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Application and Adaptation of WEPP to the Traditional Farming Systems of the Ethiopian Highlands

(With Special Emphasis on the New Breakpoint Climate Data Generator, BPCDG)

*Gete Zeleke**

ABSTRACT

The Ethiopian highlands are the largest mountain complex in Africa; the threat of land degradation they now face is greater than ever before, resulting from several thousand years of human settlement and agriculture. Understanding the process of soil erosion, its causes, and its impacts on such a fragile environment must be the cornerstone for devising effective control mechanisms and appropriate land management practices. This study focuses on the application and adaptation of WEPP (Water Erosion Prediction Project) to the traditional farming systems of the area. The hillslope application of WEPP was tested on cultivated plots in Anjeni Research Unit, Gojam. A breakpoint climate data generator (BPCDG) was developed, as a standalone program to create a climate input file for WEPP using standard weather data sets. Particular attention was given to this aspect of methodological improvement, so that the new program could be used in any part of the world. Likewise, other input parameters were generated based on local conditions and the model was calibrated for the Geen-Ampt effective hydraulic conductivity (Kb) and soil erodibility parameters. The overall results show that the model over-predicts runoff and slightly under-predicts soil loss. The latter is contrary to the findings of similar studies in the US. The average Nash-Sutcliffe model efficiency obtained for predicting runoff using optimized hydraulic conductivity (Kb) was 0.53 for selected events, 0.28 for annual values, and 0.43 for average annual values. The model does better in predicting soil loss, with model efficiencies of 0.74, 0.58, and 0.72 respectively. The sensitivity analysis and calibration process reveals that the model is less sensitive to changes of Kb during the peak rainy season in the area. It seems that runoff is not influenced by Kb at this important period of the season. Despite the slight bias observed in predicting runoff, the results are promising and WEPP performs very well using the new climate data generator (BPCDG), which is an important step towards future applications of this model. **Keywords: WEPP, soil loss, runoff, land degradation, farming system, Ethiopian highlands, erosion modeling, model validation, model efficiency, BPCDG, climate.**

INTRODUCTION

The Ethiopian highlands, which were and are predominantly inhabited by an agrarian society, now face severe threat of land degradation than ever before. Favorable climatic and ecological conditions (sufficient rainfall, moderate temperature, and well-developed soil) were the basis for early development of agricultural systems in the highlands of Ethiopia (Hurni, 1988b). As population pressure increased the clearing of forests for cultivated land on steeper slopes and in marginal areas accelerates soil erosion over a long period of time, which gradually led to soil deterioration in these areas. In this sense, the present land degradation problem can be considered as a direct result of past agricultural practices (Hurni, 1988b, Gete Zeleke, 2000). Various studies carried out in the country consider soil erosion as a major cause of land degradation. However, most of these studies, with the exception of the Soil Conservation Research Program (SCRP[†]), describe soil erosion based upon qualitative observations. In this regard, the works of Bossart (1998), Herweg and Ludi (1999) and Herweg and Stillhardt (1999), based on SCRP results, can be cited as an example of the effort towards quantified description. Understanding the processes of soil erosion, its causes, and, its impacts on such a fragile environment, must be a cornerstone for devising effective control mechanisms and appropriate land management practices. But monitoring of soil erosion processes on such a corrugated landscape requires installation of various gauging stations. This is rather expensive and often unaffordable. However, recent scientific developments demonstrate that the knowledge required can be successfully gained by applying soil erosion prediction technologies.

The WEPP (Water Erosion Prediction Project) erosion model is one of the new generation prediction technologies, which can be adapted to the case of the Ethiopian highlands. Detailed descriptions of model components and processes considered in WEPP can be found in Flanagan and Nearing (1995). Considerable validation tests and sensitivity analyses of the WEPP model on the hillslope scale have been done under the US conditions (Nearing et al., 1990, Flanagan, 1991, Zhang et al., 1996, Risse et al., 1994, 1995a, 1995b). However, not much has been done outside the US, particularly under traditional farming systems. Accordingly, the hillslope application of the WEPP model was tested and validated using measured data sets from traditionally managed on-farm soil erosion monitoring test plots (TP) and experimental plots (EP) in Anjeni Research Unit, Gojam, North-western Ethiopia. Four different soil types, three slope ranges (12 and 28% two plots each, but of different size, and one 22%), two slope lengths (15 and 30 meters), a total of 879 selected events, 18 plot years, and five different traditionally managed cropping scenarios were used (Tables 1 and 2).

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[†]SCRP was started in 1981 in collaboration between the University of Bern, Switzerland, and the Ministry of Agriculture, Ethiopia. This was the only project tried to describe soil erosion processes and associated problems of the country under the traditional farming condition in more systematic and scientific manner. This study is also based on the data from this program.

The most important issue after model construction is the question of where and how the model has to be validated. According to Quinton, (1994), the model can only be validated if the set of demands from it and the environment where it is to be used are specified. Then, depending on the sets of demands placed on the model, the user decides its acceptance or rejection. However, thorough evaluation of the accuracy and reliability of model predictions using substantial testing and validation procedures is essential before any model is accepted or rejected (Zhang et al., 1996). In other words, the user must have confidence in the model before using it (Quinton, 1994). This can be achieved in two ways: by applying the model to situations similar to those in which it will be used and showing that it performs adequately, and by demonstrating that the model is based on sound science.

