Uncertainty Analysis of the WEPP Soil Erosion Model

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Abstract

Predictions from hydrologic and erosion models contain a large degree of uncertainty. The Modified Point Estimate Method (Harr, 1989) used in conjunction with a response surface exploration technique (Brooks, 1958) provides a simple, computationally efficient, and powerful tool for evaluating uncertainty of predictions by natural-resource models. The method allows analysis of models with a large number of input parameters which may be correlated and for which the exact input parameter distribution is unknown. The method was applied to the Water Erosion Prediction Project single rainfall-event erosion model. Sixty treatment combinations were selected to determine WEPP output uncertainties for a wide range of soil, crop, management, topographic, and storm conditions. The levels of the treatment combinations were randomly selected to span the entire factorial space of the 28 WEPP inputs, but with a finite number of treatment combinations. Five WEPP outputs were studied: peak runoff rate, average soil loss, average deposition, sediment yield, and sediment specific surface enrichment ratio. Maximum and average output uncertainties, given by the coefficient of variation, were determined for each output of the 60 treatments. Maximum coefficients of variation for peak runoff rate, soil loss, sediment yield, and sediment enrichment ratio were 196, 267, 323, and 47%, respectively. Average coefficients of variation for the same set of variables were 65, 99, 106, and 13%, respectively. Coefficient of variation was less for larger runoff and erosion events, which account for a large percentage of the total soil loss at a location over extended time periods. Significant, positive correlations existed between the coefficients of variation of peak runoff average soil loss, and average soil loss and sediment yield, indicating that the uncertainty in average soil loss and in sediment yield may be directly related to the uncertainty in peak runoff rate. **Keywords.** Erosion, Modeling, WEPP.

Introduction

The determination of prediction uncertainty for process-based natural resource models, such as the WEPP model, is an important step in model prediction reliability analyses (Beck, 1983). In this study, the Point Estimate Method (PEM) (Rosenblueth, 1975) as modified by Harr (1989) was used. The Point Estimate Method may be used on complex models with large numbers of input parameters where minimal distribution information is available. The PEM also accounts for correlation between input parameters.

Coefficients of variation for model outputs may vary greatly depending upon the input domain for individual model runs. It would be desirable, therefore, to identify the magnitudes and conditions under which the WEPP model yields the highest uncertainties (worst-case scenarios), as well as the average output uncertainty for a wide variety of modeling conditions. Brooks (1958) presented a surface exploration technique for identifying subregions (e.g., maxima) on multi-dimensional response surfaces. Using the Brooks surface exploration technique, one may estimate the number of treatment levels necessary to determine the desired proportion of the factor space where the responses are maximized.

Nearing et al. (1990) performed a linear sensitivity analysis of the WEPP erosion model. Traditional linear sensitivity analysis has several limitations (McCuen and Snyder, 1986), including: a) the linear analysis does not fully characterize non-linear response, b) the linear analysis is univariate, whereas sensitivity of the model to a variable is dependent upon the magnitude of other variables, and c) the traditional linear approach uses single-valued inputs, whereas inputs are actually random variables with distributions associated with them.

The objective of this study is to use the Modified Point Estimate Method and the Brooks surface exploration technique to evaluate prediction uncertainties for the WEPP erosion model. The analysis examines only the effects of random variation of input parameters and takes into account neither errors associated with internal, fixed model parameters nor the model's structural errors. Average and maximum uncertainties are reported for levels of input parameters which characterize a wide range of environmental conditions to which the model might be applied under cropland agricultural situations. The combination of methods introduced provides a powerful tool for evaluating uncertainties of estimates from complex, process-based natural resource models such as the WEPP erosion model.

Background

The WEPP Model

The WEPP model (Lane and Nearing, 1989) is the result of a joint effort of several U.S. federal agencies and

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universities to develop process-based, computer-driven soil erosion prediction technology. The WEPP model has been presented in detail elsewhere (Lane and Nearing, 1989; Nearing et al., 1989). An overview is given here.

The model conceptually has six components: climate generation, hydrology and runoff hydraulics, plant growth and residue decomposition, soils, erosion, and irrigation. The model can be used in either a continuous simulation mode or a single-event mode. This study dealt only with the event version, which encompasses primarily the hydrology and erosion components of WEPP. In the event version of the model, inputs for soil, storm, plant residue and canopy, and slope topography characterize conditions relative to a single rainfall event. The model predicts soil loss on the slope profile, sediment deposition on the profile, sediment yield from the end of the slope, runoff, and sediment enrichment ratio.

The hydrology component of the model (Hernandez et al., 1989) uses the Green and Ampt equation to calculate infiltration, and runoff routing is computed by the kinematic wave equation. The erosion subcomponent of the WEPP model is based on the steady-state mass balance sediment equation (Nearing et al., 1989). The equation incorporates source terms for the generation of sediment from interrill and rill areas. The rill term may be either positive or negative, depending upon whether net detachment or net deposition is active in the rill. Parameter estimation for the model is based on an extensive two-year field study of 36 cropland and 11 rangeland experimental sites across the continental United States. (Elliot et al., 1989).

