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A Study on the Effects of Sensitive Parameters Errors on Digital Soil Erosion Simulation

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Abstract: A combined runoff-sediment model is used to simulated soil erosion processes and predict soil loss of land surface. The Stanford Watershed Model (SWM) is used as runoff generator for this model. Effects of sensitive parameters errors on soil erosion characteristics are investigated. These characteristics include peak erosion and mean monthly erosion rates. Three different methods are used for the analysis, namely; first-order uncertainty analysis method; direct investigation technique and mean-maximum likelihood method. The aim is to quantify sensitive parameters errors propagation and to gain an appreciation of the approximate magnitudes of model output uncertainty caused by different levels of sensitive parameters uncertainty. Model output uncertainty ranges between (4.000-83.115)% for mean monthly erosion against (4.680-83.098)% for peak erosion. Uncertainty in simulated erosion due to sensitive parameters uncertainty is subsequently analyzed. The probability of peak erosion values occurrence due to sensitive parameters error are investigation. Based on the result obtain, high and moderately parameters are identified. Appropriate conclusion are drawn and suggestion for future work are introduced.

Key words: Soil erosion, first-order uncertainty analysis, direct investigation, mean-maximum likelihood, peak erosion, mean monthly erosion, sensitive parameters errors

INTRODUCTION

Basic to all engineering problems is design and basic of all design are measurements and wherever measurements are made, errors are made, the single exception being when the measurement is a discrete count. Since no measurement is free from error, steps must be taken to evaluate the accuracy and the precision of the measurement. To preclude a falls sense of accuracy, one must investigate the nature of error, as well as the sources, types and magnitude of error made of various stages of the measurement operation and the interrelation among errors (Austin, 1978). The planning and management of water resource system are dependent upon information relating to the spatial and temporal distribution to provide for the reduction of precise information and therefore, planning and management decisions are subjected to hydrological uncertainty in addition to uncertainties of a non-hydrological nature (Ali, 1998). Level recorder data usually contain errors. In order to attain maximum reliability, the size of errors in recorded data should be reduced to as much as possible. The best way of reducing errors is prevention. The effectiveness of an error prevention procedure depends on filed precautions, the quality and frequency of field checks and field check reports regarding the quality of equipment and their maintenance (Van Der Schaaf, 1984). Data collected over years are organized in variety of formats and stored on various media. Transformation and management of data are often tedious and difficult. In the current literature, so many studies deal with the major sources of modeling uncertainty (Ali, 1998; Austin, 1978; Borah and Haan, 1990). Errors in simulation occur for a number of reasons, among them:

1. Model parameter estimates.
2. Input data, consisting of climate, topography, vegetation type, soil characteristics and antecedent conditions which vary throughout the watershed and cannot be precisely measured.
3. Physical laws of fluid motion are unduly simplified (Hromadka and McCuen, 1989).

Error in hydrological models have been analyzed from different viewpoints using a variety of approaches. An important topic is the estimation of error bounds on simulated and sediment yield graphs produced using complex watershed models.

Estimation of the model parameters: Parameters estimation is the process by which the parameters of a hydrological model are estimated for particular application. Model parameters should a symptomatically approach their true values as the amount of information

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used for estimation gets very large (Haan, 1995). Parameter estimation is made more difficult by increasing the number of parameters to be estimated, the lack of correspondence between individual parameters and measurable physical properties of the catchment, multiple objectives, limited data and pronounced seasonality in hydrological regime. Some criteria that might be used for estimating model parameters include (Haan, 1989):

1. Direct measurement of physical properties in the field or in the lab.
2. Indirect measurement of physical properties through their relationships with other hydrological processes and watershed characteristics.
3. Compliance with published tables and charts.
4. Optimization of some objective functions.
5. Personal judgment of goodness of fit of simulated hydrographs to observed hydrographs.

Parameter estimation for hydrological models may be difficult because (Fleming, 1975):
1. Errors in data.
2. Amount of computations involved in many models.
3. Restriction on appropriate values for some of the parameters.
4. Thresholding in some of the model relationships.
5. Specification of appropriate criteria for parameter selection.
6. Correlation among parameters.

Study objectives: The current study is aimed to satisfy the following objectives:
1. To identify errors bounds of simulated erosion due to uncertainty in model sensitive parameters estimated values.
2. To provide an estimate of percentage error in simulated erosion due to the utilization of errors contaminated input data.
3. To provide an estimate of the probability of the occulting of the Peak simulated erosion due to the utilization of errors contaminated input data.

MATERIALS AND METHODS

The models used in this study: The complicated nature of sediment problem indicates the need to use highly reliably compressive and physically best simulate model to assess soil erosion output (Al-Kadhimi, 1982). The models used in this study are as follows:

Stanford Watershed Model (SWM): The original version of this model (SWM-IV), developed by Linsely and Kihler (1975), has undergone numerous modifications and reversions. SWM is a conceptual, lumped, continuous and general used model consisting of a number of storage units with flow between them prescribed by approximate physically based relationships. These relationships are generally expressed as functions of the current storage and physical characteristics of each unit. Data requirements are related by the use of these approximate expressions, which requires the use of fitted parameters (El-Kadi, 1989; Hussein, 1998). The model is based on water-balance accounting within the catchment boundary, catchment units represent differing soil types, vegetation, land use, physical characteristics and precipitation are defined as catchment segments. Each segment is described by a set of parameters representing specific physical features of the segment.