Prior to the model testing and validation processes, understanding of the major functions, input requirements, output options, operating time dimensions and basic limitations of the model, in part or in general, is essential. Many authors, such as DeCoursey (1988), Stephenson and Freeze, (1974 quoted in Quinton, 1994), and Nash and Sutcliffe, (1970) give particular emphasis to this step of the model validation process. In general, validation of a physically based model requires a perfect knowledge of initial and boundary conditions as well as model outputs; the major hindrance is the complexity of boundary conditions and their variability in space and time, rather than any difficulty in the physical law. On the other hand, modeling of a complex system implies simplification of boundary conditions and substantial reduction processes. This is often a source of variance between model predictions and measured values. In this regard, it is only possible to indicate the discrepancy when major generalizations in the model and the accuracy level of measured data sets for validating the model are known.

Liu et al., (1997) indicate that model evaluation can include several steps, such as sensitivity of the model to the changes of input parameters, evaluation of confidence limits, and comparison of model prediction to measured data sets. James and Burges (1982) and de Roo (1993) suggest similar procedures. Most authors emphasize that the model has to be calibrated for those parameters that cannot be measured directly on the field.

The main objective of this study is to test and validate the hillslope application of the WEPP erosion model to the traditional farming systems of the Northwestern Ethiopian highlands. Development of data processing frameworks in order to use the SCRP database to validate process-based models is one of the specific objectives. The intention was also to develop a standalone program that generates a breakpoint climate file for WEPP from observed weather data sets. It is assumed that the latter will solve the problem related to the lack, mainly outside USA, of long-term statistical weather data sets, required by CLINGEN.

MATERIALS AND METHODS

Model testing and validation procedures illustrated in Figure 1 was developed for this study. Re-calibration of the model (dotted line) and model modification (words in italics) shown in Figure 1 (at end of paper) were not used, but indicate the possible courses of action to be followed during model testing and validation processes. At this point, it must be born in mind that, even though the above-mentioned processes are necessary steps during model validation, this does not ensure a one-to-one prediction from complex erosion models like WEPP. This was perfectly demonstrated by Nearing (1998). However, careful model construction, experimental design, measurement, adjustment, and screening of error data sets greatly reduce discrepancies between model prediction and measured values.

After the required parameters were identified, the basic modules, and the assumptions and generalisations made in the measured data sets (Herweg and Ostrowski, 1997) and in the model itself, were critically evaluated. Major differences or limitations were identified and common evaluation frameworks were developed (Gete Zeleke, 2000). Based on the criteria defined, measured data sets with expected errors were screened. This was done to avoid misinterpretation of model predicted and measured values, in light of Quinton's statement (1994) that unsuccessful model prediction is not always the fault of the model but can also result from measured data sets.

Different data sets were compiled to prepare the necessary input files using various means, including direct measurement, computer program development, and reviews of the literature.

A standalone program (BPCDG)[‡] was developed to generate a breakpoint climate input file using actual observed weather data sets (Gete Zeleke et al., 1999). The climate component of the WEPP model (CLINGEN) generates daily climatic data and provides a storm intensity input, assuming a storm with a single intensity peak and described by a double exponential function. However, this program requires long-term monthly statistical weather data parameters for each station. Some of these data sets are difficult to compile in many countries outside the US. The BPCDG gives an alternate solution to this problem, and is also advantageous because it allows the direct use of observed weather data sets. A preliminary model test was done to check the performance of WEPP using the new climate file generated by BPCDG, and subsequent adjustment of this program was undertaken until model performance was satisfactory. After this exercise, sensitivity analysis was done to identify parameters for which the model is most sensitive (under local conditions).

Soil and topography parameters were generated from a detailed soil survey conducted in January 1997. Profile pits were dug close to each Test and Experimental Plot to reduce the spatial variability of parameters. Soil chemical and physical properties were analyzed in the National Soil Laboratory. Initial condition scenarios related to soils were taken from this survey data (Table 1). Parameters that are related to crop agronomic practices were collected from direct field surveys (1996 and 1997) and from on-farm field trials (see Gete Zeleke, 2000). Crop-specific generic parameters were derived from different sources, (D.C Flanagan and M. A. Nearing, 1995, van Heemst, H. D. J., 1988, Driessen and Konijn, 1992).

Maximum effort was made to quantify the surface effect properties of the traditional ox-plough, '*Maresha*' (see Table 3). This implement was designated as *Maresha*-

[‡]The latest version of BPCDG (Breakpoint Climate Data Generator) can be found on the WEPP web site: http://topsoil.nserl.purdue.edu/weppmain/wepp.html

1, 2, 3/4 and 5/6, which represents the sequence of plowing. For instance, 1st plowing, 2nd plowing, etc (*Maresha*-4 and 6 are similar to *Maresha*-3 and 5, respectively). Basically, there are two kinds: light (1 and 5/6) and heavy (2 and 3/4). The local farmers use the light implement during very dry and wet conditions. When deep penetration and relatively wide ridge spacing is required, they use the heavy implement, and even then the depth of the plough is adjusted according to surface conditions. To quantify these values a number of field measurements were done in 1996/97.

