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Statistical Distributions of Soil Loss from Runoff Plots and WEPP Model Simulations

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ABSTRACT

Soil conservation measures may be better designed with the knowledge of daily distributions of erosion. Collecting reliable data to determine daily erosion distributions is costly; however, new process-based soil erosion models have the potential to simulate extended records. The objectives of this study were to analyze frequency distributions of measured daily soil loss values and to determine if the Water Erosion Prediction Project (WEPP) model accurately reproduced statistical distributions of the measured daily erosion series. A Log-Pearson Type III (LP III) distribution was fitted to measured and WEPP-predicted soil loss values from six sites for periods ranging from 6 to 10 yr. Cumulative soil loss as a function of storm recurrence interval was used to show the relative contributions of large and small storms to total soil loss at each site. Results showed that both measured and predicted frequency curves fell within the 95% confidence range of the LP III distributions. This was true both using weather data from the site for the period of monitoring as well as when using synthetic weather series generated with the CLIGEN model. Thus the results were encouraging in terms of using WEPP in conjunction with CLIGEN to generate long-term daily soil loss frequency distributions, which can contribute toward alleviating the problem of having only a short monitoring period for measured erosion. Cumulative soil loss results indicated that large storms contributed a major portion of the erosion under conditions where cover was high, but not necessarily under conditions of low cover.

LAND USE and land management decisions relative to soil erosion have been most often based on average annual soil loss. This has been primarily due to the fact that existing erosion prediction models were not designed to estimate erosion on an event or daily basis. However, the frequency distribution of daily soil loss values can give additional information for aiding land management decisions, such as the amount of daily soil loss for a given return period or the frequency of a daily soil loss value that is of practical importance. For example, the frequency of the days during which an impoundment is partially or totally filled is critical for the design and maintenance strategy of that impoundment. Analyses of frequency curves allow us to estimate how much of the total soil loss at a site is caused by frequent, small events compared with rare, large events. Such information is important in order to design optimum management practices and to determine the impacts of the sediment delivery to downstream hydraulic structures or water bodies. While frequent but small erosion events may not be so important for the water quality of a receiving water body because of the lower concentrations associated with them, they need to be taken into account for a hydraulic structure such as a low-grade channel or a detention pond that would fill up regularly.

When little or no erosion data exist at a site, the WEPP model (Flanagan and Nearing, 1995) can be used to obtain long series of daily soil loss values from which the frequency distributions can be obtained. Prior to the development of the WEPP model, others attempted to estimate the frequency of event soil loss using the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978). Istok and Boersma (1986) computed the joint frequency distribution of two events to estimate the frequency of specific climate conditions that result in high erosion rates, such as rainfall on a frozen soil surface or on a melting layer of snow. This method was used because there are often not enough erosion data to directly calculate the frequency of large erosion events, whereas precipitation and temperature data are commonly available. A similar conceptual approach was used in a study by Mills et al. (1986) to estimate soil loss probabilities. Probability distributions were calculated for the SCS runoff curve number and the USLE cover and management (C) and support and practice (P) factors. Those distributions were then used jointly to calculate probability distributions of soil loss using the modified universal soil loss equation (MUSLE) as given by Williams and Berndt (1977). Others proposed to introduce a stochastic component due to the seasonal variability of climatic variables in the estimation of soil loss using the USLE, which resulted in a stochastic representation of soil loss (Snyder and Thomas, 1987; Thomas et al., 1988; Hession et al., 1996). This allowed decisions based on a probabilistic estimate of annual soil loss associated with a known risk.

An inherent problem in prior analyses is the use of the USLE as a basis of erosion prediction. The USLE was not designed to be used as an event model, and in fact is designed specifically to average out variability (Wischmeier and Smith, 1978). It is not apparent that the analyses based on USLE and MUSLE will represent the natural variability in system characteristics or the interactions between climate, soil consolidation, tillage, crop cover, residue, roots, soil moisture, and the myriad of other dynamic factors that cause erosion variability. With a continuous simulation, event-based, erosion model such as WEPP, it may now be possible to generate long series of event-based erosion predictions using representative precipitation and temperature data, soil characteristics, topography, and management practices. If WEPP accurately reproduces daily soil loss distributions, the long-term erosion rates and the frequency of various magnitudes of erosion events can be calculated.

The objectives of this study were to determine and analyze the frequency distributions of daily soil loss at different sites and to determine whether the WEPP model could duplicate the empirical distributions using both measured and generated weather sequences. To achieve this goal, we first studied the frequency distribu-

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tions of measured soil loss values on six sites for periods ranging from 6 to 10 yr. A theoretical distribution was fitted to each empirical distribution. The data were then compared with the distributions of soil loss values predicted with the WEPP model during the same periods. The possibility of calibrating the WEPP soil parameters by comparison of the frequency distributions of measured and predicted soil loss was investigated. In order to obtain better estimates of the frequency of extreme events, we used the CLIGEN weather generator (Nicks et al., 1995) to generate long series of soil loss values. Finally, we developed an analysis for calculating the fraction of total soil loss caused by events within different frequency ranges, along with results for the study sites.