The land erosion model: In the modeling of soil erosion from the land surface, the land erosion model subdivides the catchment into three segments by altitude, i.e., upland, midland and lowland. Each segment is characterized by a width ~ length and slop. This representation is shown in Fig. 1. The amount of soil of each particle size fraction available to the agents of erosion in each segment is represented in the model by the top soil storage (Fig. 2). The storage of each particle size is enhanced or depleted by the input or output rates. However, the model constrains this process by maintaining the total mass of top soil storage at a constant value, i.e., there is always the same amount of total soil available to the agents of erosion. This is chivied in the model by the Top Soil Exposure Function (TSE) in Fig. 2. The distribution of the particle size within this top soil store, however, does not remain constant. The erosion output rate depletes the storage of the most erodible particle size at a much faster rate than the less erodible particle sizes. Thus, in the obscene of soil disturbance, the erosion rate will deplete the top soil storage by removing much fines and only relatively little of the coarser particle size, while the top soil exposure rate entrances the total top soil at an overall rate equals to the gross removal rate, thus keeping the storage constant. But since the top soil exposure rate supplies the top soil storage by particle size amount similar in distribution to the surrounding subsoil, the rate of removal of fines is then bound to be greater than their rate of replenishment and the opposite is true for the less erodible particles. Accordingly, the particle size distribution of the top soil becomes coarser with time and the layer itself becomes armored. Erosion from an upslope segment feed the top soil store with relatively fine soil. If the rate of erosion from upslope exceeds the erosion on the current segment then the deposing this relatively fine materials occurs. This soil enters deposition storage wih may or may not be a temporary storage state. In very flat slopes, deposition is always occurring on such slopes. The erosion from upslope always exceeds the current erosion and consequently the deposition storage grows continuously and erosion takes place from this deposition storage . In many cases, however, this deposition may build up over

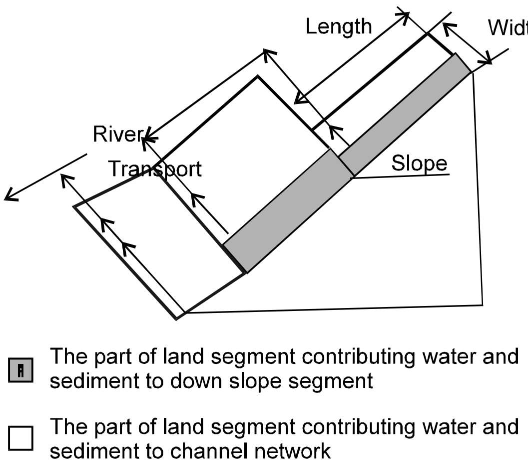

Fig. 1: Representation of a catchment by land erosion model (Hussein, 1998)

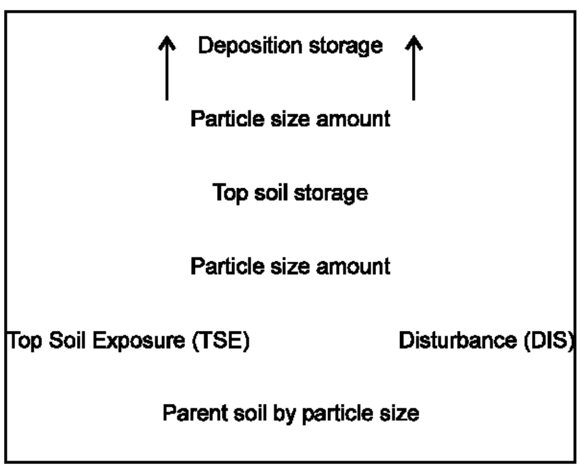

Fig. 2: Top soil storage representation in the land erosion model (Hussein, 1998)

time as temporary store of erodible soil a waiting an extreme storm event, with the highly erosional combination of intense rainfall and substantial overland flow. Such a combination would wash the erodible material into the channel system. In the obscene of erosion, soil disturbance feeds the top soil store with sediment from beneath. Such sediment the particle size distribution of the gross soil and thus contains a relatively higher proportion of fines than does the armored top soil. In such case the top soil exposure would then become negative, its rate being such the total amount of top soil store remains constant (Al-Kadhimi, 1982; Hussein, 1998).

Linkage to runoff component (Runoff Sub-Model): In its simulation of soil erosion, the land erosion model utilized hourly rainfall and runoff generated and stored to a modified version of Stanford watershed model. The Stanford watershed model was modified to enable catchment segmentation (El-Kadi, 1989). Catchments segmentation provides better representation of spatial variation of hydrologic, topographic, climatic and vegetal processes. A physically based routing procedure similar to that of (HSP) model was used instead of the original empirical one. Surface runoff is generated on hourly basis by the model and stored together with rainfall on certain computer storage. The land erosion model utilizes these data and use them in conjunction with its input data to simulate sediment yield from the catchment.

Input data requirements: Input data to land erosion model can be classified into three groups:

i. Hydrologic data.
ii. The model process parameters.
iii. Calibration and verification data.

Description of these data types are shown in Table 1. Process parameters have been sub-divided in Table 2 into three categories:

a. Parameters estimated from physical characteristics.
b. Coefficients estimated from laboratory and field experimentation.
c. Parameters estimated by trial calibration and adjustment.

Theory and results: Erosion of a catchment is considered as the final result of the interaction between the physical and climatic characteristics of the catchment. In this chapter, the effects of input data errors on simulated erosion are investigated. The analysis includes simulation of erosion of two cases, sensitive land erosion parameters and physical characteristics of catchment. The theories that are used to analysis the effects of data-base errors on simulated erosion are describe, these theories can be classified as:

1. First-order uncertainty analysis.
2. Direct investigation method (Reliability and its parameters).
3. Mean-maximum likelihood analysis.

First order uncertainty analysis: A description of First-Order Uncertainty Analysis (FOA) will be given here. The (FOA) is useful in obtaining approximate means and variances for random variables, the base of approximations is a truncated Taylor series.

Table 1: Input data requirement for the land erosion model (Al-Kadhimi, 1982)

Data type	Description
Hydrological data	Hourly rainfall, both intercepted and un intercepted obtained from runoff sub model.
Model process parameters	Parameters estimated from physical characteristics. Constants obtained from lab and field experimentation. Parameter obtained by calibration.
Calibration and verification data	Monthly sediment yield from sediment rating curve.