To determine goodness of fit between measured and predicted values, the Nash and Sutcliffe (1970) model efficiency (ME) and basic linear regression coefficients were used during calibration, sensitivity analysis, and validation processes. The first validation test was conducted on two test plots, and predicted values were compared to selected measured data sets. The results were evaluated and a decision was made to calibrate soil parameters. Similar studies showed an improvement in model performance after soil parameters were calibrated (Risse et al., 1994, 1995a and 1995b, Zhang et al., 1996, Nearing et al., 1991, Baffaut et al., 1998).

The model was calibrated for Green-Ampt effective hydraulic conductivity and soil erodibility parameters. The optimization method used by Risse et al., (1994 and 1995b) was followed to calibrated Kb, where the least square error (LSE) or index of disagreement (Nash and Sutcliffe, 1970) was used as an objective function applied to observed and predicted runoff values for selected events. For some plots, the LSE function did not perform well and other methods were employed. For erodibility parameters, the method followed by Baffaut et al., (1998), James and Burges (1982) (based on the work of Hocke and Jeeves, 1961 and Lumb et al., 19975) was used. The calibration results are presented in Table 4, and a sample of the optimization curve is shown in Figure 2 (for details, see Gete Zeleke, 2000).

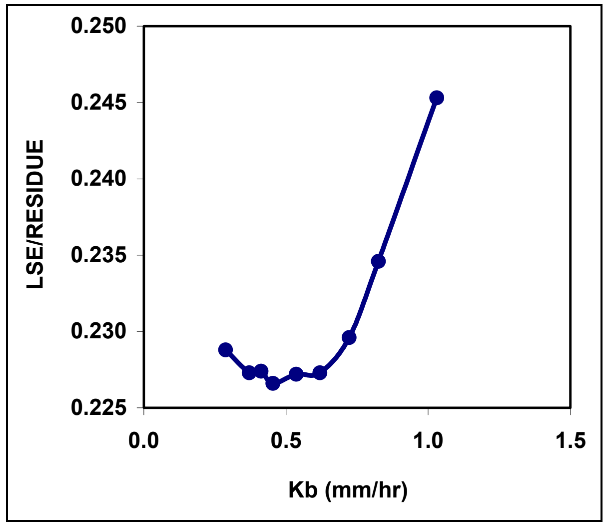

Figure 2. Sample plot showing the response of the LSE between measured and WEPP-predicted runoff values for selected events for Test Plot 1. Each point represents one iteration of the calibration process. The residual variance is calculated as $\Sigma(Yo\text{-}Ym)^2$, where Y_0 is observed runoff and Ym is the mean of selected runoff events.

RESULTS AND DISCUSSION

Runoff

Simulated and measured runoff for selected events are plotted in Figure 3 (a). The model tends to over-predict smaller events and under-predict larger events. Medium events are partly under-predicted. This was clearly seen in Figure 3 (b), where runoff values less than 10 mm are over-predicted, and values between 10 and 15 mm are partly over-predicted. Runoff events greater than 15 mm are generally under-predicted. The trends observed on an event basis were also observed on annual and average annual basis (Figure 4a and b). In both cases years with smaller runoff records were over-predicted. This bias was observed in other studies by Kramer and Alberts (1995), Risse et al., (1994 and 1995b), and Zhang et al., (1996). Their major conclusion was that this bias, i.e. over-prediction of smaller events and under-prediction of larger events, cannot be corrected through calibration because it is inherent in the Green-Ampt equation used in WEPP and in some other components related to surface hydrology in the model. This was also observed during the calibration and sensitivity analysis exercise, where the model become less sensitive to changes in hydraulic conductivity after a certain point, and especially during the peak rainy season in the area.

The performance of the model was also statistically evaluated on an event, annual and long-term average annual basis for selected events. The model does better in predicting event values than annual total and average annual values, where the model efficiency (ME) was 0.53, 0.28, and 0.43, respectively (Table 5). Coefficients of determinations were 0.64, 0.69, and 0.69, respectively, and did not display much difference. The fact that average errors in all cases are negative indicates a model bias in over-predicting runoff (Table 5). A similar trend was observed by Zhang et al., (1996). Besides the bias in the model itself, the general trend of over-prediction is slightly influenced by the results from TP4 (Table 6). Moreover, it can also be partly explained by the different management practices for crop types used in the study.

The analysis based on crops (Table 7 and Figure 5) demonstrates that the model over-predicts runoff for typical local crops (*Teff* and Horse Bean). The fact that some of the generic values for these crops were derived from other similar crops might affect the crop growth routines of the model, possibly causing this variation. Moreover, the unique cultural practices of *Teff*, i.e. surface trampling, might also call for special adjustment factors. Further investigation of soil erosion processes under these crops, particularly *Teff*, and accurate quantification of their generic and agronomic characteristics through crop agronomy research seem essential.