The WEPP model predicts off-site rates of erosion, including sediment yield from the slope profile and sediment enrichment ratio, as well as on-site erosion rates, such as detachment and deposition rates. Enrichment ratio refers to the degree of enrichment in fines due to the preferential depositional process. The enrichment ratio is given by (Foster et al., 1989):

$$\mathrm{ENRATO} = SS_{sed} / SS_{soil} \tag{1}$$

where

ENRATO = enrichment ratio (unitless),
SS_{sed} = specific surface area of the sediment ($m^2\ g^{-1}$), and
SS_{soil} = specific surface area of the *in-situ* soil.

Model Output Uncertainty

Model output uncertainty comes from three sources: structural uncertainty, input uncertainty, and parameter uncertainty (Troutman, 1985; Vincens et al., 1975). Structural uncertainty arises from the inadequacy and the incompleteness of the model in representing the physical system being studied. Input uncertainty refers to the spatial and temporal variability of the input data, measurement errors, etc. Parameter uncertainty refers to the uncertainty associated with internal model parameters which are fixed and not usually adjusted by the user. This study does not address the issue of structural error or internal parameter error.

Model input parameters are random variables because of spatial and temporal variability and errors in measurement. Model outputs are also random variables because any variable which is a function of a random variable is itself a random variable (Haan, 1977).

The Point Estimate Method (Rosenblueth, 1975) requires that two discrete points be assigned to represent the variation about the mean of the input and output variables. An advantage of the Point Estimate Method is that exact descriptions of probability distributions are not necessary. Only variance of distributions are required in the analysis. A limitation of the Point Estimate Method is that the method estimates output expected values and variance, but not detailed information of the output distributions.

A complete description of the Point Estimate Method may be found elsewhere (Rosenblueth, 1975). A brief overview of the procedure is given here. For two correlated variables, the *Mth* moment of a dependent variable $y = y(x_1, x_2)$ is:

$$E\left(y^M\right) = p_{++}\, y_{++}^{\ M} + p_{+-}\, y_{+-}^{\ M} + p_{-+}\, y_{-+}^{\ M} + p_{--}\, y_{---}^{\ M} \tag{2}$$

where

$$y_{\pm\pm} = y\left(E[x_1] \pm s[x_1],\ E[x_2] \pm s[x_2]\right) \tag{3}$$

and

$$p_{++} = p_{--} = 1 + \rho / 2^n \tag{4}$$

and

$$p_{+-} = p_{-+} = 1 - \rho / 2^n \tag{5}$$

In the above equations p is the weighting factor which is a function of the correlation coefficient, ρ, between x_1 and x_2. The exponent, n, in the denominator of equations 4 and 5 represents the number of input variables, which is two for the bivariate case in the above example. The symbols E and s represent expected values and standard deviations, respectively.

For M = 1 in equation 2, the expected value E(y) (or first moment) of the distribution of the dependent variable is obtained. For M = 2, $E(y^2)$, or the second moment, is attained, and the variance of y is simply:

$$s^2[(y)] = E\left[\left(y^2\right)\right] - \left(E[y]\right)^2 . \tag{6}$$

Except for univariate cases, the above method does not account for skewness, because the number of unknowns would exceed the number of known relationships. Therefore, in using Rosenblueth's (1975) method one implicitly assumes symmetrical distributions for multivariate cases. Dissymmetry can be incorporated into the Point Estimate Method using a third point to characterize distributions (Bolle, 1988). That method, however, requires the assumption that all input distributions have the same skewness coefficient, which is unlikely in most cases.

Since the number of factors required for the Point Estimate method increases exponentially (2^n) with the number of input variables, n, the number of weighting factors gets exceedingly high when n becomes large. With 30 correlated variables, for example, the number of factors, and hence model executions, required is greater than 10 .

Recognizing that limitation, Harr (1989) proposed a modification to Rosenblueth's (1975) method, which consisted of transposing all correlated input distributions to the eigen-space. In the transposed coordinate system, the correlated input variables become mutually independent, which reduces the number of factors in the analysis to 2n, instead of 2^n, as in the original Point Estimate Method. Harr (1989) compared the two methods and showed that the Modified Point Estimate Method closely approximated Rosenblueth's (1975) original procedure for both linear and non-linear transfer functions. The reader is referred to Harr (1989) for a full discussion of the Modified Point Estimate Method.

The assumption of symmetry for input and output distributions in the Point Estimate method will limit its application if precise definition of the form of the output distribution is desired and if precise definition of the input distribution is available. In many, and perhaps most, cases in natural resource modeling applications, the form of the input parameter distribution is unknown or very poorly defined. In those cases the use of a method such as Monte Carlo, which uses that information, is not necessary. Assumption of symmetry in those cases is standard procedure, even when the Monte Carlo method is used.

