionally, the 11 validation sites were also used to compare values of Kb calibrated to curve number predictions to those calibrated to measured runoff data. When K<sub>b</sub> was calibrated to measured data, the algorithm described in Risse (1994) was used. This algorithm was slightly different than the one used to calibrate to curve number predictions as it used the least squares error between the measured and predicted event runoff values as the objective function rather than average annual runoff.

Nash and Sutcliffe (1970) introduced a term called the model efficiency to evaluate the goodness of fit between predicted and measured runoff. It is defined as:

$$ME = 1 - \frac{\sum (Y_{obs} - Y_{pred})^2}{\sum (Y_{obs} - Y_{mean})^2}$$
 (5)

where ME is the model efficiency, Yobs is the measured output, Y<sub>pred</sub> is the output predicted by the model, and Y<sub>mean</sub> is the mean measured output for all the events. In many cases, the model efficiency is similar to the coefficient of determination (r2 from linear regression); a value of one indicates perfect agreement between the measured and predicted values and decreasing values indicate less correlation between the two. However, the model efficiency compares the predictions to the line of measured equals predicted rather than the best regression line through the points. If the model results are highly correlated but biased, then the model efficiency will be lower than the coefficient of determination. Much like the coefficient of determination, the model efficiency can be negative indicating that the average value of the output is a better estimate than the model prediction.

# RESULTS AND DISCUSSION

Development of an Estimation Equation

To ensure that this curve number approach would provide reasonable values of K<sub>b</sub>, the values calibrated to curve number predictions were compared to values that were calibrated to measured data for the 11 validation sites. Over all 11 sites, the difference between the values calibrated to curve number predictions of runoff and those calibrated to measured data ranged from -125 percent to +44 percent (Table 3). The value calibrated to the curve number predictions was higher than the value calibrated to measured data at eight of the 11 sites. This was primarily because the curve number approach tended to underpredict runoff at most of the sites (Table 4). Another source of variation between the calibrated values of Kb was the use of different objective functions. As described earlier, the K<sub>b</sub> calibrated to the measured data used the minimum least squared error from a series of events as the objective function because data was not collected during the winter at many of the sites. The Kb calibrated to curve number runoff used the average annual runoff as the objective function. The fact that the two methods use different climate and management information could also explain some of the differences between the K<sub>b</sub> values. While both management files represented fallow conditions, the times and amounts of tillage vary between the two. The curve number runoff was generated using an assumed climate file while the measured runoff occurred under specific climatic conditions and used measured climatic data. Curve number predictions represent average conditions occurring over a long period of time instead of the specific conditions of the measurement period. Considering these differences between the methods and the amount of variability in measured conductivities and those estimated using other equations, the use of this curve number method seemed acceptable.

Having established that the  $K_b$  values calibrated to the curve number runoff for these 11 sites seemed reasonable, the values for the 32 additional soils were determined (Table 2). Regression analysis was then used to determine which soil properties could be used to estimate these values of  $K_b$ . The soil properties investigated were limited to sand, clay, silt, very fine sand, field capacity, wilting point, organic matter, CEC, and rock fragments as these properties were thought to be easily obtainable or relatively easy to measure. In addition, several transformations and interactions were tested. The variables that exhibited the highest correlations were percent sand  $^{1.81}$  (r=0.88), percent silt- $^{1.06}$  (r=0.92), and CEC- $^{0.54}$  (r<sup>2</sup>=0.71). While developing an equation to predict  $K_b$ ,

it was evident that a few of the soils with very high clay contents and low values of  $K_b$  were being overpredicted despite any specific model structure. Therefore, these soils were separated and two equations were developed. While several equations provided nearly equivalent values of  $r^2$ , the following equations were selected based on their simplicity and the standard error of the estimates:

For soils with greater than 40 percent clay (n=4):

$$K_b = 0.0066 \exp\left(\frac{244}{\% clay}\right) \tag{6}$$

For soils with less than or equal to 40 percent clay (n=39):

$$K_b = -0.265 + 0.0086 \% sand^{180} + 11.46 CEC^{-0.75}$$
 (7)