Soil loss

Model-predicted and measured values for selected events are plotted in Figure 6a. The model tends to over-predict soil loss (<0.5 kg m^{-2}) for smaller runoff events, while soil loss values greater than 1 kg m^{-2} are under-predicted (Figure 6b). Values between 0.5 and 1 kg m^{-2} are partly over-predicted. Under-prediction of soil loss for larger events was observed by Kramer and Alberts (1995), Zhang et al., (1996), and Nearing (1998). Similar trends

Table 1: Topsoil properties and physical characteristics of each plot (measured in January 1997)

Plots	Clay (%)	Sand (%)	Gravel >2mm (%)	V.F.S. (%)	CEC (Meq/100g soil)	OM (%)	*BD* (gcm^{-3})	SAT (%)	Aspect (degree)	Slope (m)	Length (m)
TP1	59	13	8.17	0.98	28.6	2.196	1.283	49.787	138	28	15
TP2	47	21	0	0.44	28.2	3.672	1.219	54.525	330	12	15
TP4	65	17	0	0.49	26.2	2.573	1.325	42.661	298	22	15
EP1	41	25	0	0.87	38.6	3.945	1.361	46.134	138	28	30
EP2	47	21	0	0.44	28.2	3.672	1.219	54.525	330	12	30

Note: V.F.S 'very fine sand with particle sizes 0.053-0.106 nm', BD 'bulk density (gcm^{-3})', SAT represents percentage of soil porosity filled by water at initial survey, Gravel 'particle size >2mm', CEC 'Cation exchange Capacity', OM 'Organic Matter content', Clay and Sand are percentages in the texture class, TP 'Test Plot' and EP 'Experimental Plot'.

Table 2: Selected years and number of events and cropping scenarios for each plot.

Plot type	Selected year	Number of events selected	Crop types	Area (m^2)
TP1	1987	65	Barley (1st)	30
	1989	52	Niger-seed	
	1990	56	Field Pea	
	1992	47	Wheat	
TP2	1987	45	*Teff*‡	30
	1989	49	Barley (1st and 2nd)†	
	1992	47	*Teff*	
TP4	1987	47	Wheat	30
	1989	49	Horse bean	
	1990	47	*Teff*	
	1992	52	*Teff*	
EP1	1987	55	Barley (1st)	180
	1989	44	Nug	
	1990	42	Field pea	
	1992	41	Wheat	
EP2	1987	45	*Teff*	180
	1989	48	Barley (1st and 2nd)	
	1990	48	Horse bean	
Total		879		

†This is a traditional practice where local farmers grow Barley two times a year.

‡Teff (Eragrostis) is a stable food crop that originated in Ethiopia and is used mainly to prepare the daily meal, a flat pancake called 'enjera'. It requires fine seedbed preparation, and usually the crop doesn't give good ground cover during heavy rainfall periods.

Table 3: Operation parameters for Ethiopian traditional ox-plough: 'Maresha'.

Implement type or practice	Ridge height (cm)	Ridge interval (cm)	Tillage depth (cm)	Random Roughness†	Surface Disturbance † (%)
Maresha-1	13.04	36.04	11.76	0.048	50
Maresha-2	12.26	34	12.50	0.052	65
Maresha-3/4	14.67	42.43	12.50	0.055	85
Maresha-5/6	9.41	27.72	10.10	0.045	100
Trample‡	0.00	0.00	1.00	0.01	99

† These values have to be interpreted with caution.

‡ Trample is not a farm implement but a traditional practice of Teff cultivation, in which the finely prepared seedbed is trampled by livestock immediately before sowing (see also Gete Zeleke, 1998, unpublished).

Table 4: Estimated (using the regression equation) and calibrated soil parameters.

Plots	Estimated values (using the regression equation)				Calibrated values			
	Ki ($Kg.s.m^{-4}$)	Kr ($s.m^{-1}$)	τ_c (*pascal*)	Kb (mm/hr)	Ki ($Kg.s.m^{-4}$)	Kr ($s.m^{-1}$)	τ_c (*pascal*)	Kb (mm/hr)
TP1	2.80133×10^6	0.00691	3.5	0.4126	2.50133×10^6	0.00294	4.150	0.45
TP2	3.46289×10^6	0.00691	3.5	1.1862	2.46289×10^6	0.00400	4.000	3.50
TP4	2.47055×10^6	0.00690	3.5	0.2817	2.47655×10^6	0.00250	5.015	5.05
EP1	3.79367×10^6	0.00694	3.5	2.5350	2.89513×10^6	0.00226	5.220	4.25
EP2†	3.46289×10^6	0.00691	3.5	1.1862	2.46289×10^6	0.00300	5.000	3.50

†Though the soil is similar to TP2, the values related to rill erosion (Kr) and rill initiation (τ_c) were adjusted (see Gete Zeleke, 1999 for complete description of the reasons).

