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EROSION PARAMETER IDENTIFICATION IN OVERLAND FLOW AREAS:

APPLICATION OF A GLOBAL AND LOCAL SEARCH ALGORITHM

by

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for my husband, Mario

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ABSTRACT

Two optimization algorithms and two objective functions were applied to determine erosion parameters for a physically-based, event-oriented model designed to simulate the processes of sedimentation for small watersheds. Three different flow-induced erosion equations were also tested with the four optimization procedures to examine the predictive capabilities of the equations. Synthetic error-free data as well as data contaminated with correlated and random error provided the means for determining the effectiveness of the four optimization procedures studied. After selecting the most effective optimization procedure and flow-induced erosion equation, the model was tested using sediment data from rainfall simulator plots and a small experimental watershed. The results from the rainfall simulator studies indicated that a structural problem may exist within the model. The agreement between simulated and observed responses for the watershed events studied indicated that the model was capable of describing sedimentation processes when they occurred on a larger scale.

INTRODUCTION

Soil erosion is one of the major hazards threatening land productivity. The loss of sediment and associated nutrients through runoff and soil erosion can reduce productivity and lead to vegetation losses and further increases in the rates of soil erosion (Gifford and Busby, 1973). The transport of sediment from hillslopes into adjacent water bodies can also negatively impact reservoir capacities, water-based outdoor recreation, and fisheries. Thus, the ability to predict soil erosion under current and alternate land-use conditions is important in managing land and water quality.

Physically-based erosion models are potentially capable of providing information on the amount, timing and sources of sediment production. However, a major problem in the application of physically-based models is in parameter identification (Lopes, 1987; Blau et al., 1988; Page, 1988). Parameters, which can be defined as coefficients, are usually represented in an erosion model as the soil's ability to withstand erosion and are termed soil erodibility parameters. Considerable research has been conducted to relate measurable physical and chemical properties to soil erodibility parameters (Romkens et al., 1977; Meyer and Harmon, 1984; Musaed, 1994). However, parameter evaluation is often accomplished by some manual or automated calibration procedure. Although a manual procedure is subjective and may not generate an optimum parameter set, it usually produces parameter values that can be related to some physical properties of the watershed. Automated calibrated procedures, although more objective, have experienced problems such as convergence to local minima and producing parameter values that effectively minimize the objective function but conceptually have no meaning (Hendrickson et al., 1988).

Despite the inability of automated optimization algorithms to find an unique optimal parameter set, their use is widespread in conceptual rainfall-runoff modeling (Dawdy and O'Donnell, 1965; Johnston and Pilgrim, 1976; Pickup, 1977; Sorooshian and Gupta, 1983; Gupta and Sorooshian, 1985; Hendrickson et al., 1988). As physically-based erosion models replace the empirically-based Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), the use of automated techniques in erosion modeling has increased (Lopes, 1987; Page, 1988; Blau et al., 1988; Luce and Cundy, 1994). However, although physically-based models are conceptually superior to empirical models, as with empirical models, their accuracy is still dependent on the accuracy of their input parameters. Unless the best set of parameter values associated with a given calibration data set can be found, a reasonable degree of confidence cannot be placed in the accuracy of model predictions.

Different reasons have been cited for the inability of automated optimization algorithms to find unique optimal parameter values including parameter interaction (Lopes, 1987), parameter insensitivity (Blau et al., 1988) and optimization procedures that are not powerful enough to do the job (Duan et al., 1992). The problem may lie in either the model structure, selected objective function, optimization method used, or some combination of these factors (Duan et al., 1992).

Problem Statement

Improved estimates of soil erosion are needed in order to address concerns about nonpoint pollution and land productivity. For example, long term estimates generated by the Universal Soil Loss Equation are inadequate for making erosion predictions under alternate land uses or on an event basis. Subsequent advances in erosion technology have led to the development of physically-based models that conceptually divide erosion into two separate processes: 1) erosion caused by raindrop impact and 2) erosion induced by overland flow. However, in order to apply such models, parameters that describe the soil's susceptibility to erosion must be identified.

The accuracy of model predictions is dependent on the sensitivity and accuracy of its input parameters. The ability of an automated optimization procedure to determine input parameters is dependent on model structure, selected objective function, and optimization algorithm employed. This study compared optimal parameter values determined by two different optimization procedures and two different objective functions for three flow-induced erosion models. An assessment of the optimization algorithms' capacity to determine the erosion parameters for each of the models established the appropriateness of both the model and optimization procedure for use in erosion prediction when using the Watershed Erosion and Sediment Yield Program (WESP) (Lopes, 1987).