Over all 43 soils, this combination of equations had an  $r^2$  of 0.78. From the equation it is apparent that the sandy soils have higher baseline conductivities. Since the CEC is dependent not only on the clay content, but also the exchange capacity of the clay, it accounts for the reduction in conductivity due to the clay as well as differences in clay types. Equations (6) and (7) were robust enough to predict realistic values of  $K_b$  for most naturally occurring soils so no limits were established. Equation (6) was developed for soils with extremely high clay contents. Equation (7) and most

others that were tested in the regression analysis tended to overestimate  $K_b$  for these clayey soils. By separating these soils out from the remainder of the data, we not only improved the estimates of  $K_b$  for the clay soils, but also gained an improvement in the value of  $r^2$  for the other soils.

TABLE 3. Baseline Conductivities Calibrated to Measured Data and Curve Numbers Predictions (all values in mm/hr).

Site	Opt. K <sub>b</sub> from CN Method	Op. K <sub>b</sub> from Measured Data	Percent Difference	
Bethany	7.81	3.48	-124	
Castana	1.86	2.47	25	
Geneva	8.59	5.13	-67	
Guthrie	13.67	18.22	25	
Holly Springs	0.68	0.47	-45	
Madison	1.81	1.56	-16	
Morris	9.96	17.65	44	
Pendleton	2.64	1.56	-69	
Presque Isle	8.20	4.66	-76	
Tifton	26.52	20.69	-28	
Watkinsville	29.69	19.76	-50	

<sup>\*</sup>Percent difference calculated as 100\*(Khmeas-KhCN)/Khmeas.

Table 2 and Figure 1 compare the calibrated values of  $K_b$  to those estimated with Equations (6) and (7). Generally, the estimates were close to the calibrated

TABLE 4. Average Event Runoff and Error Measured and Predicted by Three Models (all values in mm).

		WEPP Opt. K <sub>b</sub> *		WEPP E	st. K <sub>b</sub> **	SCS Curve Number		
Site	Measured Average Runoff	Average Runoff	Average Mag. Error***	Average Runoff	Average Mag. Error***	Average Runoff	Average Mag. Error***	
Bethany	14.5 ± 15.7	14.1 ± 15.6	5.17	12.8 ± 14.9	5.40	10.0 ± 14.1	6.59	
Castana	$11.5 \pm 8.4$	$10.1 \pm 9.2$	4.61	$15.1 \pm 10.9$	5.35	$11.8\pm10.0$	5.50	
Geneva	$7.9 \pm 11.0$	$6.7 \pm 10.2$	4.07	$4.1 \pm 8.2$	4.41	$6.0 \pm 10.5$	5.07	
Guthrie	$10.9 \pm 14.4$	$9.9 \pm 14.8$	3.88	$8.7 \pm 14.2$	4.05	$10.5 \pm 16.1$	4.90	
Holly Springs	$15.2 \pm 17.3$	$14.6 \pm 16.3$	4.14	$8.5 \pm 13.0$	7.30	$12.6\pm16.3$	5.57	
Maison	$8.0 \pm 11.8$	$7.1 \pm 9.5$	3.92	$8.8 \pm 10.2$	4.11	$6.7 \pm 8.3$	4.48	
Morris	$5.6 \pm 6.9$	$4.1 \pm 6.6$	3.13	$8.8 \pm 9.8$	4.79	$8.7 \pm 10.4$	6.10	
Pendleton	$3.2 \pm 2.8$	$2.2 \pm 3.1$	2.08	$0.4 \pm 1.1$	2.87	$1.8 \pm 2.8$	2.54	
Presque Isle	$6.9 \pm 8.4$	$4.8 \pm 7.1$	4.16	$2.9 \pm 5.4$	4.52	$4.8 \pm 9.1$	5.58	
Tifton	$19.0 \pm 16.6$	$17.8 \pm 16.4$	7.09	$14.0 \pm 15.1$	7.78	$21.1 \pm 20.2$	8.75	
Watkinsville	$13.4 \pm 14.2$	$12.7 \pm 15.6$	4.23	$12.6\pm15.3$	4.28	$11.9\pm16.0$	5.61	
Average	10.5	9.5	4.23	8.7	4.99	9.6	5.51	

<sup>\*</sup>WEPP using hydraulic conductivity calibrated to measured data.