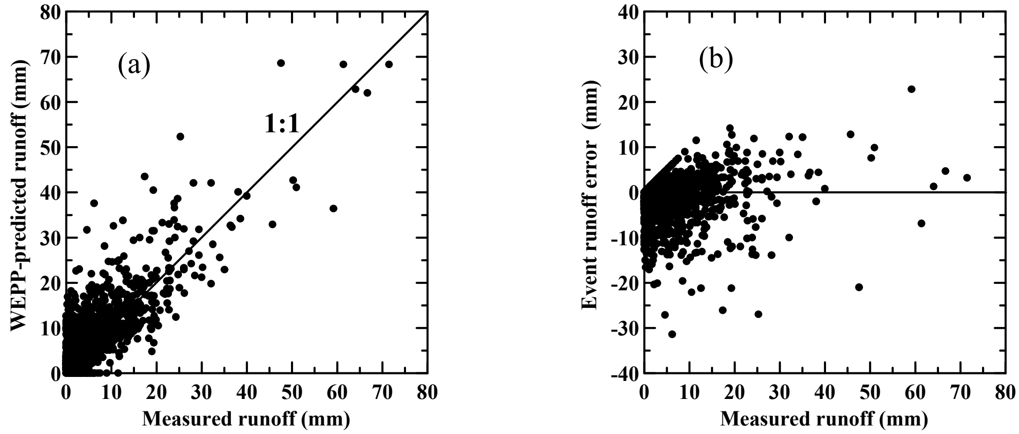

Figure 3: Comparison of WEPP-predicted and measured runoff values on an event basis (a), and model bias in predicting different event sizes (b), n = 879, r^2 = 0.64, and ME = 0.53. Note: event runoff error = measured – predicted.

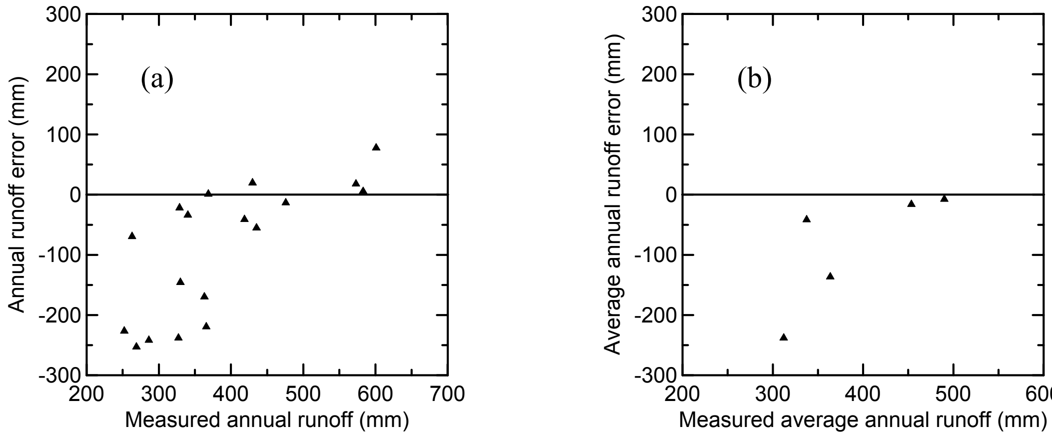

Figure 4: Errors in predicting annual total (a) and long-term (average) annual runoff values (b). For annual total values, n = 18, r^2 = 0.69, and ME = 0. 28. For average annual runoff, n = 5, r^2 = 0.69, and ME = 0.43.

Table 5: Summary of the statistical descriptions of WEPP-predicted and measured runoff on an event, annual total, and average annual bases.

Parameter	Runoff (mm)		
	Event	**Annual total**	**Average annual**
Mean measured values	7.97 ± 8.63	389.44 ± 109.3	391.40 ± 76.71
Mean predicted values	9.8 ± 9.17	478.76 ± 80.45	479.38 ± 69.05
Ave. Error	-1.83 ± 5.636	-89.32 ± 109.32	-87.98 ± 98.3
Ave. R^2	0.64	0.69	0.69
Ave. ME	0.53	0.28	0.43

Note: Error = measured – predicted

Table 6: Long-term average annual values of runoff for selected events on plot basis.

Plots	Runoff (mm)			Slope	Intercept	r^2	ME
	Measured	**Predicted**	**Error**				
TP1	490.00	497.60	-7.60	0.746	2.401	0.70	0.70
TP2	453.60	469.70	-16.10	0.783	2.437	0.73	0.72
TP4	312.10	550.10	-238.00	1.193	3.643	0.68	-0.25
EP1	337.60	379.20	-41.60	0.904	1.626	0.75	0.71
EP2	363.70	500.30	-136.60	0.962	3.204	0.60	0.25
Average	**391.40**	**479.38**	**-87.98**	**0.917**	**2.662**	**0.69**	**0.43**

Table 7: Summary of the statistical description for WEPP-predicted and measured runoff and soil loss values based on crop types, for selected events, and the entire simulation period.