Table 2: Model process parameters (Al-Kadhimi, 1982)

Parameter	Description
a. Parameters estimated from catchment characteristics	
Length	Segment length (m)
Width	Segment width (m)
Slope	Segment slope.
Chan	Proportion of segment contribution to channel network, percent
ORGCON	Organic content
PS	Particle size (mm)
b. Coefficient obtained from laboratory and field experimentation	
c. Parameters obtained by calibration	
CDIS	Top soil disturbance rate

Theory: Let us assume a function y = g(x). If the coefficient of variation is not large (depends upon the degree of non-linearity of g(x) in the region around the mx, the following approximations are valid:

$$E(y) = E[g(x)] = g(E[x]) \quad (1)$$

$$Var.\ [y] = Var.[g(x)] = Var.[x] \left(\frac{dg(x)}{dx} \Big| mx \right)^2 \quad (2)$$

or :

$$\sigma y = \left(\frac{dg(x)}{dx} \Big| mx \right) \sigma x \quad (3)$$

Where:

$\frac{dg(x)}{dx}|mx$: Signified the derivative of g(x) with respect to x, at mx

E: The expected value.

Var.: The variance.

σ: The standard deviation.

mx: The main value of the variable x.

The justification for these approximations lies in the observations that the variance of x is small, x is very likely to be lie close to mx and hence a Taylor series expansion of g(x) about mx is suggested:

$$g(x) = g(mx) + (x\text{-}mx) \left(\frac{dg(x)}{dx} \Big| mx \right) + = \frac{(x - mx)^2}{2} \left(\frac{d^2g(x)}{dx^2} \Big| mx \right) + - - - \quad (4)$$

Keeping the only first two terms in the expansion and taking the expectation of both sides, we obtained the stated approximation for E[g(x)], since E[x - mx] = 0. Similarly, by keeping the same terms and finding the variance of both sides yields the approximation in equation (2), since Var.[g(mx)] = 0 and:

$$var. \left\{ \left(\frac{dg(x)}{dx} \Big| mx \right) (x - mx) \right\} = \left(\frac{dg(x)}{dx} mx \right)^2 \quad (5)$$

Clearly, if the coefficient of variation of x is less than 10%, the error involved in this approximation is less than 1%. Moreover, in order to use this method, equation (5) showed be written as:

$$Var.[y] = \sum_{i=1}^{n} \left(\frac{\partial y}{\partial xi} \Big| \mu xi \right)^2 \ Var.[xi] \quad (6)$$

In which µxi = The mean value of parameter xi (Ali, 1998).

Reliability and its parameters (Direct investigation method): In order to proceed further with uncertainty and error evaluation, the various parameters of reliability need to be explained and as follows:

Mean: The best known and most useful "average" is the arithmetic mean, usually referred to as the mean; it is' calculated by adding all observation and dividing the sum by the total number of observations (Benjamin *et al*., 1970).

Scatter: The way that the different value lie about this average is called the dispersion or scatter. Scatter is used to study certainty and uncertainty. Scatter of the values in a set of observations is an indication of their reliability. Wide dispersal bespeaks less reliable data than observations that lie closely distributed about the mean (Benjamin *et al*., 1970; Hudson, 1981).

Variance and standard deviation: The mean deviation dose not tell the manner in which the values dispersed. Indeed, one set of measurement may have errors of variable sizes, several very large, a few mediums and several very small. Yet both sets of measurements may have the same average error. Comparing the mean deviation of the two sets of data would give a false indication. In mean deviation, there would be no indication of the distribution (scatter) of the values in each set. There would be no penalty for large errors and no reward for small ones. Fortunately, a better and more usually used measure at scattering is the standard deviation. This is the square root of the mean of the square of the deviations (variations) of the observations from their arithmetic mean. It is usually symbolized by small sigma (σ)and is also frequently called the mean square error. Another measure of the scatter is variance, defined as the square standard deviation. The Coefficient of Variation (CV) may also be used and is defined as a ratio of the standard deviation to the mean of a given sampler or set (Austin, 1978; Haan, 1995; Harpar, 1989).

The mean and the maximum likelihood method: When many measurements give different result, we often average results. Common sense suggests that the average will be a true measure than individual measurements, which can be distorted by quirks in the measuring process. In certain circumstances, mathematical theory justified the common sense approach. To investigate this, we introduce the normal curve (Walter, 1984). The bell-shaped curve is the normal probability density curve but its use as a tool is rather limited. Frequently, a simple variant of this curve can be used, namely, the normal probability distribution curve (Austin, 1978). Because so many measurement processes involve normal density curves, we need some special information about them. A curve with the equation:

$$y = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (7)$$

A specific interpretation of is contained in the following rules:

1. Approximately 68% of the area under a normal curve is contained between the line x = μ-σ and x = μ+σ.
2. Approximately 95% of the area under a normal curve is contained between the line x = μ-2σ and x = μ+2σ.
3. Approximately 98% of the area under a normal curve is contained between the line x = μ-3σ and x = μ+3σ.

The area under probability density curve between x = a and x = b represents the probability that x (a particular measurement) will have a value between a and b.

$$L(\mu,\sigma) = \int_a^b \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \quad (8)$$

This integral is not easily evaluated. There are tables that will help (Borah and Haan, 1990; Fiorentino and Gabriele, 1984).

Methodology of the analysis: Hussein (1998) used a natural soil erosion data for AL-EZAME catchment in IRAQ to calibrated the Land Erosion Model and make the sensitivity analysis for the model parameters, below is a brief explanation of the sensitive land erosion model parameters:

1. The coefficient of soil detachability by rainfall (CDTCHP).
2. The coefficient of proportionality in the function of detachment by rainfall (CSPL).
3. The coefficient of proportionality in the function of detachment by runoff (CSCR).
4. The coefficient of effective friction (CEFFIC).
5. The coefficient of top soil disturbance rate (CDIS).
6. The coefficient in the function which expresses the up lift distance of a particle (EXPY).