<sup>\*\*</sup>WEPP using hydraulic conductivity calculated using Equations (6) and (7).

<sup>\*\*\*</sup>Average Mag. Error is the mean of the absolute values of the residuals.

values with an average magnitude of error of 3.29 mm/h and an average difference of 42 percent. The differences between the calibrated and estimated values tended to be evenly distributed as suggested by the average error of -0.04 and the distribution of points on either side of the one to one line in Figure 1. Many soils that did exhibit larger differences are anomalies with special conditions that altered the infiltration rates. For example, the Bonifay soil had a calibrated K<sub>b</sub> of 60.16 mm/h which was only estimated at 36.4 mm/h. While this may seem like a large error, in terms of predicted runoff there was little difference between these values. Because this soil is classified in hydrologic soil group A, the curve number method predicts very little runoff. Since the Green-Ampt equation becomes less sensitive to K<sub>b</sub> at these higher values, the calibrated hydraulic conductivity must be raised more to obtain the necessary reduction in runoff. The estimated value agreed closely with the measured value of 34.8 mm/h. The Mexico soil was at the opposite extreme. It had a calibrated value of 0.34 mm/hr estimated as 1.08 mm/hr. This was one of the few soils in hydrologic soil group D and was placed in this group due to its highly restrictive subsurface layers. Using an analysis of surface layer properties there is no way to account for this type of condition. The percolation routines in WEPP should account for this condition, however, and the runoff predictions should be adjusted accordingly through the soil moisture term. Soils such as these, which were classified in either hydrologic soil groups A or D, tended to be the most difficult to predict based on soil properties alone. This displays an inherent advantage of the empirical curve number approach. Curve numbers can be assigned based on knowledge of the complete soil conditions and not just the measured soil properties of the infiltration zone.

# Comparison of $K_b$ to Measured Values

The difficulty with obtaining accurate measurements of effective hydraulic conductivity lies in defining appropriate soil conditions and in the fact that there are a wide variety of methods for measuring conductivity which produce widely varying results. Hydraulic conductivity varies not only temporally due to soil tillage, crusting, and consolidation, but also with other factors such as moisture content and hydraulic gradient across the soil profile. Therefore, to establish some sort of baseline, there needs to be a standard method to be used for the measurement of effective conductivities. Most values of hydraulic conductivity reported in the literature or soil surveys are measured under saturated conditions on soil cores. For agricultural areas, these values are generally

much higher than the effective values determined in the field and are also higher than the calibrated baseline values presented in Table 2. Many different types of permeameters and other instruments have also been used to measure saturated hydraulic conductivities. These instruments generally produce results similar to those measured on soil cores (Gupta et al., 1993). Bouwer (1969) showed that the Green-Ampt effective conductivity should be less than the saturated value because of entrapped air and suggested estimating it as half of the saturated value.

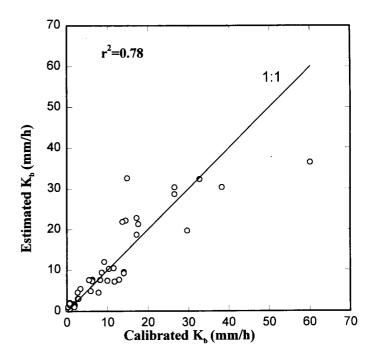


Figure 1. Estimated Values of Baseline Conductivity Plotted Against Those Calibrated to Curve Number Predictions.