	Runoff (mm)			Soil loss (kg m^{-2})		
Crop types	Errors	R^2	ME	Errors	r^2	ME
Teff	-79.18	0.70	**0.25**	1.09	0.81	0.68
Barley	-101.90	0.75	0.55	-1.18	0.74	0.70
Wheat	-20.63	0.70	0.68	0.18	0.77	0.73
Horse bean	-211.45	0.58	**-0.98**	3.67	0.63	0.00
Field Pea	-8.10	0.72	0.63	2.55	0.55	0.45
Niger-seed	-62.40	0.69	0.47	0.05	0.68	0.59

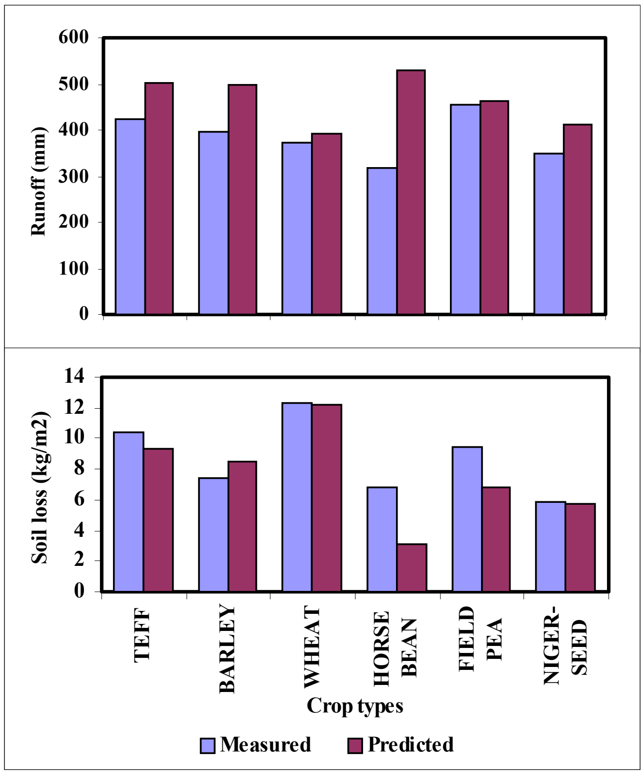

Figure 5: WEPP-predicted and measured runoff and soil loss values for all selected events and major crops (management) used in this study.

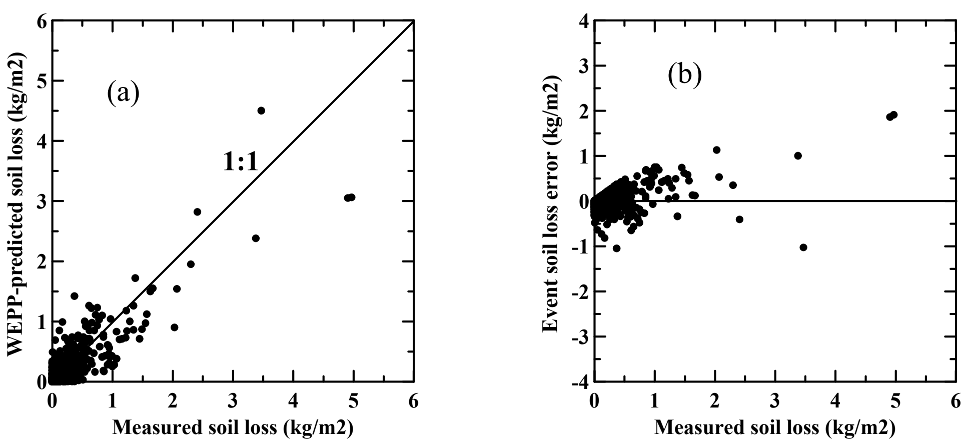

Figure 6: Comparison of WEPP-predicted soil loss with measured soil loss values on an event basis (a), n = 879, r2 = 0.74, and ME = 0.74; model bias in predicting different event sizes (b). Note: the bias towards over-prediction of smaller values was high when parameters calibrated on short slope length plots were used on longer plots (see Gete Zeleke, 2000).

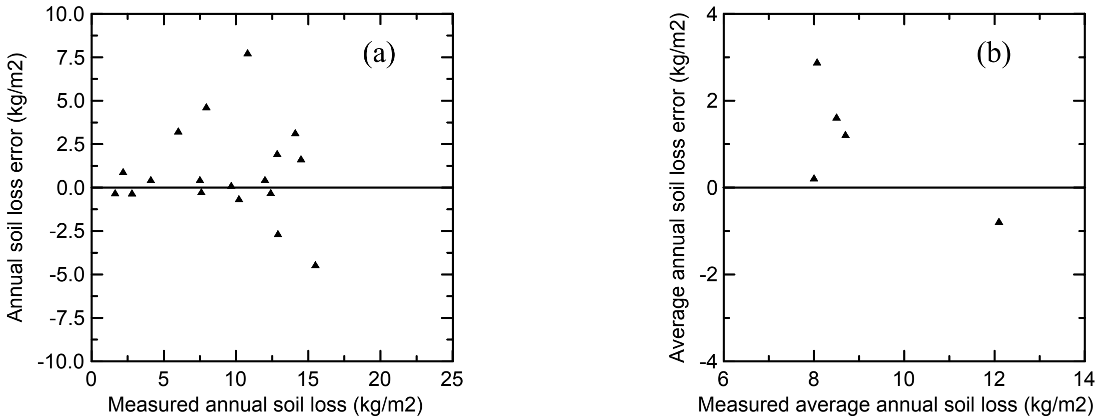

Figure 7: Errors in predicting annual total (a) and long-term annual average (b) soil loss values. For annual total values, n = 18, r^2 = 72, and ME = 0.58. For long-term annual average values, n = 5, r^2 = 79, and ME = 72.