MATERIALS AND METHODS

Overview

Daily soil loss data were analyzed in terms of recurrence interval. The WEPP model results were calibrated to the measured results by use of 95% confidence limits of a theoretical distribution (the LP III). We calibrated by adjusting the WEPP soil erodibility parameters so that all predicted data points lay within the 95% confidence bands of the LP III distributions, which were derived from the measured data. The CLIGEN model was used to generate synthetic weather inputs for WEPP, and the resulting predicted soil losses were compared in the same manner as was done with the WEPP predictions using the measured weather data. Percentage contributions to total soil loss from five categories of return period daily values were calculated for each of the data sets.

Data

Data for this study were obtained from the US National Repository of Soil Loss Data located at the USDA-ARS National Soil Erosion Research Laboratory in West Lafayette, IN. The data were collected on natural rainfall and runoff plots from various locations. Several sites located in the eastern USA were selected for study based on length of records, the number of events recorded, and the uniformity of the management practices (Table 1). The longest period of record that had a consistent management practice was identified and used for each data set. For all sites, winter and summer events had different statistical properties, which resulted in a nonhomogeneous sample on a monthly basis; e.g., the events occurring from November through April for example did not have the same characteristics as events occurring from May through October for the Holly Springs, MS, data (Table 1). The homogeneity of the sample was necessary to ensure that recurrence intervals were correctly estimated. For example, if erosion was lower during winter than during summer, a high-erosion winter event might be quite rare. If summer and winter events were studied together, the soil loss for such an event would likely be exceeded by soil loss values of summer events. Consequently, the recurrence interval of that event would not reflect its rarity during a winter period. The Mann–Whitney test (Bobée and Ashkar, 1991) was used to obtain homogeneous samples (Table 1).

Plotting of Probability Distributions

As an alternative to event frequency, we used the event recurrence interval, i.e., return period. This method allowed easy comparison between different sites and management practices without needing to refer to the number of events. The recurrence interval T_x is related to the frequency with which the soil loss (SL) exceeds the value X, $P(\mathrm{SL} \geq X)$, the number of years of data, Nyears, and the total number of events within that period, Nevent:

$$T_x = \frac{\mathrm{Nyears}}{\mathrm{Nevent}\ P(\mathrm{SL} \geq X)} \qquad [1]$$

To calculate the frequency of exceedance, daily soil loss values were ranked in increasing order. The empirical frequency for the kth event was calculated with the Cunnane formula (Cunnane, 1978):

$$P_k = 1 - \frac{k - 0.4}{N + 0.2} \qquad [2]$$

where P_k is the empirical frequency of exceedance of the kth event and N is the total number of events during the period. The P_k term was then used in place of $P(\mathrm{SL} \geq X)$ in Eq. [1].

Fitting of Probability Distributions

For each site, empirical probability distributions were plotted and a theoretical probability distribution was fitted to the empirical curve using the Hydrological Flood Analysis (HFA) software (Bobée and Ashkar, 1991). This program, originally designed for the study of extreme floods and other variables in water resources management, offers various distributions such as the Pearson III or the LP III, and distributions from the Generalized Gamma group. For each choice of a distribution, several methods for estimating its parameters are available. All events, including those with very small soil loss, were considered to plot empirical distributions and to fit theoretical ones. Although each small daily soil loss value does not contribute greatly to the long-term total soil loss at a site, the

Table 1. Characteristics of the data used in the study.

Site	Cropping	Soil	Soil taxonomy	Replicates	Years	Range of years	Homogeneous period	Annual rainfall
				no.	no.			mm
Bethany, NY	fallow	Shelby silt loam	fine-loamy, mixed, mesic Typic Argiudoll	1	10	1931–1940	May–August	841
Madison, SD	fallow	Egan silty clay loam	fine-silty, mixed, mesic Udic Hapludoll	2	6	1962–1970	May–August	544
Madison, SD	corn, moldboard plowed	Egan silty clay loam	fine-silty, mixed, mesic Udic Hapludoll	3	6	1962–1970	April–August	544
Madison, SD	corn, mulched	Egan silty clay loam	fine-silty, mixed, mesic Udic Hapludoll	3	6	1962–1970	April–August	544
Holly Springs, MS	fallow	Loring silt loam	fine-silty, mixed, thermic Typic Fragiudalf	2	6	1963–1968	May–October	1276
Morris, MN	fallow	Barnes loam	fine-loamy, mixed Udic Haploboroll	2	6	1962–1971	April–September	591

cumulative effects of all small events may indeed be substantial.

Goodness-of-fit was determined using criteria as suggested by Bobée and Ashkar (1991) for hydrologic data in general. We considered the fit to be acceptable if all of the measured data points fell within the 95% confidence interval of the fitted distribution. The LP III distribution was found acceptable for all of the measured data sets using this criterion. Different methods of estimating parameters for the theoretical distribution were possible with the program used (Bobée and Ashkar, 1991). In choosing a fitting method for each data set, special consideration was given to the fitting for high recurrence intervals: if several estimation methods produced similar results, the distribution that yielded the smallest 95% confidence interval for high return periods was selected.