Although time consuming and costly, the measurement of the effective conductivity in the field under simulated rainfall would be expected to produce the best estimates for  $K_b$ . Many of the soils used in this study were part of the WEPP cropland erodibility experiments (Elliot et al., 1989). In this study, infiltration on 500 mm by 700 mm infiltration plots was measured under simulated rainfall and the effective conductivities were calculated by backward solution of the Green-Ampt equation. Since these plots were tilled immediately prior to applying the rainfall, these effective conductivities should be equivalent to the values of  $K_b$ . Four replicates were run for each plot and the average measured effective conductivity for each site is reported in Table 2. Figure 2 presents a

plot of the measured values of  $K_b$  compared to the curve number calibrated values. It is apparent from the figure that the effective conductivities measured under simulated rainfall display more variability than the values predicted using Equations (6) and (7). This is especially true for the lower values of  $K_b$ . This is important as the predicted runoff is much more sensitive to changes in the hydraulic conductivity in the lower range than it would be to differences at larger values. It is also apparent that the measured values are generally higher than the calibrated values. This may be due to differences between simulated and natural rainfall or some other facet of the measurement or calibration procedure.

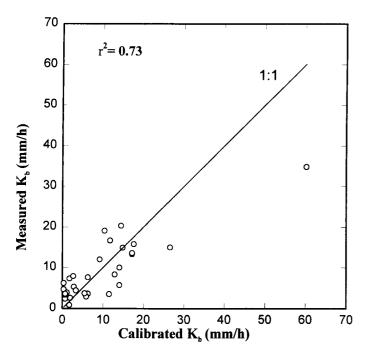


Figure 2. Baseline Hydraulic Conductivities Measured Under Simulated Rainfall Plotted Against Those Calibrated to Curve Number Predictions.

## Error Associated With WEPP Runoff Predictions

Table 4 presents the simple statistics obtained from a comparison of the measured runoff for each event to WEPP predictions using optimized and estimated values of  $K_b$  as well as curve number predictions. At most of the sites, all of the methods predicted mean values of runoff that were comparable to the measured means. All three methods slightly underpredicted the overall mean event runoff for all 11 sites. The standard deviation of the means is a good indication

of the distribution of the individual event predictions. At most of the locations, there was little difference between the standard deviations of the means. However, the curve number predictions did display a slightly higher average standard deviation than the predictions obtained from WEPP or the measured values. This was probably because the curve number method is more sensitive to the rainfall amount than the WEPP predictions. The average magnitude of error is probably the most significant statistic as it indicates how close the predicted values are to the measured values. In terms of this indicator, WEPP using the optimized values of K<sub>b</sub> supplied the best predictions with an overall average error of 4.23 mm. More important, WEPP using the estimated values of K<sub>b</sub> produced a lower average error (4.99 mm) than the curve number method (5.51 mm).

While a comparison of the means and error terms is a reliable indication of the net differences between the measured values and the predictions, the regression statistics and model efficiencies are much better indicators of the complete fit of the individual observations. WEPP using optimized values of Kb had the highest model efficiency and correlation coefficient at all of the sites (Table 5). Since the values of  $K_b$  were calibrated to minimize the least squared error term this result could only be expected. Although the use of estimated values of Kb had a minor effect on the correlation coefficient (reduction of 0.02), the average model efficiency dropped from 0.65 to 0.42. Most of this reduction can be attributed to a few sites (Castana, Morris, and Pendleton) where the estimated values of K<sub>h</sub> were either much lower or higher than the optimized values. The reason the correlation coefficients did not change as much as the model efficiencies is because the use of estimated values of K<sub>b</sub> resulted in predictions that were either too high or low, yet, still displayed approximately the same amount of linearity. This illustrates the importance of using the model efficiency to compare results as opposed to the correlation coefficient. The predictions obtained from WEPP using the estimated values of K<sub>b</sub> had higher model efficiencies than the predictions obtained from the curve number method at all of the sites except Holly Springs. The overall average model efficiency was 0.14 higher and the average correlation coefficient was 0.15 higher. This suggests that the predictions from WEPP and the Green-Ampt infiltration model were not only closer to the measured values but also displayed more appropriate variability.