The analysis of the effects of input sensitive parameters errors on simulated erosion was done in three directions, these are:

First order uncertainty analysis method: Even for a moderately complex model, it is usually impossible to obtain analytical expression for the partial derivative needed for the first order equations. Means and standard deviations for the model parameters and initial values of the simulated erosion were chosen. The model was initially run using the mean parameter values to obtain the first order approximation to the mean simulated erosion. The model was then rerun repeatedly, incrementing each parameter one at a time by a small amount Δx (Δx = 0.05μx was used here where μx is the mean value of the parameter). After each running, the affected parameter was returned to its mean value. The change in output due to a change in parameter value, ΔE/Δx, is an approximation of the partial derivative of the model with respect to a specific used parameter. Partial derivatives were calculated for each month of the simulation. After the model had been rerun for all uncertain parameters, the calculation in equation (6) was performed to obtain the variance for each month erosion, thus giving approximate error bounds on the output due to uncertainty in the parameters.

Direct investigation method: Errors were introduced to each sensitive land erosion parameter value in a

Table 3: The value of the sensitive parameter and the parameters error

Parameter	Calibrated value (Hussein, 1998)	Error%	Parameter error value
CDTCHP	144.000	+15	165.600
		+10	158.400
		+5	151.200
		-5	136.800
		-10	129.600
		-15	122.400
CSPL	5.205×10^{-3}	+15	5.986×10^{-3}
		+10	5.726×10^{-3}
		+5	5.465×10^{-3}
		-5	4.945×10^{-3}
		-10	4.684×10^{-3}
		-15	4.42×10^{-3}
CSCR	5.350	+15	6.153
		+10	5.885
		+5	5.618
		-5	5.083
		-10	4.815
		-15	4.548
CEFFIC	1.000	+15	1.150
		+10	1.100
		+5	1.050
		-5	0.950
		-10	0.900
		-15	0.850
CDIS	1.000	+15	1.150
		+10	1.100
		+5	1.050
		-5	0.950
		-10	0.900
		-15	0.850
EXPY	2.000	+15	2.300
		+10	2.200
		+5	2.100
		-5	1.900
		-10	1.800
		-15	1.700

percentage of ± (5, 10, 15). The error values of the parameters are shown in Table 3. The effects of errors in the above cited parameters on simulated erosion are investigated.

Mean-maximum likelihood method: If each sensitive parameter in land erosion model has two sets of values due to percentage + (5, 10, 15) errors and percentage - (5, 10, 15) errors in basic values respectively. The peak erosion values have also two sets. To know which the set of peak erosion values can be considered and to find the final value of peck erosion, the mean-maximum likelihood method is used.

RESULTS AND DISCUSSION

Table 3 show the basic values of studied parameters together with their error values. These values were then used in the model to simulate land soil erosion. Simulated erosion values thus obtained were then analyzed using the three above maintained methods, i.e., first order uncertainty analysis method, direct investigation method and mean-maximum likelihood method and as follows:

First-order uncertainty analysis method: Table 4-9 show the variance of monthly simulated erosion due to error (5%) in the values of the parameters CDTCHP, CSPL, CSCR, CEFFIC, CDIS and EXPY. Figure 3-8 show error bounds on monthly simulated erosion for these parameters. Form the analysis the standard deviation was varied from (0.0116) for parameter (EXPY) to (0.023) for parameter (CSPL). The Coefficient of Variation (CV) obtained in the range of (0.01176) for parameter (EXPY) to (0.026) for parameter (CSPL).The obtained model variance with respect to parameters (EXPY) and (CSPL) are in the range (22.9 x 1-2 to 1.2 x 10-5) and in the range (2.54 x 10-3 to 2.5 x 10-7), respectively. The model variance with respect to each other parameter are approximately the same and obtained in the range (1 x 10-2 to 2.5 x 10-7). From the results, it was found that the

Table 4: First-order-uncertainty analysis for monthly erosion due to error in parameter (CDTCHP)

Parameter	Parameter value (μx_i)	Error%	Parameter error value	Δx_i	Var. (x_i)
CDTCHP	144	+5%	151.2	7.2	12.96
Month	Simulated erosion value (E)	Simulated erosion error value	ΔE	(∂E/∂xi)	Var. (E)
Oct.	1.5	1.4	-0.1	-0.014	2.54×10^{-3}
Nov.	2.2	2.1	-0.1	-0.014	2.54×10^{-3}
Dec.	0.026	0.025	-0.001	-0.14×10^{-3}	2.5×10^{-7}
Jan.	0.16	0.15	-0.01	-1.4×10^{-3}	2.5×10^{-5}
Feb.	4.1	3.9	-0.2	-0.028	0.01
Mar.	2.0	1.9	-0.1	-0.014	2.54×10^{-3}
Apr.	0.084	0.08	-0.004	$-0.56\times10^{-}$	4×10^{-6}
May.	0.37	0.36	-0.01	-1.4×10^{-3}	2.5×10^{-5}
Jun.	0	0	0	0	0
Jul.	0	0	0	0	0
Aug.	0	0	0	0	0
Sep.	0	0	0	0	0

Table 5: First-order-uncertainty analysis for monthly erosion due to error in parameter (CSPL)