The WEPP Model and Parameters

The WEPP model is a continuous simulation model for predicting daily soil loss and deposition due to rainfall, snowmelt, and irrigation. Input parameters include daily rainfall or snowmelt amounts and intensity, and parameters that describe the soil textural characteristics and erodibility, the plant growth and residue decomposition, the management practices, and the topography. Among the parameters for erosion prediction, some are updated on a daily basis: ground cover, plant growth, residue tracking, soil surface sealing, soil surface roughness, soil moisture content, canopy cover characteristics (Flanagan and Nearing, 1995). Others are user specified: baseline hydraulic conductivity, rill and interrill erodibilities, and critical shear stress.

The WEPP simulations for this study were based on soil, slope, management, and climate files prepared by Risse et al. (1995a,b) and Zhang et al. (1996). Erodibilities and critical shear stress values were estimated with the WEPP prediction equations given in the WEPP user's manual (Flanagan and Livingston, 1995). The Green–Ampt baseline hydraulic conductivity values were optimized to minimize differences between predicted and measured runoff volumes for selected events under freshly tilled fallow conditions (Risse et al., 1995a,b). Other soil parameters were obtained from site information or by averaging information from different sources for the soil.

Management and slope input files were built based on experimental data from site records. Climate files included measured daily rainfall, durations, and maximum intensities, and minimum and maximum temperatures. The remainder of the variables in the WEPP climate file were generated by the CLIGEN model using these measured values and the CLIGEN input parameters of the nearest weather station.

Calibration of the Soil Parameters

The soil parameters, rill and interrill erodibilities and critical shear stress, were adjusted based on the comparison of the distributions of measured and predicted soil loss values. The parameter values were adjusted until the estimated soil losses were within the 95% confidence intervals of the LP III distributions. As we gained more experience with the process, the following guidelines to adjust the parameter values were identified:

All soil loss values were related to the interrill erodibility. However, large erosion events, for which the interrill erosion was proportionally less important than the rill erosion, were less sensitive to the interrill erodibility value than were small events.

Only the larger soil loss values were sensitive to the rill erodibility value. If overland or surface water flow shear stress is lower than the critical shear stress for a given storm, there is no rill erosion and the rill erodibility value has no influence. When the low values of soil loss fit well the measured distribution but the higher ones did not, we adjusted the rill erodibility.

The value of the critical shear stress controls the threshold beyond which rill erosion occurs. An increase in its value caused a shift of the middle section of the curve toward higher recurrence intervals at the same time than it caused a decrease in the amount of rill erosion. This parameter controlled the shape of the curve as well as the magnitude of soil loss for the large events.

While similar distributions of measured and estimated soil loss do not necessarily mean the model was accurate in predicting day-by-day soil loss, it ensures that the predictions' statistical characteristics were similar to those of the observed sample.

Although not of primary importance relative to the statistical distributions, we found it useful to quantify the day-by-day predictive capability of the WEPP model before and after calibration using the model efficiency (Nash and Sutcliffe, 1970). The model efficiency is expressed as

$$\mathrm{ME} = 1 - \frac{\sum(Y_{\mathrm{obs}} - Y_{\mathrm{pred}})^2}{\sum(Y_{\mathrm{obs}} - Y_{\mathrm{pred}})^2} \quad [3]$$

where Y_{obs} (g/m^2) is measured soil loss, Y_{pred} (g/m^2) is predicted soil loss, Y_{mean} (g/m^2) is mean measured soil loss per event (g/m^2), and ME is model efficiency. The model efficiency can range from $-\infty$ to 1, and the closer the value is to one, the better are the individual daily predictions.

The CLIGEN Model

The program CLIGEN is used to generate continuous simulation climate files for use by WEPP and other models. The CLIGEN input files include a station file (list of all U.S. stations available to run with the program) and state files that contain the statistical representation of weather data for the stations in each state. Weather data statistics for >1400 stations within the USA are available to run with CLIGEN. For each station, parameters describe the climate conditions on a monthly basis. These parameters were derived from the analysis of weather records with durations between 20 and 90 yr.

From this file of statistical data, CLIGEN generates, for as many simulation years as desired, the daily rainfall amount, duration, time to peak, and peak intensity as a ratio to average intensity. It also generates minimum and maximum daily temperatures and dew points, as well as solar radiation, wind direction, and wind velocity.

RESULTS AND DISCUSSION

Measured Distributions

Figure 1 shows a typical example of a LP III distribution fitted to the empirical distribution of soil loss values along with its 95% confidence interval. In all cases, the LP III with parameters estimated by the direct method of moments gave a good fit according to our quantitative criterion that all measured points were within the 95% confidence interval of the fitted distribution. For the fallow plot in Madison, SD, the generalized method of moments gave a slightly better fit to the data than did the direct method of fitting; however we chose the direct method because it was consistant to use the same fitting