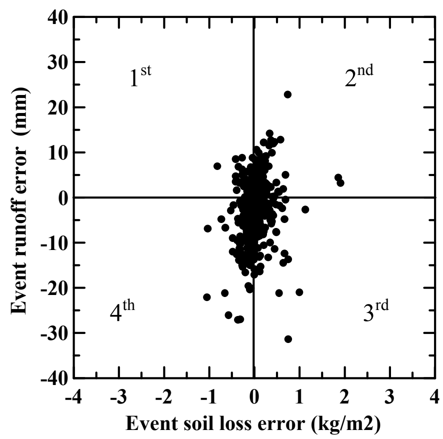

Figure 8: Event runoff errors plotted against event soil loss errors to indicate the possibility of error reproduction.

Table 8: Summary of the statistical description of soil loss on an event, annual total, and average annual basis

	Soil loss (kg m^{-2})		
Parameter	**Event**	**Annual total**	**Annual average**
Mean measured values	0.187±0.399	9.149±4.415	9.074±1.717
Mean predicted values	0.170±0.345	8.319±5.337	8.060±2.887
Average error	0.017±0.202	0.83±2.69	1.01±1.39
Average R^2	0.74	0.72	0.79
Average ME	0.74	0.58	0.72

Table 9: Long-term average annual soil loss values for selected events by plot

	Soil loss (k gm^{-2})						
Plots	**Measured**	**Predicted**	**Error**	**Slope**	**Intercept**	**R^2**	**ME**
TP1	12.10	12.9	-0.80	0.795	0.059	0.68	0.65
TP2	8.07	5.20	2.87	0.603	0.007	0.88	0.77
TP4	8.00	7.80	0.20	0.749	0.038	0.78	0.78
EP1	8.70	7.50	1.20	0.675	0.036	0.86	0.81
EP2	8.50	6.90	1.60	1.016	-0.036	0.73	0.61
Average	**9.07**	**8.06**	**1.01**	**0.767**	**0.021**	**0.79**	**0.72**

were also seen in annual totals and average annual values (Figure 7a and b).

The statistical analysis shows that the model does better in predicting soil loss by event, and on an annual and average annual basis, compared to runoff. The model efficiencies in predicting soil loss for selected events were 0.74, 0.58 and 0.72 respectively (Table 8). Likewise, the average coefficients of determinations were 0.74, 0.72, and 0.79 respectively.

The differences between coefficients of determinations and model efficiency for all cases were smaller, indicating the model was less biased in predicting soil loss than runoff. This was also seen in the regression analysis, where the intercept values for long-term average annual runoff and soil loss were 2.66 and 0.021, respectively (Tables 6 and 9). The intercept for soil loss is close to zero, indicating less bias. Though the ME is high, the trends from event to annual total and average annual values were similar to those for runoff prediction.

In general, the average errors in both cases were positive, indicating the bias in the model towards under-predicting soil loss (Table 8). This can be partly explained by the fact that the measured soil loss under Horse Bean is high for the crop under consideration; there seems to be an error in the measured data set (Figure 5 and Table 7).

Error reproduction

Figure 8 indicates that some of the errors in soil loss prediction could be partly attributed to the bias in the runoff predictions. In fact, a trend of one-to-one error reproduction is not always the case, because there are factors influencing soil loss other than runoff. A few larger under-predictions of soil loss did not well fit with high under-predictions for runoff (2nd quadrant).

Similarly, few extreme over-predictions of runoff correspond to smaller under-predictions of soil loss (3rd quadrant), and few extreme runoff over-predictions correspond to smaller over-predictions of soil loss (4th quadrant). However, except in a very few extreme cases, errors in runoff correspond to errors in soil loss, confirming the importance of good hydrological simulation to accurately predict soil erosion processes. This result further confirmed the previously mentioned bias in the model in conceptualizing erosion processes, most probably with regard to components related to runoff.

CONCLUSION

It was observed that the model over-predicts smaller events and under-predicts larger events, for both runoff and soil loss. Nearing (1998) argued that these types of bias should be expected when the model is performing very well. He found similar trends using a very accurate model and identical plots.

Evaluation of the overall results indicates that the model over-predicts runoff in all cases and slightly under-predicts soil loss in four of the five cropping scenarios. The reaction of the model to changes of Kb, particularly during the peak rainy season, was very low. This might indicate that runoff was controlled more by matrix potential and saturation than by hydraulic conductivity in the area (Nearing, 1999 personal communication). Since the user has no control over these variables, the above-mentioned bias cannot be easily corrected. It seems appropriate to recommend an improvement in the hydrologic component of the model so that the user can have control over important variables or assumptions apart from Kb.