Parameter	Parameter value (μx_i)	Error%	Parameter error value	Δx_i	Var. (x_i)
CSPL	0.005205	+5%	0.005465	2.6×10^{-4}	1.69×10^{-8}
Month	Simulated erosion value (E)	Simulated erosion error value	ΔE	(∂E/∂xi)	Var. (E)
Oct.	1.5	1.6	0.1	384.615	2.5×10^{-3}
Nov.	2.2	2.3	0.1	484.615	2.5×10^{-3}
Dec.	0.026	0.027	0.001	3.846	2.5×10^{-7}
Jan.	0.16	0.17	0.01	38.461	2.5×10^{-5}
Feb.	4.1	4.3	0.2	769.231	0.01
Mar.	2.0	2.1	0.1	384.615	2.54×10^{-3}
Apr.	0.084	0.088	0.004	15.385	4×10^{-6}
May.	0.37	0.39	0.02	76.923	1×10^{-4}
Jun.	0	0	0	0	0
Jul.	0	0	0	0	0
Aug.	0	0	0	0	0
Sep.	0	0	0	0	0

Table 6: First-order-uncertainty analysis for monthly erosion due to error in parameter (CSCR)

Parameter	Parameter value (μx_i)	Error%	Parameter error value	Δx_i	Var. (x_i)
CSCR	5.35	+5%	5.6175	0.2675	178.9×10^{-8}
Month	Simulated erosion value (E)	Simulated erosion error value	ΔE	(∂E/∂xi)	Var. (E)
Oct.	1.5	1.44	-0.06	-0.224	8.981×10^{-4}
Nov.	2.2	2.112	-0.088	-0.329	1.937×10^{-3}
Dec.	0.026	0.025	-0.001	-0.004	2.5×10^{-7}
Jan.	0.16	0.153	-0.007	-0.026	1.2×10^{-5}
Feb.	4.1	3.936	-0.164	-0.613	6.726×10^{-3}
Mar.	2.0	1.92	-0.08	-0.3	1.611×10^{-3}
Apr.	0.084	0.081	-0.003	-0.011	2.166×10^{-6}
May.	0.37	0.355	-0.015	-0.056	5.613×10^{-5}
Jun.	0	0	0	0	0
Jul.	0	0	0	0	0
Aug.	0	0	0	0	0
Sep.	0	0	0	0	0

Table 7: First-order-uncertainty analysis for monthly erosion due to error in parameter (CEFFIC)

Parameter	Parameter value (μx_i)	Error%	Parameter error value	Δx_i	Var. (x_i)
CEFFIC	1.000	+5%	1.050	0.050	6.25×10^{-4}
Month	Simulated erosion value (E)	Simulated erosion error value	ΔE	(∂E/∂xi)	Var. (E)
Oct.	1.5	1.600	0.100	2.000	2.5×10^{-3}
Nov.	2.2	2.300	0.100	2.000	2.5×10^{-3}
Dec.	0.026	0.027	0.001	0.020	2.5×10^{-7}
Jan.	0.16	0.170	0.010	0.200	2.5×10^{-5}
Feb.	4.1	4.300	0.200	4.000	10×10^{-3}
Mar.	2.0	2.100	0.100	2.000	2.5×10^{-3}
Apr.	0.084	0.088	0.004	0.080	4×10^{-6}
May.	0.37	0.390	0.02	0.400	1×10^{-4}
Jun.	0	0	0	0	0
Jul.	0	0	0	0	0
Aug.	0	0	0	0	0
Sep.	0	0	0	0	0

parameter (EXPY) is very sensitive and the parameters (CSPL) is insensitive parameter. Other parameters are moderately sensitive.

Direct investigation method: Table 10 show statistical evaluation of the effects of individual sensitive parameters errors on simulated erosion. Results were analyzed as in the below:

1. Errors of (+5 to +15)% in the value of the parameter (CDTCHP) causes errors of a bout (-4.878%) to (-12.195%) on peak erosion and (-5.023%) to (-13.264%) on mean monthly erosion, All error of (-5 to -15)% cases an error of about (4.878%) to (17.073%) on peak erosion and (5.126%) to (16.471%) on mean monthly erosion the Coefficient of Variation (CV) is varies from (0.0258 to 0.0710) for positive errors and from (0.025 to 0.0761) for negative errors. The effects of negative errors are more than that of positive ones, as shown in Fig. 9.

Table 8: First-order-uncertainty analysis for monthly erosion due to error in parameter (CDIS)

Parameter	Parameter value (μx_i)	Error%	Parameter error value	Δx_i	Var. (x_i)
CDIS	1.000	+5%	1.050	0.050	6.25×10^{-4}
Month	Simulated erosion value (E)	Simulated erosion error value	ΔE	(∂E/∂xi)	Var. (E)
Oct.	1.5	1.582	0.082	1.640	1.681×10^{-3}
Nov.	2.2	2.320	0.120	2.400	3.6×10^{-3}
Dec.	0.026	0.027	0.001	0.020	2.5×10^{-7}
Jan.	0.16	0.169	0.009	0.180	2.025×10^{-5}
Feb.	4.1	4.323	0.223	4.446	12×10^{-3}
Mar.	2.0	2.109	0.109	2.180	2.97×10^{-3}
Apr.	0.084	0.088	0.004	0.080	4×10^{-6}
May.	0.37	0.390	0.02	0.400	1×10^{-4}
Jun.	0	0	0	0	0
Jul.	0	0	0	0	0
Aug.	0	0	0	0	0
Sep.	0	0	0	0	0

Table 9: First-order-uncertainty analysis for monthly erosion due to error in parameter (EXPY)

Parameter	Parameter value (μx_i)	Error%	Parameter error value	Δx_i	Var. (x_i)
EXPY	2.000	+5%	2.100	0.100	2.5×10^{-3}
Month	Simulated erosion value (E)	Simulated erosion error value	ΔE	(∂E/∂xi)	Var. (E)
Oct.	1.5	1.900	0.400	4.000	40×10^{-3}
Nov.	2.2	2.786	0.586	5.860	86×10^{-3}
Dec.	0.026	0.033	0.007	0.070	1.2×10^{-5}
Jan.	0.16	0.203	0.043	0.430	4.622×10^{-4}
Feb.	4.1	5.193	1.093	10.930	229×10^{-3}
Mar.	2.0	2.533	0.533	5.330	71×10^{-3}
Apr.	0.084	0.106	0.022	0.220	1.21×10^{-4}
May.	0.37	0.469	0.099	0.990	24.5×10^{-4}
Jun.	0	0	0	0	0
Jul.	0	0	0	0	0
Aug.	0	0	0	0	0
Sep.	0	0	0	0	0