METHODS

The single-storm version (Version 90.1, Lane and Nearing, 1989) of the WEPP model was used in the study to avoid non-stationary problems with the parameters such as would occur with the continuous simulation version. The WEPP outputs used in the study were selected according to their relevance to prediction schemes. The outputs are described in Table 1. Model inputs for the single-event WEPP model are listed in Table 2. Because the input variables KR, SHCRIT, ORGMAT, KI, and DAYDIS do not enter in the computation of the output PEAKRO, those inputs were not used in the uncertainty analysis for PEAKRO. A separate analysis for PEAKRO was conducted.

The input data used in the simulation experiment were divided into four groups: soil data, crop-management data, storm data, and topography data. The soil and crop-management data corresponded to actual plot data, and the measurement and spatial variability within the plots was assumed to be the source of uncertainty in the soil and crop-management inputs. The storm and topography data, on the other hand, were synthetic, and the uncertainties associated with them were assumed to be only due to measurement errors.

TABLE 1. WEPP output variables used in the uncertainty study

Output	Description (Unit)
PEAKRO	Peak runoff rate on the profile (mm h^{-1})
AVSLOS	Average soil detachment rate on the portion of the profile experiencing net soil loss (kg m^{-2})
AVDEP	Average soil deposition on the portion of the profile experiencing net deposition (kg m^{-2})
AVLOST	Average sediment yield leaving the profile per unit width of field boundary (kg m^{-2})
ENRATO	Sediment specific surface area enrichment ratio (unitless)

TABLE 2. WEPP single-storm model input variable descriptions

#	Variable Name (Unit)	Description
1	SAT (unitless)	Initial soil saturation level
2	KR (s m^{-1})	Rill soil erodibility parameter
3	SHCRIT (Pa)	Soil critical shear stress parameter
4	BD (g cm^{-3})	Soil bulk density
5	SSC (mm h^{-1})	Soil hydraulic conductivity
6	THETDR (unitless)	15-bar soil moisture content
7	SAND (%)	Sand content of soil
8	CLAY (%)	Clay sontent of soil
9	ORGMAT (%)	Organic matter content of soil
10	CEC (me 100 g^{-1})	Soil cation exchange capacity
11	RFG (%)	Rock fragment content of soil
12	CANCOV (unitless)	Plant canopy cover
13	INRCOV (unitless)	Interrill ground residue cover
14	RILCOV (unitless)	Rill ground residue cover
15	KI (kg s m^{-4})	Interrill soil erodibility parameter
16	XDEL1 (m)	Slope length of upslope segment
17	XSLP1 (unitless)	Slope grade of upslope segment
18	XDEL2 (m)	Slope length of middle slope segment
19	XSLP2 (unitless)	Slope grade of middle slope segment
20	XDEL3 (m)	Slope length of downslope segment
21	XSLP3 (unitless)	Slope grade of downslope segment
22	RAIN (mm)	Precipitation amount
23	STMDUR (h)	Duration of precipitation
24	TIMEP (unitless)	Ratio time to peak/duration of rainfall
25	IP (unitless)	Ratio max. intensity/average rainfall intensity
26	RRINIT (m)	Initial soil random roughness
27	RFCUM (mm)	Cumulative rainfall since last tillage
28	DAYDIS (days)	Days since last disturbance by tillage

In order to evaluate output coefficients of variation for typical but distinct situations, the data corresponding to three soils, two plant types, three tillage practices, and three crop stages were selected.

The soils chosen were: 1) Miami silt loam (fine-silty, mixed, mesic, typic Hapludalf); 2) Cecil sandy-loam (fine-loamy, mixed, mesic typic Kanhapludult); and 3) Heiden clay (fine, montmorillonitic, thermic, udic Chromusturt). These soils present distinct textural, chemical, and mineralogical properties, and occur in three diverse regions of the United States (Indiana, Georgia, and Texas, respectively).

The soil data were subdivided into basic soil-property and erodibility data. The basic soil-property data corresponded to the textural, physical, and chemical data collected and analyzed by the USDA-Soil Conservation Service (1989a, b, c). The erodibility data consisted of the erodibility parameters, hydraulic conductivity, and bulk density data, collected by Elliot et al. (1989). Although the basic soil property and the erodibility data were collected from the same field, they were not all gathered within the same experimental unit, and therefore the correlation between them was unobtainable. Only the data within each unit could be analyzed for correlation.

The two plant types selected were corn (*Zea mays*), and soybeans (*Glycine max*). These two crops were chosen because of their wide distribution and because of their distinctive crop canopies and residue biomass covers. The tillage practices for the simulation experiment were conventional tillage (CT), chisel plowing (CP), and no-till (NT). These practices are commonly used in the United States, and they result in differing amounts of residue left on the surface, surface random roughness, and state of soil consolidation.

The plant-canopy and residue data used in the simulation experiment were those of E. E. Alberts (personal communication, 1989). These data consisted of canopy and ground-cover data from corn and soybeans plots at three different crop stages, namely, 30, 50, and 65 days after planting. Those stages corresponded to an average of 5.4, 58.2, and 78.4% of canopy cover for corn, and an average of 9.7, 55.6, and 88.8% of canopy cover for soybeans, respectively. The three crop stages are representative of the canopy cover range found in the field.