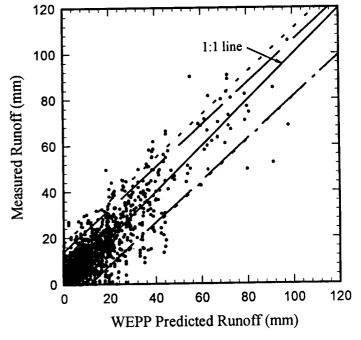
Many of these statistics are very useful when comparing models, however, they are of little use to the end users. Confidence intervals provide the user with information on which to base future decisions. Confidence intervals were developed using SAS regression analysis for the 2500 event observations at these 11

TABLE 5. Regression Statistics and Model Efficiencies Comparing Measured Event Runoff to Predictions by Three Models.

	WEPP Opt. Kb				WEPP Est. K <sub>b</sub>				SCS Curve Number			
Site	Slp	Int	r2	ME	Slp	Int	r2	ME	Slp	Int	r2	ME
Bethany	0.90	1.11	0.83	0.82	0.86	0.31	0.82	0.81	0.81	-1.66	0.80	0.72
Castana	0.85	0.28	0.61	0.48	0.97	3.60	0.56	0.12	0.75	3.25	0.40	0.10
Geneva	0.80	0.38	0.75	0.73	0.64	-0.94	0.75	0.62	0.76	0.03	0.63	0.58
Guthrie	0.96	-0.59	0.87	0.86	0.92	-1.39	0.88	0.85	1.01	-0.56	0.82	0.77
	0.88	1.18	0.87	0.87	0.70	-2.34	0.88	0.69	0.85	-0.27	0.81	0.79
Holly Springs	0.33	1.42	0.78	0.77	0.75	2.85	0.75	0.74	0.60	1.90	0.72	0.69
Madison	0.71	-0.16	0.65	0.59	1.01	3.26	0.51	-0.21	0.69	4.85	0.22	-1.06
Morris	0.77	-0.16 -0.05	0.40	0.06	0.22	-0.33	0.34	-0.69	0.43	0.41	0.20	-0.33
Pendleton		-0.03 0.48	0.53	0.45	0.48	-0.36	0.56	0.32	0.49	1.39	0.21	-0.25
Presque Isle	0.62	2.17	0.70	0.43	0.76	-0.42	0.69	0.59	0.87	4.53	0.51	0.24
Tifton	0.82				1.00	-0.87	0.86	0.84	1.01	-1.63	0.81	0.74
Watkinsville	1.02	-1.02	0.87	0.84	1.00	-0.01	0.00	V.0-1	1.01	2.00		
Average	0.82	0.47	0.71	0.65	0.76	0.31	0.69	0.42	0.75	1.07	0.55	0.27

locations (Figure 3). These confidence intervals depict a bias for event size. They indicate that WEPP using either value of K<sub>b</sub> tended to over predict runoff on the small events and under predict runoff on the larger events. This error is relatively insignificant on the smaller events with an over prediction of less than one mm for events with measured values of runoff less than 5 mm, however, it could become significant on the larger events. These confidence intervals should be used with caution. Since they were developed using only natural runoff style plots, which are often very narrow and long, the results will only apply to these types of conditions. The results from multiple overland flow elements or larger plots may be different. Additionally, the results from soils that may not represent this set of data may produce different results. Nevertheless, this type of analysis should be useful as it does present an accurate assessment of the range of values which one would expect under these conditions.