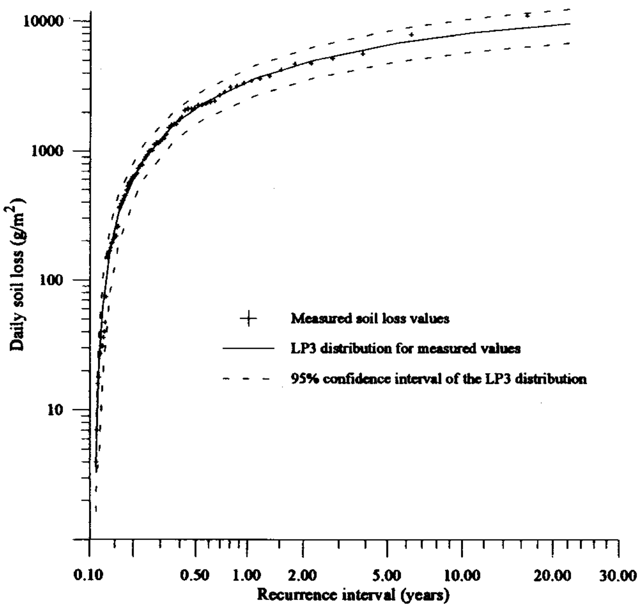

Fig. 1. Empirical and theoretical frequency distributions of daily soil loss on the fallow plot at Bethany from 1931 to 1940.

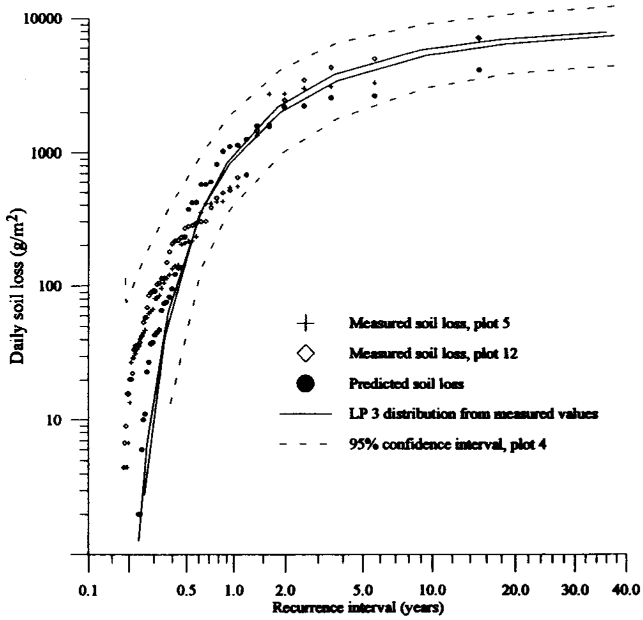

Fig. 3. Comparison of distributions of measured and predicted daily soil loss on the fallow plot at Madison, SD, from 1962 to 1970.

method for all of the data sets. For some sites (Morris, MN, and the corn [*Zea mays* L.] plots in Madison, SD), the LP III distribution with the direct method of moments was the only distribution for which all measured daily soil loss were within the 95% confidence interval. For all other sites, the LP III distribution was the best one in that it resulted in the smallest 95% confidence intervals. The fitted distributions for predicted events were also found to be LP III distributions with parameters estimated by the direct method of moments (Fig. 2–7).

The choice of an LP III distribution for daily soil loss was in agreement with the study by Zuzel et al. (1993) at a site in northern Oregon. After restricting the analysis to events producing >25 g/m^2, they fitted the soil loss values to a lognormal probability distribution, which is a special case of the more general LP III distribution. When the coefficient of skewness converges toward zero and the coefficient of kurtosis converges toward 3, the LP III converges toward the lognormal distribution (Bobée and Ashkar, 1991).

The probability density function of a LP III is given by (Bobée and Ahskar, 1991)

$$f_{LP}(u; \alpha, \lambda, m) = \frac{|\alpha|}{\Gamma(\lambda)} e^{-\alpha(\log u - m)}[\alpha(\log u - m)]^{\lambda-1} \frac{\log_{10} e}{u} \quad [4]$$

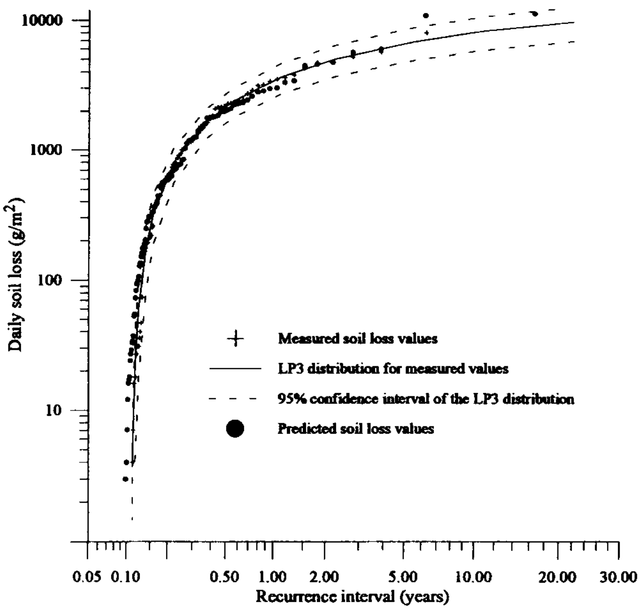

Fig. 2. Comparison of distributions of measured and predicted daily soil loss on the fallow plot at Bethany from 1931 to 1940.