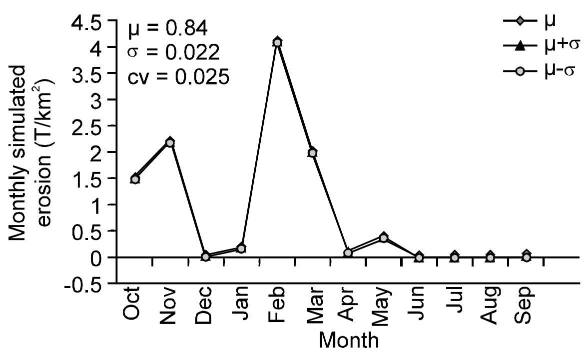

Fig. 3: Error bounds for monthly erosion due to error (5%) in parameter value (CDTCHP)

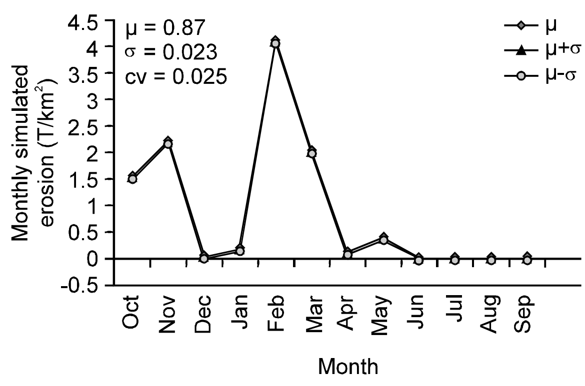

Fig. 4: Error bounds for monthly erosion due to error (5%) in parameter value (CSPL)

2. Errors of (+5 to +15)% in the value of the parameter (CSPL) causes errors of about (4.878%) to (14.634%) on peak erosion and (5.126%) to (14.437%) on mean monthly erosion. Negative errors have approximately the same effects, as shown in Fig. 10. The Coefficient of Variation (CV) is varies from (0.0250 to 0.0673) for positive errors and from (0.0263 to 0.0822) for negative errors.

3. Errors of (+5 to +15)% in the value of the parameter (CSCR) causes errors of about (-4.000%) to (-13.610%) on peak erosion and (-4.000%) to (-13.609%) on mean monthly erosion. An error of (-5 to-15)% causes an error of error about (4.805%) to (20.000%) on peak erosion and (4.805%) to (19.98%) on mean monthly erosion the Coefficient of Variation (CV) is varies from (0.0204 to 0.0730)

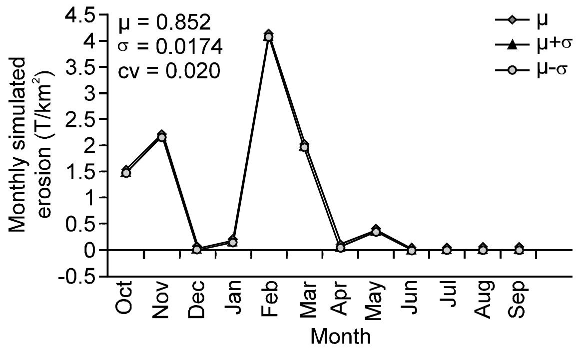

Fig. 5: Error bounds for monthly erosion due to error (5%) in parameter value (CSCR)

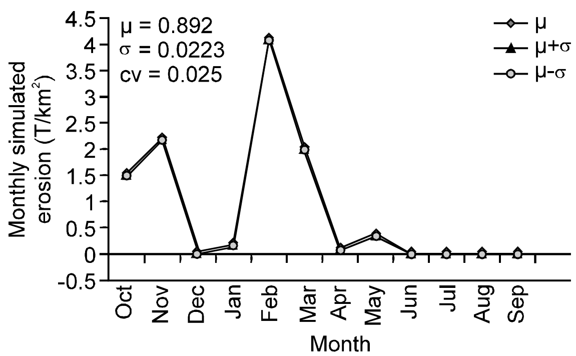

Fig. 6: Error bounds for monthly erosion due to error (5%) in parameter value (CEFFIC)

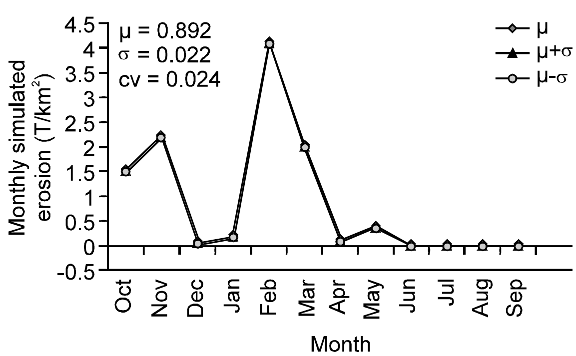

Fig. 7: Error bounds for monthly erosion due to error (5%) in parameter value (CDIS)

for positive errors and from (0.0235 to 0.0909) for negative errors The effects of negative errors are more than that of positive ones, as shown in Fig. 11.