The topographic data used in the experiment corresponded to typical S-shaped slope profiles with four levels of slope lengths (XDEL) and three levels of slope grades (XSLP) for each slope segment. Because the data for the precipitation and topographic inputs were synthetic, and because their uncertainties were assumed to be due to measurement errors only, those inputs were assumed to be independent.

In order to obtain a finite number of treatment combinations that would reasonably represent the wide factor space, spanned by the 28 WEPP inputs (23 for PEAKRO) and their levels, a surface exploration method procedure, the Random Method (Brooks, 1958) was used. In that method, the number of trials (treatment combinations) required so that the experimenter has a probability, S, of finding at least one treatment combination which would fall in the optimum subregion, a, of the factor space which maximizes the response is (Brooks, 1958):

$$n = \log(1 - S) / \log(1 - a) \tag{7}$$

For a probability S = 95%, and a proportion a = 5% of the total factor space, equation 7 yields n = 60 treatment combinations, which was the number used in this study.

Since Brook's method is used to randomly select treatment combinations that span the whole factor space, the mean of the responses of the selected treatment combinations is an unbiased estimator of the true response surface mean. Therefore, the random method was used to estimate the means as well as coefficients of variation of the WEPP predictions for the modeling conditions studied.

The procedure for randomly selecting the treatment combinations for the simulation experiment was as follows. A random number generator (Press et al., 1988) was used to randomly generate the levels of model inputs (in the case of the synthetic data), and the levels of the class variables (in the case of the soil and crop-management data). If soil 1 (Miami) was selected, for example, all basic soil property and erodibility data would be nested with that soil. Similarly, if soybeans were chosen as the crop type, conventional tillage was chosen as the tillage practice, and 1 July was selected as the crop stage, then all the crop-management data would be nested with those crop and tillage types. In the case of the synthetic data (topographic and storm data) the levels were selected directly from the random sampling procedure.

Sixty trials were required by the Random method for the specified probability levels, therefore, 60 randomly selected treatment combinations were generated and used in the uncertainty analysis study.

Uncertainty Analysis

The Modified Point Estimate Method (Harr, 1989) was coded in FORTRAN according to the input and output specifications of the WEPP model. The discussion about the generation of stochastic inputs for WEPP, and the computation of the expected values and coefficients of variation for the model outputs, was given in detail by Chaves (1990). Because the Modified Point Estimate Method required 2 × 28 point estimates (2 × 23 for the output PEAKRO) for each treatment combination, and because 60 treatment combinations were assigned by the Random method for the specified probability levels, a total of 3,360 simulations (2,760 for PEAKRO) were run, using the WEPP model as the transfer function.

Results and Discussion

The maximum coefficients of variation of the WEPP outputs for the range of conditions studied are given in Table 3. Although the results in Table 3 represent only worst-case scenarios for the conditions studied, the uncertainty propagation was severe for all model outputs, except ENRATO, when compared to the overall average uncertainty for the model inputs. The average coefficient of variation for the 28 input parameters for all the conditions considered was 21%.

Average indices of model output reliability were calculated for all sixty treatment combinations (Table 4). The average coefficients of variation in Table 4 are arithmetic means of the coefficients of variation in all 60 simulations. The expected values in Table 4 are the average of the expected values in the 60 trials.

The results of Table 4 indicate that the average output uncertainty for all treatment combinations was about one third of the maximum output uncertainties (Table 3). The results in Table 4 also indicate that the error propagation was significant for each of the model outputs except ENRATO. The average uncertainty associated with the output PEAKRO, for example, was three times higher than the overall average coefficient of variation of the model inputs (21%). The average coefficients of variation of the outputs AVSLOS, AVDEP, and AVLOST were almost five-fold the average input coefficient of variations. An important point, which is discussed in more detail below, is

TABLE 3. Maximum coefficients of variation for the WEPP outputs with the corresponding expected values (correlated case)

	PEAKRO ($mm\,h^{-1}$)	AVSLOS ($kg\,m^{-2}$)	AVDEP ($kg\,m^{-2}$)	AVLOST ($kg\,m^{-1}$)	ENRATO
E[ ]	21.36	0.13	0.03	8.06	1.63
CV[ ](%)	196.05	267.08	320.37	323.41	47.26

TABLE 4. Average coefficients of variation for the WEPP outputs with the averages of the expected values (correlated case)

	PEAKRO ($mm\,h^{-1}$)	AVSLOS ($kg\,m^{-2}$)	AVDEP ($kg\,m^{-2}$)	AVLOST ($kg\,m^{-2}$)	ENRATO
E[ ]	122.78	1.41	0.87	153.96	1.11
CV[ ](%)	64.58	98.91	105.66	106.60	12.87

TABLE 5. Average coefficients of variation for the WEPP outputs with the averages of the expected values (independent case)

	PEAKRO ($mm\,h^{-1}$)	AVSLOS ($kg\,m^{-2}$)	AVDEP ($kg\,m^{-2}$)	AVLOST ($kg\,m^{-1}$)	ENRATO
E[ ]	121.11	1.43	0.89	155.70	1.12
CV[ ](%)	65.10	87.10	110.77	101.09	12.64

that the maximum coefficients of variation (Table 3) were all (except ENRATO) associated with low expected values.