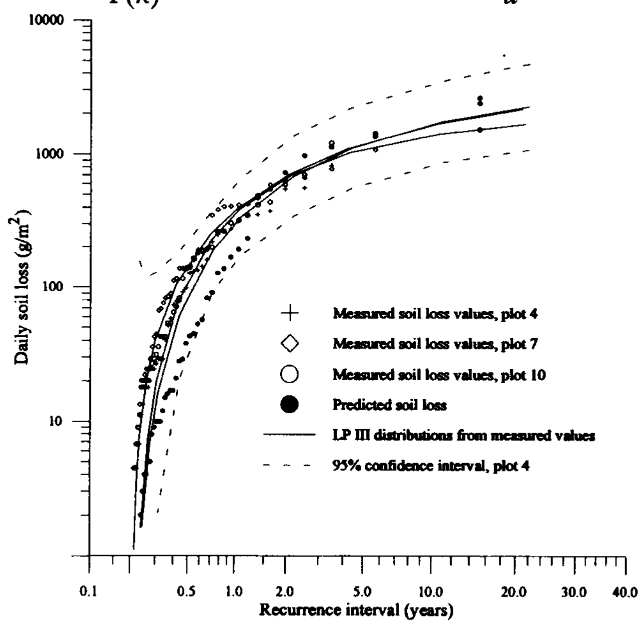

Fig. 4. Comparison of distributions of measured and predicted daily soil loss on the turn-plowed corn plot at Madison, SD, from 1962 to 1970.

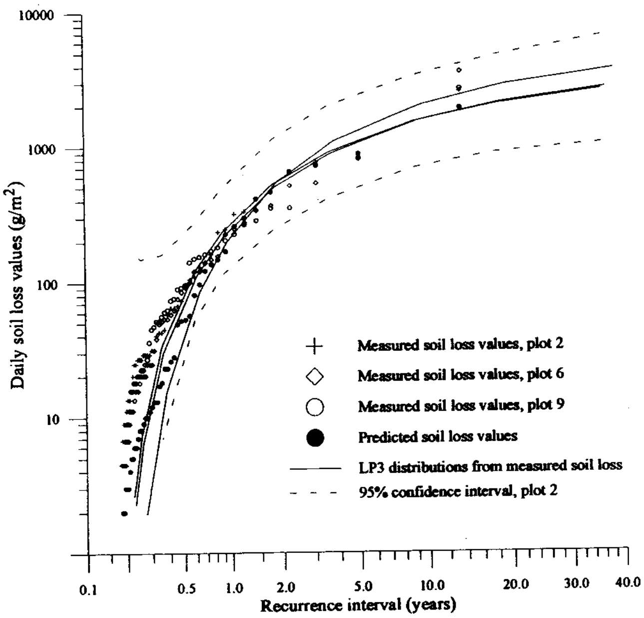

Fig. 5. Comparison of distributions of measured and predicted daily soil loss on the mulched corn plot at Madison, SD, from 1962 to 1970.

where u is the random variable of interest (in this case soil loss), and α, λ, and m are the scale, shape, and position parameters, respectively, for the distribution. The cumulative distribution function, $F(x)$, is the probability that the variable of interest takes a value $\leq x$. The probability density function and the cumulative distribution function are related as

$$F(x) = \int_{-\infty}^{x} f(u)\mathrm{d}u \qquad [5]$$

In our analysis, the determination of the distribution parameters by the direct method of moments always

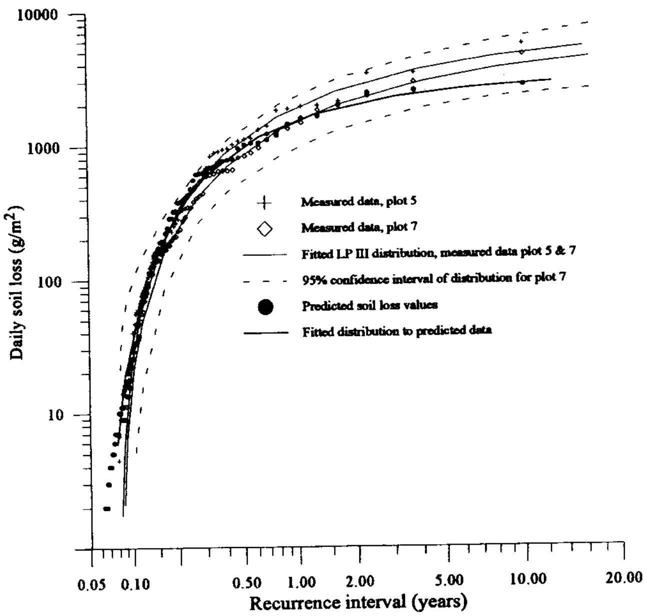

Fig. 6. Comparison of distributions of measured and predicted daily soil loss on the fallow plot at Holly Spring, MS, from 1963 to 1968.