Annual estimates of runoff were also analyzed at each location for both the WEPP model and the curve number method. Measurements of runoff were not taken at several locations (Castana, Madison, Morris, and Presque Isle) for the entire year. At these locations, the dates on which the collection of data began and ended (usually April through November) were recorded and only the events within this time period were included in this analysis. Table 6 presents the mean values of annual runoff, average magnitude of error, and model efficiencies from each model at all of the locations. In general, the results from this analysis were fairly consistent with the results from the analysis comparing the methods on an event basis. WEPP using optimized values of Kb had the highest



\_\_\_\_ 95% C.I. for Calibrated K<sub>b</sub>

- - 95% C.I. for Estimated K<sub>b</sub>

Predictions made using calibrated K<sub>b</sub>

Figure 3. Upper and Lower 95 Percent Confidence Intervals for WEPP Predictions of Runoff on an Event Basis.

TABLE 6. Statistics Comparing Values of Total Annual Runoff for Each Model.

Site	Measured		WEPP Opt. Kb*			WEF	P Est. Kb	**	SCS Curve Number			
				Average			Average			Average		
	n	Average	Average	Error*	ME	Average	Error*	ME	Average	Error*	ME	
Bethany	10	222 ± 77	231 ± 52	52	0.28	205 ± 48	48	0.25	175 ± 49	68	-0.35	
Castana**	12	$102 \pm 52$	$95 \pm 46$	21	0.78	184 ± 61	46	0.02	$125 \pm 50$	26	0.59	
Geneva	10	168 ± 93	$172 \pm 50$	<b>52</b>	0.57	$110 \pm 39$	75	0.16	$79 \pm 40$	93	-0.59	
Guthrie	15	154 ± 88	141 ± 74	26	0.83	$121 \pm 69$	37	0.69	$78 \pm 44$	77	-0.35	
Holly Springs	8	$557 \pm 136$	$514 \pm 131$	61	0.73	$299 \pm 90$	258	-2.96	$216 \pm 91$	341	-5.76	
Madison**	10	56 ± 33	$51 \pm 35$	19	0.46	$65 \pm 41$	25	0.24	$69 \pm 58$	31	-0.75	
Morris**	11	40 ± 4	$34 \pm 31$	13	0.81	$75 \pm 53$	34	0.15	$33 \pm 38$	36	-0.23	
Pendleton	10	71 ± 53	$71 \pm 32$	65	-0.87	$27 \pm 18$	62	-1.18	$60 \pm 24$	45	-0.05	
Presque Isle**	9	107 ± 88	$75 \pm 48$	39	0.52	47 ± 34	60	0.04	89 ± 44	48	0.19	
Tifton	8	289 ± 119	231 ± 90	78	0.37	171 ± 78	124	-0.55	$135 \pm 79$	155	-1.50	
Watkinsville	6	$431\pm173$	$398 \pm 156$	56	0.86	$392 \pm 150$	57	0.85	$395 \pm 186$	53	0.88	
Average	10	200, 86	183, 68	44	0.49	151, 62	75	-0.21	132, 65	88	-0.72	

<sup>\*</sup>Average error calculated as the average of the absolute value of predicted-measured annual runoff.

average model efficiency at 0.49 and the lowest average error at 44 mm or 22 percent of the average annual runoff. The average model efficiency and magnitude of error both showed that WEPP using estimated values of Kb performed better than the curve number method. While the average model efficiency was negative, which usually indicates that the use of the mean would produce better results than the model, the extremely low model efficiencies at Holly Springs and Pendleton dominate the positive values resulting in this negative average. Only three of the eleven sites had negative model efficiencies suggesting that the WEPP predictions were usually better than the mean. Conversely, eight of the eleven sites had negative model efficiencies when the curve number method was used. Therefore, it would be safe to assume that the average annual value of runoff for a given location would be a better estimate than the results obtained from the curve number method for this data set. The standard deviation of the annual values of runoff show the year to year variability in annual runoff. While the average of the standard deviations from each of the prediction methods were fairly consistent ranging from 62 to 68, none of the methods predicted the amount of deviation observed in the measured data (Figures 4a-c). All of the methods do an acceptable job of mimicking the trends in the measured data, however, at almost every location there are at least one or two years where the measured runoff is significantly different from that predicted by any of the methods. The shape of the plots obtained from WEPP using either method for obtaining Kb were usually the same. The predictions obtained using the estimated values of K<sub>b</sub> were usually either shifted above or below those determined using the optimized values. This is evidence that the

hydraulic conductivity has only a minor effect on the distribution of runoff.