The results in Tables 3 and 4 indicate that the maximum and average output uncertainties increased from the output PEAKRO through the output AVLOST. Interestingly, that is also the sequence of processes in the WEPP model, namely, soil detachment (AVSLOS) is driven by runoff, deposition (AVDEP) uses sediment load and runoff rate as inputs, and sediment yield (AVLOST) depends on both soil detachment and deposition rates. Therefore, the increase in uncertainty from PEAKRO to AVLOST was possibly caused by the interdependence between the WEPP outputs.

The effect of input correlation on the average output uncertainty was examined by carrying the uncertainty propagation analysis in the same 60 treatment combinations assuming complete independence between the model inputs, but keeping the same means and coefficients of variation used in the correlated (actual) case. The average coefficients of variation for the five model outputs, with the average means, are given in Table 5 for the independent case.

Neglecting correlation between inputs did not greatly affect the means and the coefficients of variation of the WEPP outputs for the conditions studied. In the absence of input correlation, the average output uncertainty increased by 0.8 and 4.8% for PEAKRO and AVDEP, and decreased by 13.5, 5.5, and 1.9%, for the outputs AVSLOS, AVLOST, and ENRATO, respectively. The above results suggest that, on the average, no significant synergetic (variance increase) or antithetic (variance reduction) effects due to input correlation occurred for the conditions studied. However, significant positive or negative correlations between inputs on a particular treatment combination might have caused the coefficient of variation to change significantly in some particular runs.

In order to examine model output uncertainty over the entire range of output means, the coefficients of variation of the WEPP model outputs were plotted against their respective expected values. The plots corresponding to the outputs PEAKRO, AVSLOS, AVDEP, AVLOST, and ENRATO are given by figures 1 through 5, respectively.

Coefficient of variation of PEAKRO increased exponentially as the expected value in PEAKRO decreased (fig. 1). There are, however, a few points in the lower-left side of figure 1, indicating that some of the low-valued means had low uncertainties. Similar trends were apparent in figures 2, 3, and 4. Figures 1 through 5 were made recognizing that plots of the coefficient of variation versus the expected value can lead to spurious correlation (Kenney, 1982) and therefore should not be used for correlation purposes. However, figures 1-5 do show the behavior of the output coefficient of variation, and hence the relative prediction uncertainty in the entire range of the expected values.

Coefficients of variation were least for simulated events which had high mean values. A large percentage of erosion

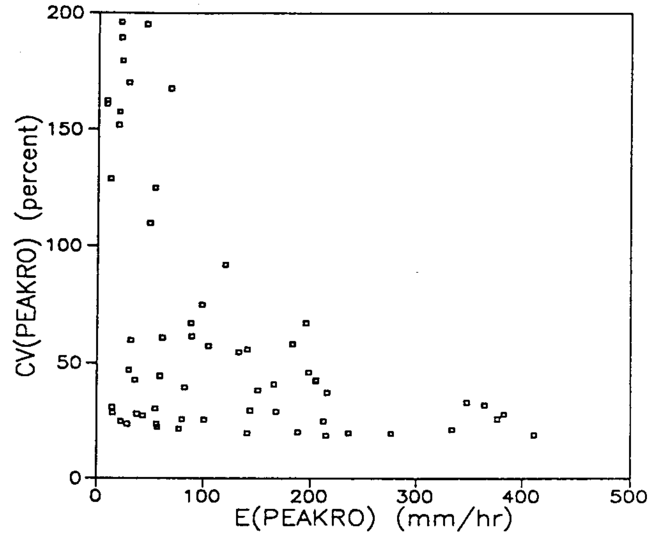

Figure 1–Coefficient of variation of peak runoff, PEAKRO, vs. the expected value of PEAKRO.

occurs over a small percentage of higher magnitude rainfall events (Wischmeier, 1962; Thomas and Snyder, 1986). Thus, the result that coefficients of variations were lower for the events of greater magnitude of erosion is favorable in terms of calculating accurate erosion estimates based on long-term simulations. The single-event WEPP model is used as a basis for the continuous simulation version of WEPP. Estimates of long-term averages of erosion will be affected much more by the larger events, which have lower prediction uncertainties, than by the smaller events, which have the greater uncertainties.

The points with high coefficients of variation (CV > 100%) in figures 1-4 show common behaviors, namely, their stochastic realizations (y_j) systematically had both zero and non-zero values for certain treatment combinations with low-valued means. On the other hand, the low-valued outputs that yielded low coefficients of

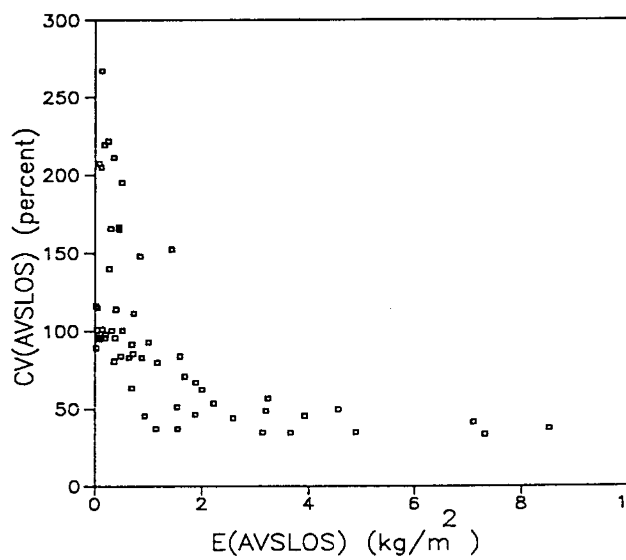

Figure 2–Coefficient of variation of average soil loss on the portions of the profile experiencing net soil loss, AVSLOS, vs. the expected value of AVSLOS.