4. Errors of (+5 to +15)% in the value of the parameter (CEFFIC) causes errors of about (4.878%) to (14.634%) on peak erosion and (4.172%) to (14.437%) on mean monthly erosion. Figure 12 show that that errors have the same effects on peak erosion. The effects of the negative errors are more

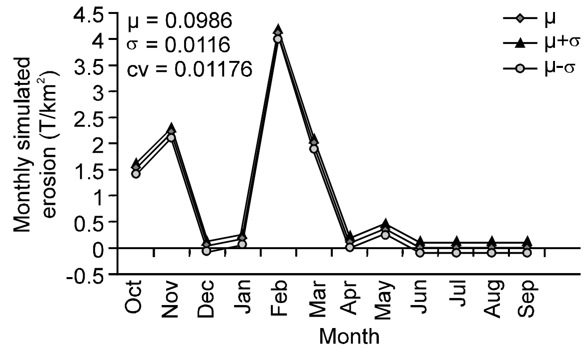

Fig. 8: Error bounds for monthly erosion due to error (5%) in parameter value (EXPY)

Table 10: Statistical evaluation of the effects of individual sensitive parameters errors on erosion

		Error%		
Parameter	Error%	MME	PE	CV
CDTCHP	+15	-13.264	-12.195	-0.0710
	+10	-9.103	-9.756	-0.0477
	+5	-5.023	-4.878	-0.0258
	-5	5.126	4.878	0.0250
	-10	12.299	12.195	0.0532
	-15	16.471	17.073	0.0761
CSPL	+15	14.437	14.634	0.0673
	+10	9.287	9.756	0.0444
	+5	5.126	4.878	0.0250
	-5	-5.126	-4.878	-0.0263
	-10	-11.023	-9.756	-0.0583
	-15	-15.195	-14.634	-0.0822
CSCR	+15	-13.609	-13.610	-0.0730
	+10	-8.046	-8.000	-0.0419
	+5	-4.000	-4.680	-0.0204
	-5	4.805	4.805	0.0235
	-10	11.986	12.000	0.0566
	-15	19.989	20.000	0.0909
CEFFIC	+15	14.437	14.634	0.0673
	+10	9.287	9.756	0.0444
	+5	4.172	4.878	0.0204
	-5	-5.126	-4.878	-0.0263
	-10	-11.989	-9.756	-0.0638
	-15	-18.874	-14.634	-0.1042
CDIS	+15	12.724	12.732	0.0598
	+10	10.862	10.902	0.0515
	+5	5.437	5.439	0.0265
	-5	-9.103	-9.098	-0.0786
	-10	-14.575	-14.634	-0.0786
	-15	-19.103	-19.098	-0.1056
EXPY	+15	66.667	66.659	0.2500
	+10	47.782	47.805	0.1928
	+5	26.655	26.659	0.1176
	-5	-36.115	-36.098	-0.2204
	-10	-59.448	-59.439	-0.4320
	-15	-83.115	-83.098	-0.5518

MME = Mean Monthly Erosion; PE = Peak Erosion

than that of position ones. The Coefficient of Variation (CV) is varies from (0.0204 to 0.0673) for positive errors and from (0.0263 to 0.1042) for negative errors.

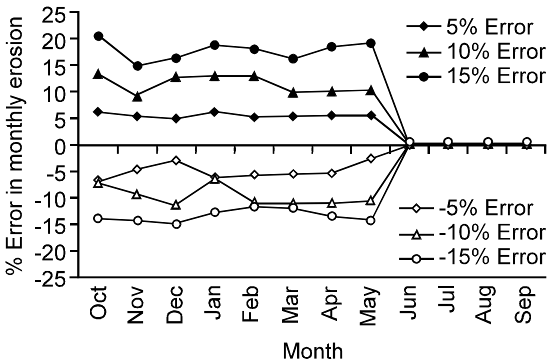

Fig. 9: Percent error in monthly erosion due to error in parameter (CDTCHP)

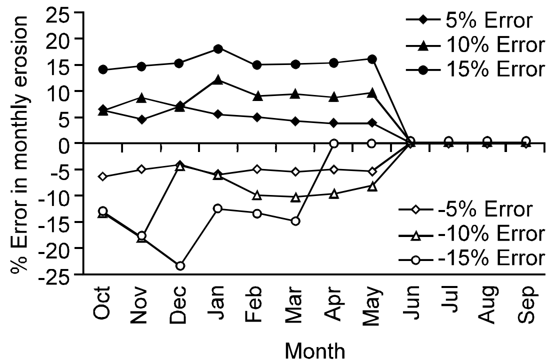

Fig. 12: Percent error in monthly erosion due to error in parameter (CEFFIC)

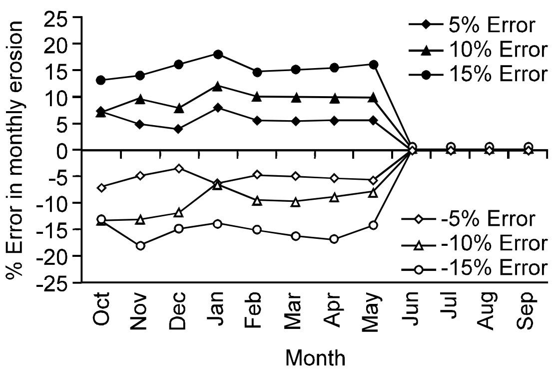

Fig. 10: Percent error in monthly erosion due to error in parameter (CSPL)

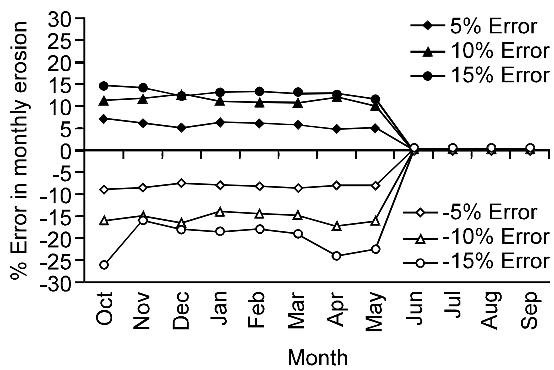

Fig. 13: Percent error in monthly erosion due to error in parameter (CDIS)