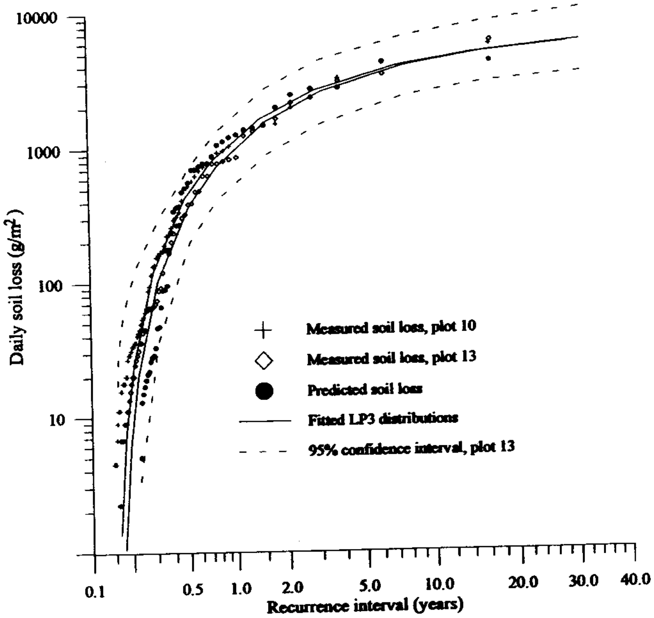

Fig. 7. Comparison of distributions of measured and predicted daily soil loss on the fallow plot at Morris, MN, from 1962 to 1971.

yielded negative values of the scale parameter α, which means that the distribution had an upper bound given by 10^m. Since the values of m were between 3.5 and 4.5, this would imply for these sites a maximum erosion rate for a given day of between 3 and 30 kg/m². Although this is not a proof that erosion on a site has an upper bound, possible limiting factors of the erosion rate could be the depth of the erodible layer, the maximum transport capacity of the runoff, the maximum probable precipitation for that site, or an interaction between these parameters. In any case, this maximum erosion rate obtained by fitting a LP III to a sample of soil loss values is uncertain, the uncertainty of which is indicated by the confidence interval associated with these high return periods.

When data for several replicates existed, a distribution was fitted for each replicate (Fig. 3–7). These were different, but within the 95% confidence interval of each other. The variation between the resulting distributions pointed out the possible variations of the results for apparently identical plots. The problem of spatial variations of soil loss is beyond the scope of this study, but one can find such discussion in Wendt et al. (1986).

Comparison of Measured and Predicted Soil Loss Distributions

The initial values of rill and interrill erodibilities as well as critical shear stress were estimated (Table 2) using the regression equations indicated in the WEPP user's summary (Flanagan and Livingston, 1995). Results showed that the distributions of predicted soil loss could be brought within the 95% confidence interval of the measured soil loss distributions using calibration (Table 2, Fig. 2–7). In addition, an increase in the model efficiency values for a majority of the data sets showed that the WEPP model was predicting more accurate individual storm erosion values (as quantified by the

Table 2. Values of the soil parameters before and after calibration.

Site	WEPP-estimated values K_r†	K_i‡	σ_c§	Calibrated values K_r†	K_i‡	σ_c§
	s m^{-1}	kg s m^{-4}	Pa	s m^{-1}	kg s m^{-4}	Pa
Bethany, NY	0.00730	4455230	3.50	0.01460	8910460	2.50
Madison, SD	0.00710	4278814	3.50	0.01420	4278814	3.00
Holly Spring, MS	0.00120	4962426	0.10	0.00650	600000	3.00
Morris, MN	0.00550	4917940	3.52	0.01250	9835880	2.50

† K_r = rill erodibility.
‡ K_i = interrill erodibility.
§ σ_c = critical shear stress.

model efficiency) using calibrated soil parameters than parameters estimated with the regression equations (Table 3). In other words, calibration of the model to fit the statistical distributions of soil loss also improved the daily event-by-event soil loss predictions.

Use of CLIGEN to Obtain Long-Term Soil Loss Distributions

In order to obtain better estimates of event frequency, the possibility of generating soil loss values during long periods using WEPP in conjunction with the CLIGEN weather generator was investigated by comparing soil loss frequency distributions estimated with a generated climate file to frequency distributions of soil loss values estimated with measured weather data. For each set of measured weather data, we used CLIGEN to construct 10 different climate files for sequences the same length as the monitoring period. We then simulated soil loss for those sequences using WEPP with the calibrated soil parameters. A frequency distribution was built for each of the 10 sequences of equal duration and then compared with the theoretical distribution fitted to the frequency distribution of soil loss values predicted with measured climate data.

Figure 8 shows the distribution for the 1931 to 1940 period for the fallow plot at Bethany, MO, as well as three of the 10-yr CLIGEN distributions, at either end and in the middle of the range of distributions. It shows that the distribution from measured weather data was within the possible 10-yr distributions; all distributions were parallel and there was no shift that would indicate that CLIGEN-generated data produce statistically different results than monitored weather data. The results from WEPP using CLIGEN inputs for the Holly Springs fallow plots of 1963 to 1968 are shown in Fig. 9. As with the case of the Bethany data, the results using the measured weather data from the 6-yr period compared well with the WEPP results using CLIGEN input. Results for the other data sets were also very good.

In light of these results, we think that the CLIGEN weather generator can be used to generate weather files

Table 3. The WEPP model efficiency (ME) in predicting soil loss before and after calibration.