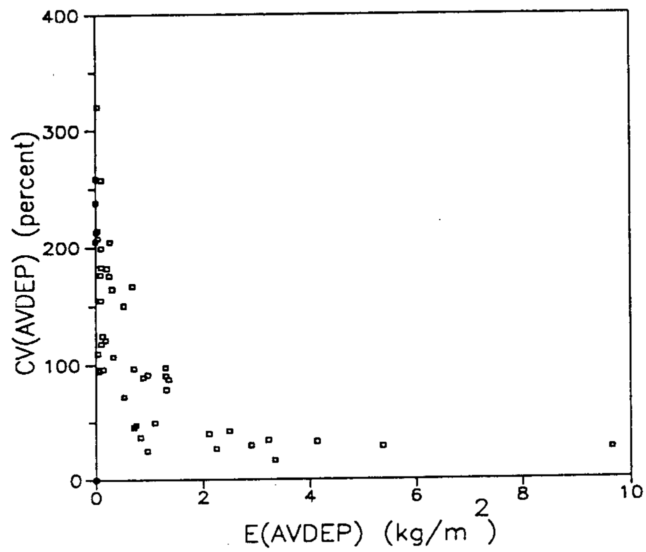

Figure 3–Coefficient of variation of average deposition on the portions of the profile experiencing deposition, AVDEP, vs. the expected value of AVDEP.

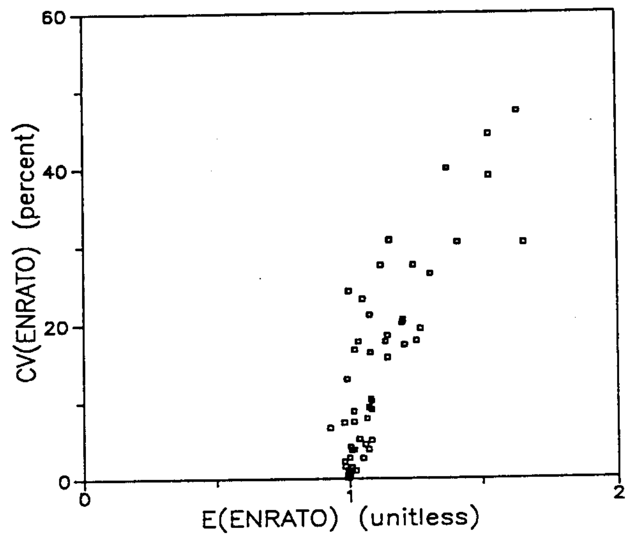

Figure 5–Coefficient of variation of sediment enrichment ratio, ENRATO, vs. the expected value of ENRATO.

variation, as given by the points in the lower-left corners of figures 1-4, had non-zero stochastic realizations. If one of the point estimates of an output y is zero, the output variance will diverge with respect to the expected value.

Although those divergences were due to the fact that a discrete, rather than a continuous uncertainty propagation method was used, the generation of alternating zero and non-zero values for some of the treatment combinations were due to a combination of particular covariance structures and the boolean (stepwise) nature of the WEPP model. The WEPP model is boolean in that computation of non-zero runoff, soil detachment, and deposition occur only after certain threshold conditions are attained. Were it not for those treatments which generated both zero and non-zero point estimates and which produced very high output uncertainty as a result, the average coefficients of variation for the outputs PEAKRO, AVSLOS, AVDEP, and AVLOST would have been significantly lower. It is likely that in those intervals of low expected values and high coefficients of variation that an alternate method of computing output variance could yield more accurate coefficients of variation than does the Point Estimate Method.

Trends found in figures 1 through 4 suggest that the coefficients of variation of the outputs AVSLOS and AVLOST depended on the uncertainty associated with PEAKRO. In order to examine a possible relationship between those output variables, graphs were plotted. Figure 6 is the plot of the coefficient or variation in the soil loss estimate (AVSLOS) versus the coefficient of variation of peak runoff rate (PEAKRO).