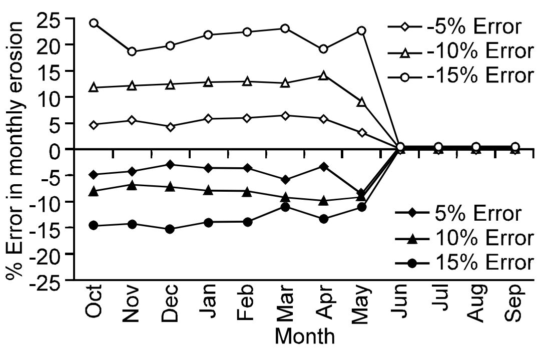

Fig. 11: Percent error in monthly erosion due to error in parameter (CSCR)

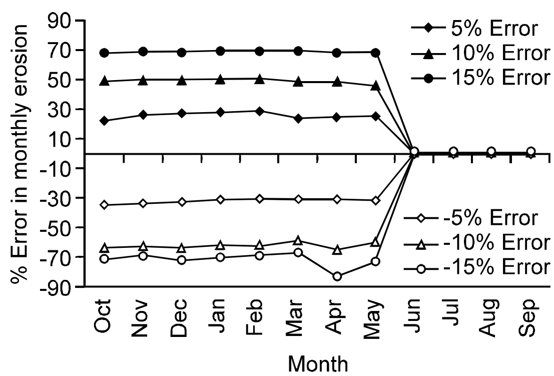

Fig. 14: Percent error in monthly erosion due to error in parameter (EXPY)

5. Errors of (+5 to +15)% in the value of the parameter (CDIS) causes errors of about (5.439%) to (12.732%) on peak erosion and (5.437%) to (12.724%) on mean monthly erosion. An error of (-5 to -15%) causes an error of about (-9.098%) to (-19.098%) on peak erosion and (-9.103%) to (-19.103'%) on mean monthly erosion the effects of the negative errors are more than that of position ones, as shown in Fig. 13. The Coefficient of Variation (CV) is varies from (0.0265 to 0.0598) for positive errors and from (0.0786 to 0.1056) for negative errors.
6. Error of (+5 to + 15)% in the value of the parameter (EXPY) causes errors of about (26.659%) to (66.659%) on peak erosion and (26.655%) to (66.667%) on mean monthly erosion. An error of (-5 to -15)% causes all error of about (-36.098%) to

Table 11: Mean-maximum likelihood analysis for individual sensitive land erosion parameters error

Parameter	Error%	Set	Peak erosion (T/km^2)	Mean of set values (T/km^2)	Probability of occurring	Cons. set	Consideration peak erosion (T/km^2)
CDTCHP	+15	A	3.6	3.733	0.946	B	4.567
	+10		3.7				
	+5		3.9				
	-5	B	4.3	4.567	0.971		
	-10		4.6				
	-15		4.8				
CSPL	+15	A	4.7	4.5	0.979	A	4.5
	+10		4.5				
	+5		4.3				
	-5	B	3.9	3.7	0.962		
	-10		3.7				
	-15		3.5				
CSCR	+15	A	3.542	3.75	0.967	B	4.603
	+10		3.772				
	+5		3.936				
	-5	B	4.297	4.603	0.978		
	-10		4.592				
	-15		4.92				
CEFFIC	+15	A	4.7	4.5	0.979	A	4.5
	+10		4.5				
	+5		4.3				
	-5	B	3.9	3.7	0.962		
	-10		3.7				
	-15		3.5				
CDIS	+15	A	4.622	4.497	0.922	B	3.515
	+10		4.547				
	+5		4.323				
	-5	B	3.727	3.515	0.973		
	-10		3.5				
	-15		3.317				
EXPY	+15	A	6.833	6.029	0.976	A	6.029
	+10		6.06				
	+5		5.193				
	-5	B	2.62	1.823	0.95		
	-10		1.663				
	-15		1.185				

Cons. = Consideration

(-83.098%) on peak erosion and (-36.115%) to (-83.115%) on mean monthly erosion the effects of the negative errors are more than that of position ones, as shown in Fig. 14. The Coefficient of Variation (CV) is varies from (0.1176 to 0.2500) for positive errors and from (0.2204 to 0.5518) for negative errors.

Mean-maximum likelihood method: The mean-maximum likelihood method is applied to determine the probability of occurring of each positive and negative errors sets in sensitive land erosion parameters. The results are tabulated in Table 11.

Results were analyzed as in the below:

1. For parameters (CDTCHP, CSCR and CDIS), the probability of occurring negative errors set is greater than that of positive one. The considered peak erosion values are equal to (4.567, 4.603 and 3.515 T/km^2), respectively.
2. For parameters (CSPL, CEFFIC and EXPY), the probability of occurring positive errors set is greater than that of negative one. The consideration peak erosion values are equal to (4.5, 4.5 and 6.029 T/km^2), respectively.

Conclusions: Based on the results obtained in this study the following conclusions can be drawn:

2. First-order uncertainty analysis can successfully be used to quantify error propagation and the associated uncertainty in model output.
3. Results of direct investigation of simulated soil erosion regarding error contaminated process parameters, reveal the following conclusions:

i. The parameter (EXPY) is more sensitive in peak and mean monthly erosion.
ii. The parameters (CDTCHP, CSPL, CSCR, CEFFIC and CDIS) proved to be sensitive.

Recommendations: The following recommendations are suggested for further studies:

1. Collection of quality field data regarding the various sources of soil erosion.
2. Conduct a real catchment simulation of soil erosion.
3. The use of first-order uncertainty analysis in conjunction with more complex watershed models.
4. Assessing parameter errors effects on soil erosion with wider ranges of uncertainties in model input data.

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