Despite the above-mentioned shortcomings, the model fairly predicts both runoff and soil loss (for selected events) with model efficiency of 0.53 and 0.74, respectively. It must also be noted that the model was validated using a data set that was not designed and collected for this purpose. Therefore, some of the variations observed can certainly be attributed to errors in the data set. In fact, a very strict data screening and selection procedure was used. Even then, there are important systematic and random errors inherent in the data that cannot be avoided by data screening (Herweg and Ostrowski, 1997). It can thus be concluded that revision of the SCRP research design and data collection system appears necessary if models like WEPP are to be applied.

Some of the major conclusions of this study regarding the future use of the model under traditional farming systems are:

A standalone program, BPCDG, which allows the user to create a breakpoint climate input file using observed weather data sets, was developed and places on the Internet for general use. The option provided prior to the development of this program creates daily climate data using different probability functions from long-term observed data sets. In the latter case, some of the parameters are rarely found outside the US.

Standard tables for major crops, management conditions, and traditional farm implements were developed, and ideas for future improvement were suggested.

A systematic model testing and validation procedure was developed.

Parameters that have to be carefully measured or calibrated were indicated during the sensitivity analysis.

An error data screening methods and a general framework that allows the use of SCRP data for such a purpose were developed.

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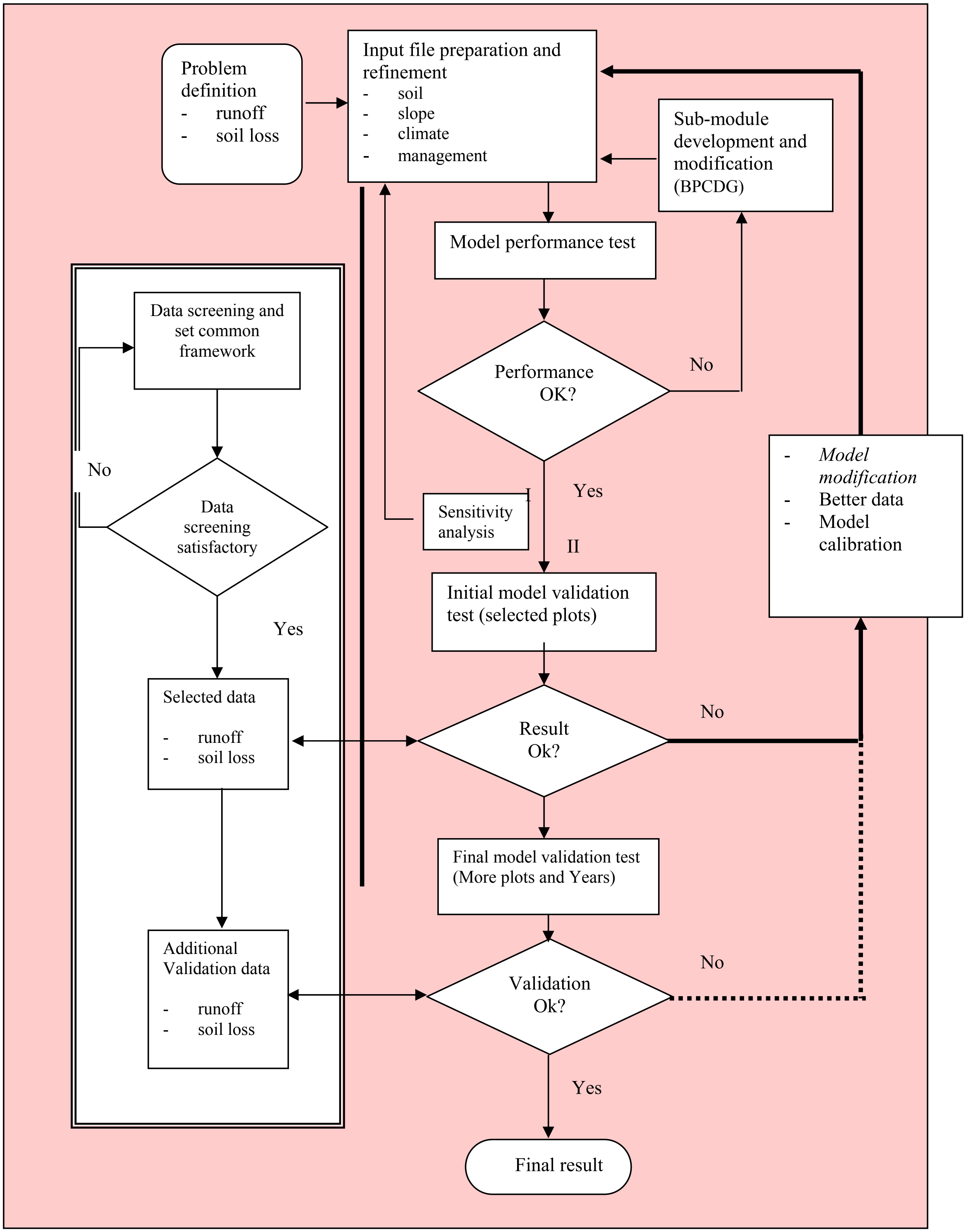

Figure 1: Model testing and validation procedures of the study. The process within the double lines indicates procedures of measured data screening and data selection. The double arrows indicate comparison and adjustment of predicted values to selected measured values. Note: the flow of the bold line indicates the last loop.