A significant, positive correlation ($r = 0.86$) was found between CV(AVSLOS) and CV(PEAKRO) (fig. 6). A high correlation ($r = 0.97$) was also found between CV(AVLOST) and CV(AVSLOS) (fig. 7). The plot of CV(AVLOST) versus CV(AVDEP), however, did not

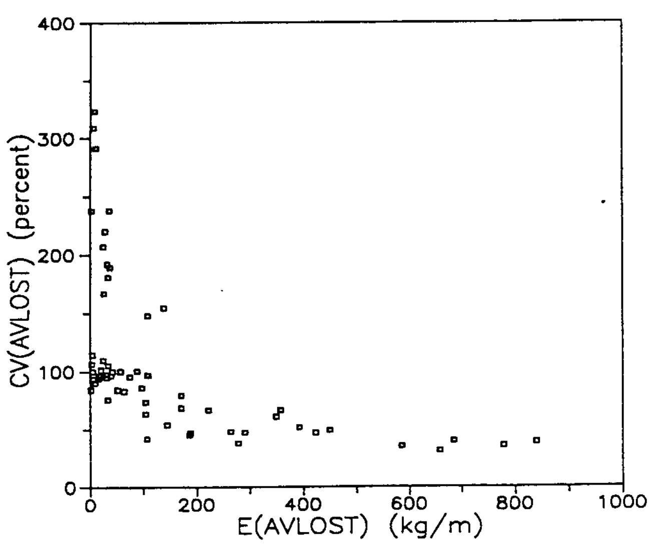

Figure 4–Coefficient of variation of sediment yield, AVLOST, vs. the expected value of AVLOST.

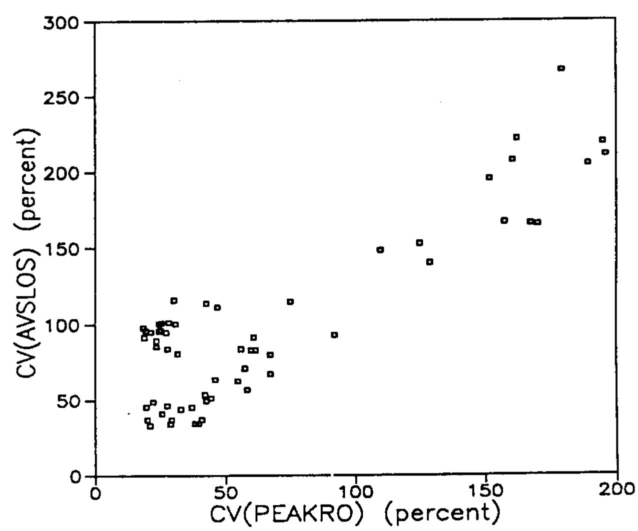

Figure 6–Coefficient of variation of average soil loss on the portions of the profile experiencing net soil loss, AVSLOS, vs. the coefficient of variation of peak runoff, PEAKRO.

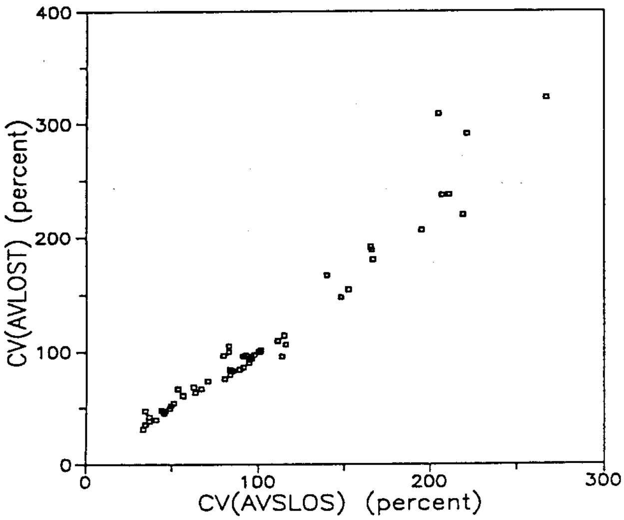

Figure 7–Coefficient of variation of sediment yield, AVLOST, vs. the coefficient of variation of average soil loss on the portions of the profile experiencing net soil loss, AVSLOS.

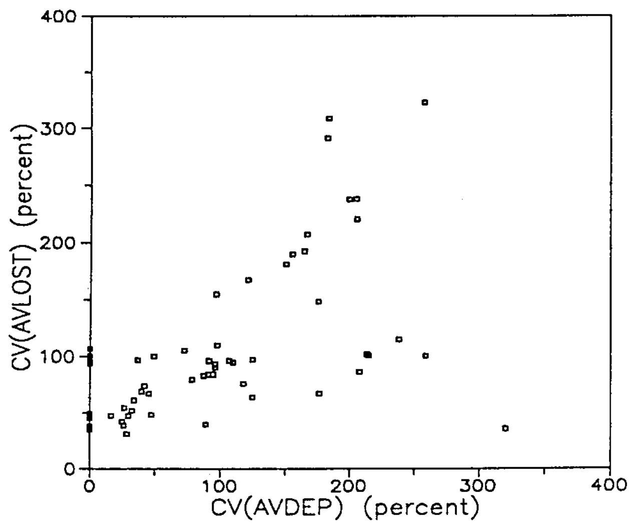

Figure 8–Coefficient of variation of sediment yield, AVLOST, vs. the coefficient of variation of average deposition on the portions of the profile experiencing deposition, AVDEP.

exhibit a strong correlation (fig. 8), although the trend was positive. It seems that the uncertainty in sediment yield (AVLOST) is related largely to the uncertainty in soil loss (AVSLOS) rather than to average deposition rate (AVDEP) for the range of conditions studied.