#### CONCLUSIONS

- 1. Baseline values of hydraulic conductivity in the WEPP model were calibrated to curve number predictions of runoff for 43 soils. The calibrated values were then used to derive an equation for estimating the baseline values of hydraulic conductivity based on the sand content and CEC of the soil. Estimated values of K<sub>b</sub> from this equation compared favorably with measured values as well as values that were calibrated to measured natural runoff plot data.
- 2. WEPP predictions of runoff using both optimized and estimated values of  $K_b$  were compared to curve number predictions of runoff and the measured values. The WEPP predictions using the optimized values of  $K_b$  displayed lower average errors and higher Nash-Sutcliffe model efficiencies than predictions obtained from the curve number method or WEPP using estimated values of  $K_b$ . WEPP predictions using estimated values of  $K_b$  were shown to produce less error and higher model efficiencies than predictions obtained from the curve number method. The runoff predictions tended to be biased high for small events and low for larger events when compared to the measured data.
- 3. Confidence intervals for runoff predictions on an event basis were developed. These intervals should be useful in assessing the accuracy of runoff predictions, however, they will only be applicable to the conditions under which they were developed.

<sup>\*\*</sup>Measurements not taken in winter at these locations.

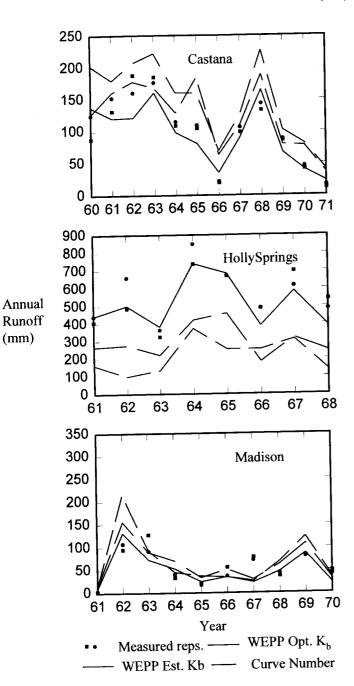


Figure 4. Annual Measured Runoff Plotted Against That Predicted by WEPP and the Curve Number Method at Castana, Holly Springs, and Madison.

#### LITERATURE CITED

Bouwer, H., 1969. Infiltration of Water Into Nonuniform Soil. Journal of Irrigation and Drainage Div., ASCE 95(IR4):451-462.

Brakensiek, D. L., 1977. Estimating the Effective Capillary Pressure in the Green-Ampt Infiltration Equation. Water Resources Research 13(3):680-682.

Chu, S. T., 1978. Infiltration During an Unsteady Rain. Water Resources Research 14(3):461-466. Elliot, W. J., A. M. Liebenow, J. M. Laflen, and K. . Kohl, 1989. A Compendium of Soil Erodibility Data from WEPP Cropland Soil Field Erodibility Experiments 1987 & 1988. NSERL Report No. 3, National Soil Erosion Research Laboratory, West Lafayette, Indiana.

Green, W. H. and G. A. Ampt, 1911. Studies on Soil Physics: 1. Flow of Air and Water Through Soils. Journal Agric. Science 4:1-24.

Gupta, R. K., R. P. Rudra, W. T. Dickinson, N. . Patni, and G. J. Wall, 1993. Comparison of Saturated Hydraulic Conductivity Measured by Various Field Methods. Trans. ASAE 36(1):51-55.