Site	Plot	ME before calibration	ME after calibration
Bethany		0.20	0.32
Madison fallow	1st plot	0.21	0.29
	2nd plot	0.21	0.34
Madison corn turn-plowed	1st plot	0.42	0.48
	2nd plot	0.45	0.57
	3rd plot	0.17	−0.29
Madison corn mulched	1st plot	0.48	0.67
	2nd plot	0.51	0.71
	3rd plot	−0.29	−0.61
Holly Springs	1st plot	0.17	0.27
	2nd plot	−0.64	0.09
Morris	1st plot	0.33	0.49
	2nd plot	0.34	0.44

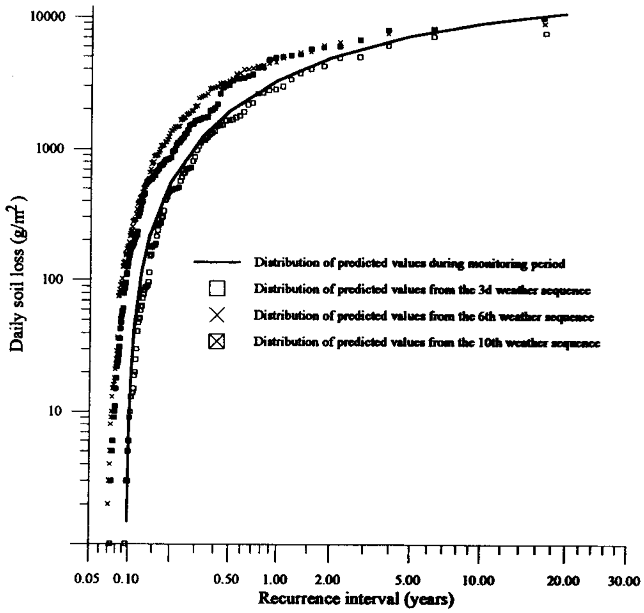

Fig. 8. Comparison of the theoretical distribution of WEPP-predicted values between 1931 and 1940 and three 10-yr-long series obtained from generated climate data for the fallow plot at Bethany, MO. The three selected sequences (3rd, 6th, and 10th) are the median and lower and upper extremes of 10 simulated distributions.

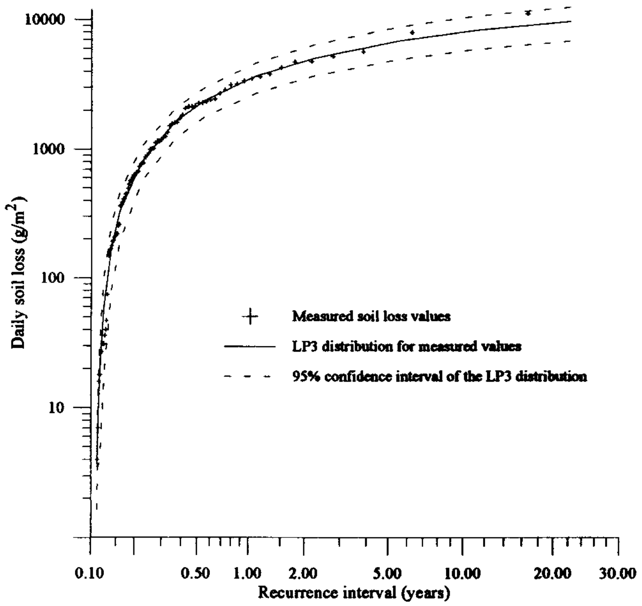

Fig. 9. Comparison of the theoretical distribution of WEPP-predicted values between 1963 and 1968 and three 6-yr-long series obtained from generated climate data for the fallow plot at Holly Springs, MS. The three selected sequences (4th, 6th, and 9th) are the median and lower and upper extremes of 10 simulated distributions.

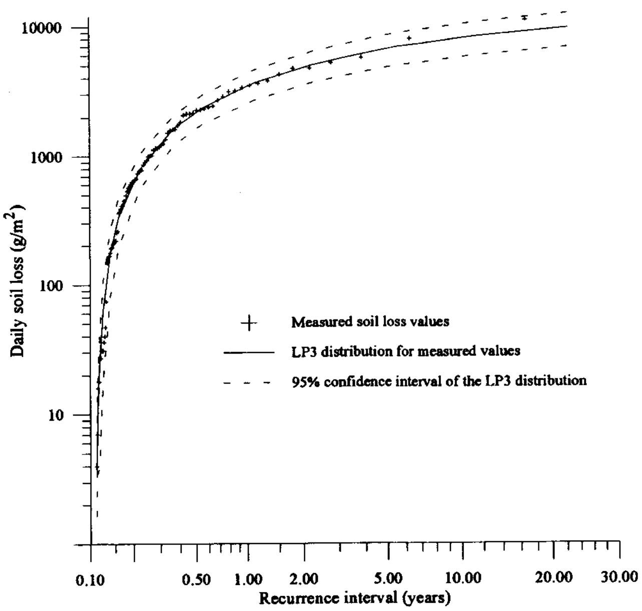

Fig. 10. Measured and predicted cumulative soil loss on the fallow plot at Bethany.

in order to compute frequency distributions of soil loss as long as the weather generator input file is representative of the climate. When weather and soil loss data are available for a few years, the soil loss frequency distribution is a valuable tool to calibrate the soil parameters. The CLIGEN generator and the WEPP model can then be used to predict soil loss during a longer period, derive a more representative frequency distribution, and better estimate soil loss values for large recurrence intervals.