Trends found in figures 6-8 suggested that the uncertainty in the outputs AVSLOS, AVLOST, and perhaps AVDEP, were directly (in the case of AVSLOS) or indirectly (in the case of AVLOST and AVDEP) controlled by the uncertainty in PEAKRO. Since the peak runoff rate is a driving mechanism for soil detachment, and since amount of deposition and sediment yield are directly dependent upon amount of detachment, the relations found between the coefficients of variation of the outputs PEAKRO and AVSLOS, AVSLOS and AVLOST, and AVSLOS and AVDEP were not surprising.

REFERENCES

Beck, M.B. 1983. A procedure for modeling. In *Mathematical Modeling of Water Quality: Streams, Lakes, and Reservoirs*, 11-41, ed., G.T. Orlob. New York: John Wiley & Sons.

Bolle, A. 1988. Approche probabiliste en mecanique de sols avec i compte la variabilité spatiale. Ph.D. diss., Ecole Polytechnique de Lausanne, Switzerland.

Brooks, S.H. 1958. A discussion of random methods for seeking maxima. *Operations Research* 6(2):244-251.

Chaves, H.M.L. 1990. Uncertainty analysis of a steady-state erosion model. Ph.D. diss., Purdue University, West Lafayette, IN.

Elliot, W.J., A.M. Liebenow, J.M. Laflen and K.D. Kohl. 1989. *A Compendium of Soil Erodibility Data from WEPP Cropland Soil Field Erodibility Experiments: 1987 and 1988*. NSERL Report No. 3. West Lafayette, IN: USDA-ARS National Soil Erosion Research Laboratory.

Foster, G.R., L.J. Lane, M.A. Nearing, S.C. Finkner and D.C. Flanagan. 1989. Erosion component. In *USDA - Water Erosion Prediction Project: Hillslope Profile Model Documentation*. NSERL Report No. 2, Ch. 10, eds. L. J. Lane and M. A. Nearing. West Lafayette, IN: USDA-ARS National Soil Erosion Research Laboratory.

Haan, C.T. 1977. *Statistical Hydrology*. Ames: Iowa State Univ. Press.

Harr, M.E. 1989. Probabilistic estimates for multivariate analyses. *Appl. Math. Modelling* 13:976-981.

Kenney, B.C. 1982. Beware of spurious self-correlations! *Water Resour. Res.* 18(4):1041-1048.

NSERL. 1989. *USDA - Water Erosion Prediction Project: Hillslope Profile Model Documentation*. NSERL Report No. 2, eds. L. J. Lane and M. A. Nearing. West Lafayette, IN: USDA-ARS National Soil Erosion Research Laboratory.

McCuen, R.H. and W.M. Snyder. 1986. *Hydrologic Modeling: Statistical Methods and Applications*. Englewood Cliffs, NJ: Prentice-Hall.

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 technology. *Transaction of the ASAE* 32(5):1587-1593.

Nearing, M.A., L. Deer-Ascough and J.M. Laflen. 1990. Sensitivity analysis of the WEPP hillslope profile erosion model. *Transactions of the ASAE* 33(3): 839-849.

Press, W.H., B.P. Flannery, S.A. Teukolsky and W.T. 1988. Vetterling. *Numerical Recipes – The Art of Scientific Computing*. Cambridge, UK: Cambridge Press.

Rosenblueth, E. 1975. Point Estimates for Probability Moments. *Proc. Nat. Acad. Sci.* (USA) 72(10):3812-3814.

Thomas, A.W. and W.M. Snyder. 1986. Stochastic impacts of farming: I. Simulation of seasonal variation of climatic risk. *Transactions of the ASAE* 29(5):1738-1743.

Troutman, B.M. 1985. Errors and Parameter Estimation in Precipitation-Runoff Modeling – I Theory. *Water Resour. Res.* 21(8):1195-1213.

USDA-Soil Conservation Service. 1989a. Water erosion prediction project soil characterization data, 1987 and 1988. Sites in Indiana, Maryland, New York, Maine, and Ohio. Lincoln, NE: SCS-National Soil Survey Laboratory.

USDA-Soil Conservation Service. 1989b. Water erosion prediction project soil characterization data, 1987 and 1988. Sites in North Carolina, Georgia, and Mississippi. Lincoln, NE: SCS-National Soil Survey Laboratory.

USDA-Soil Conservation Service. 1989c. Water erosion prediction project soil characterization data, 1987 and 1988. Sites in Oklahoma and Texas. Lincoln, NE: SCS-National Soil Survey Laboratory.

Vincens, G.J., I. Rodriguez-Iturbe and J.C. Shaake. 1975. A Bayesian framework for the use of regional information in hydrology. *Water Resour. Res.* 11(3):405-414.

Wischmeier, W.H. 1962. Storms and soil conservation. *J. Soil and Water Conservation* 17:(2)55-59.