Knisel, W. G., 1980. CREAMS: A Field Scale Model for Chemicals, Runoff, and Erosion from Agricultural Management Systems. U.S. Dept. of Agric, Conservation Research Report No. 26, U.S. Government Printing Office, Washington, D.C., 640 pp.

Lane, L. J. and M. Nearing (Editors), 1989. USDA Water Erosion Prediction Project: Hillslope Profile Model Documentation. NSERL Report No. 2, USDA-ARS, West Lafayette, Indiana.

Nash, J. E., and J. E. Sutcliffe, 1970. River Flow Forecasting Through Conceptual Models, Part1 – A Discussion of Principles. Journal Hydrol. 10(3):282-290.

Nearing, M. A. G. R. Foster, L. J. Lane, and S. C. Finkner, 1989. A Process Based Soil Erosion Model for USDA Water Erosion Prediction Project. Trans. ASAE 32(5):1587-1593.

Nearing, M. A., L. Deer-Ascough, and J. M. Laslen, 1990. Sensitivity Analysis of the WEPP Hillslope Profile Erosion Model. Trans. ASAE 33(3):839-849.

Nearing, M. A., B. Y. Liu, L. M. Risse, and X. Zhang, 1995. The Relationship Between Curve Numbers and Green and Ampt Effective Hydraulic Conductivities for Use in the WEPP Model 1995. Submitted to Trans. ASAE.

Rawls, W. J. and D. L. Brakensiek, 1983. A Procedure to Predict Green and Ampt Infiltration Parameters. Proc. of ASAE Conf. on Advances in Infiltration, Chicago, Illinois, pp.102-112.

Rawls, W. J. and D. L. Brakensiek, 1986. Comparison Between Green-Ampt and Curve Number Runoff Predictions. Trans. ASAE 29(6):1597-1599.

Rawls, W. J., D. L. Brakensiek, J. R. Simanton, and K. D. Kohl, 1990. Development of a Crust Factor for the Green Ampt Model. Trans. ASAE 33(4):1224-1228.

Risse, L. M.. 1994. Validation of WEPP Using Natural Runoff Plot Data. Unpublished Ph.D. Dissertation, National Soil Erosion Research Laboratory, Purdue University, West Lafayette, Indiana, p. 230.

Risse, L. M., M. A. Nearing, and X. C. Zhang, 1995. Variability in Green-Ampt Effective Hydraulic Conductivity Under Fallow Conditions. Accepted by Journal of Hydrology 12/94.

Skaggs, R. W. and R. Khaleel, 1982. Infiltration. In: Hydrologic Modeling of Small Watersheds, C. T. Haan, H. P. Johnson, and D. L. Brakensiek (Editors). Chapter 4, ASAE Monograph No. 5:121-166, St. Joseph, Michigan.

Sharpley, A. N. and J.R. Williams (Editors), 1990. EPIC - Erosion/ Productivity Impact Calculator: 1. Model Documentation. USDA Tech. Bulletin No. 1768.

United States Department of Agriculture, Soil Conservation Service (USDA/SCS), 1985. National Engineering Handbook, Section 4: Hydrology. U.S. Government Printing Office, Washington D.C.

Van der Zweep, R. A. 1992. Evaluation of the Water Erosion Prediction Project's Hydrologic Component on a Semi Arid Rangeland Watershed. Unpublished M.S. Thesis, University of Arizona, Tucson, Arizona.

Williams, J. R., A. D. Nicks, and J. G. Arnold, 1985. Simulator for Water Resources in Rural Basins. Journal Hydraulic Eng. 111:970-986.

Young, R. A., C. A. Onstad, D. Bosch, and W. P. Anderson, 1989.
AGNPS: A Nonpoint Source Model for Evaluating Agricultural Watersheds. Journal Soil and Water Conservation 44:169-173.

Zhang, X. C., M. . Nearing, and L. M. Risse, 1995. Green-Ampt Effective Hydraulic Conductivity Under Cropped Conditions. Submitted to Trans. ASAE.