Cumulative Soil Loss Curves

The cumulative soil loss curve is a tool with which one can visualize the amount of total soil loss for events up to a given return period. It is derived from the frequency distribution by computing for each recurrence interval the cumulative soil loss value of all events having a smaller or equal recurrence interval. Figure 10 shows the curve obtained for Bethany. The cumulative soil loss was expressed as a percentage of total soil loss during the monitoring period. This allows an easy reading of the curve and comparisons of trends between different management practices, soils, and climate. From these curves, one can estimate the necessary length of the monitoring period needed to obtain a good estimate of the long-term soil loss. In Bethany, for example, it is necessary to include events with a 5-yr return period to obtain 90% of the total soil loss; a monitoring period of 10 yr was therefore sufficient to estimate the long-term soil loss.

One can also estimate the percentage of soil loss caused by different classes of events using the following strategy. Daily soil loss values were divided into five classes according to their recurrence interval: small events with a return period <0.5 yr, common events with a return period between 0.5 and 1 yr, large events with a return period between 1 and 2 yr, rare events with a return period between 2 and 5 yr, and extreme events with a return period >5 yr. Using the cumulative curves, we then computed how much soil loss was due to each class of events (Table 4). On some plots, small but frequent events occurring at least once a year caused more erosion than the large but rare events. Events occurring at least once a year were the major source of soil loss (60%) on the fallow plots at Bethany and Holly Springs. Apart from the problems associated with loss of soil and nutrients on the field, such an erosion pattern can be a problem if the sediments were to deposit in a channel or detention pond downstream of the field. These would fill up regularly and either some procedure would be necessary to empty the sediment or some erosion control measure would have to be implemented. Erosion was more evenly distributed between small, common, and large events for the sites of Morris and Madison. Results from the corn plots in Madison showed that while the total soil loss decreased when soil conservation practices were used and the ground cover increased (no-till corn cropping vs. moldboard plowed corn cropping), the impact of rare events increased. Further conservation practices would therefore need to address the impact of those events as well as small events.

Table 4. Percentage of total soil loss (%SL) caused by events of various recurrence intervals (RT, in years).

Site	Distribution	%SL for RT <0.5	%SL for 0.5 < RT < 1	%SL for 1 < RT < 2	%SL for 2 < RT < 5	%SL for RT > 5
Bethany	Measured	37	22	16	13	12
	Predicted	37	20	15	15	13
	Long-term†	43	20	14	12	11
Madison fallow	Measured	8	11	23	31	26
	Predicted	6	24	27	25	19
	Long-term	10	21	20	20	29
Madison corn turn-plowed	Measured	11	20	20	24	25
	Predicted	3	10	24	33	31
	Long-term	4	12	16	20	47
Madison corn mulched	Measured	12	16	17	20	36
	Predicted	6	24	24	28	28
	Long-term	5	17	17	20	46
Holly Spring	Measured	37	20	16	15	10
	Predicted	45	20	16	12	6
	Long-term	40	20	14	12	14
Morris	Measured	12	21	21	24	22
	Predicted	10	25	23	24	18
	Long-term	12	22	22	20	24

† 100-yr predicted distributions.

CONCLUSIONS

A LP III distribution with parameters estimated by the direct method of moments was fitted to measured and WEPP-simulated soil loss values on 13 plots of the six sites studied. The 95% confidence interval of the LP III included all measured soil loss values.

The calibration of WEPP erosion parameters (rill and interrill erodibilities and critical shear stress) was achieved by comparison of the distributions of measured and WEPP-predicted soil loss values. For each site, the parameters were adjusted to obtain a predicted distribution of soil loss within the 95% confidence interval of the measured distribution. Three basic rules were suggested as a guideline to calibrate these parameters. The final values of the parameters were sometimes different from the initial values estimated according to the recommendations given in the WEPP user's manual, indicating the need for further understanding of these parameters (Table 2).

When the erosion monitoring period is short (<10 yr), the resulting distribution of soil loss values may not be representative of long-term conditions. In that case, we recommend calibrating the soil parameters using soil loss distributions generated from the monitored data. The WEPP model can then be used with the calibrated soil parameters to predict long series of soil loss values using either observed precipitation data or CLIGEN-generated data. In this study, the soil loss distributions obtained from WEPP in conjunction with CLIGEN-generated files were similar to those obtained with measured precipitation and temperature data as long as the CLIGEN input information was representative of the same measured weather record. Thus, WEPP is able to generate representative, long-term daily soil loss frequencies as long as the CLIGEN input is representative of the long-term weather.

Once the frequency distributions of daily soil losses were known, cumulative daily soil loss curves were developed. These curves show the amount of total soil loss caused by events of up to a given return period. When the cumulative soil loss is expressed as a percentage of total soil loss during the monitoring period, trends between different management practices, soils, and climates are easily compared. One can also use them to estimate the length of the monitoring period to obtain a good approximation of the long-term average soil loss. The monitoring period must be long enough to ensure that only events that cause <5 or 10% of the total soil loss may be missed. Such analyses help to better target the type of erosion that needs to be controlled and to better estimate the impact of the sediment delivery on hydraulic structures or receiving water bodies.

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