Objectives

The goal of this study was to determine the adequacy of optimization algorithms and objective functions in identifying unique, optimal parameter values. The specific objectives of this study were:

1. Determine the sensitivity of the estimation procedure to calibration data variability (dry, wet and very wet runs), and whether or not the selected objective function could reduce this sensitivity.
2. Assess both the algorithm's and model's sensitivity to variable and steady-state rainfall intensities.
3. Evaluate the capabilities of the selected flow-induced models to predict erosion under fully dynamic conditions.
4. Assess the ability of the selected flow-induced erosion equation in reproducing sediment graphs with physically, realistic parameter values.
5. Identify problems in model structure that inhibited the identification of unique parameter values.

Approach

In order to study the behavior of WESP in conjunction with the different optimization procedures and flow-induced erosion models, synthetic sediment concentration data, which were generated utilizing soil and rainfall characteristics based on rainfall simulator plot data, were utilized so that true values of parameters were known.

Error-free data were used to verify that algorithms and objective functions were capable of finding true parameter values when no error was present. Since correlated error may be common in sediment concentration data, two levels of correlated error were introduced into the synthetic data set utilizing a first order Markov chain model.

With the synthetic data, two and three parameter problems were posed with the objective of finding the best parameter sets to reproduce a given sediment graph. By fixing the value of one of the three parameters, parameter sensitivities and interactions were better evaluated when compared to a three parameter optimization problem. Slope gradient effects and variable antecedent moisture conditions were also identified. Given that WESP is a fully dynamic simulation model, the parameters identified from events with a single rainfall intensity were compared to parameters identified from events with variable rainfall intensity rates.

This study utilized three data types; 1) synthetic data as previously described, 2) rainfall simulator sediment concentration data from the United State Department of Agriculture - Agricultural Research Service (USDA-ARS) Water Erosion Prediction Project (WEPP) field experiments, and 3) sediment yield data collected from the USDA-ARS Kendall Watershed at Walnut Gulch. Three different equations were proposed to describe flow-induced erosion. Two optimization algorithms, one based on a local search procedure (Simplex method) and one specifically designed to find a global minimum (SCE-UA), were used for parameter identification. Two objective functions, the sum of the least square (SLS) and heteroscedastic maximum likelihood estimator (HMLE), were used to find the minimum error. Utilizing results from the synthetic data study, the most successful flow-induced erosion equation, optimization algorithm and objective function were used for identifying erosion parameters for the plot and watershed studies.

An analysis of parameter estimation error for both active and inactive parameters provided a criterion for identifying the optimal optimization procedure and flow-induced erosion model under different hydrological conditions. Other considerations included relative efficiency in avoiding local optima, continuity and shape of the response surface configurations, and algorithm's ability to attain the best value of the objective function.

Benefits

Parameter identification is of paramount importance in hydrological and erosion modeling. Without accurate parameter estimation methods, confidence cannot be placed in model predictions. Many contributions have been made to parameter identification within a conceptual rainfall-runoff framework. However, research is only recently emerging into the use of automated techniques of parameter estimation for physically-based erosion models. The major benefits of this research are increased insight into parameter identification and the further development of the WESP model. Other models may also benefit by incorporating automated optimization techniques into the parameterization process.

The derivation of an optimum parameter set in erosion modeling may depend heavily upon the calibration procedure utilized. This study contributes to an understanding of the limitations and benefits obtained from the selection of objective functions and search algorithms. An assessment of the sensitivity of the procedure (and/or the model) to variable and steady-state rainfall intensities also contributes to experimental design of future soil erosion studies utilizing rainfall simulators.

LITERATURE REVIEW

Decisions on how to control erosion and remediate erosion damage demand a knowledge of erosion risk under existing and alternative land management practices. Physically-based erosion models are potentially capable of providing this information provided that they can be properly parameterized for any given watershed. The first section of this literature review presents a brief history of important contributions to erosion modeling research. The controlling variables and parameters in erosion modeling are then described. In the final section, techniques of parameter optimization are presented within both an erosion and conceptual rainfall-runoff modeling framework.

Models of Soil Erosion

Many models used in soil erosion studies are empirical and based on defining the most important factors controlling the soil erosion process through the use of observation, measurement, experiment and statistical techniques. Zingg (1940) was the first to develop an equation that related erosion to slope steepness and length. Later developments included the addition of a climactic factor (Musgrave, 1947), and a crop factor that took into account the protective nature of different crops (Smith, 1958). This factor approach was later incorporated into the Universal Soil Loss Equation (Wischmeier and Smith, 1978), where the factors affecting the soil erosion process (rainfall erosivity, soil erodibility, topography and land use and management) were quantified. Although empirical models such as the USLE have been widely used to predict soil erosion, the factors are unique to the experimental conditions from which they were derived and should not be used under different conditions.

Empirical models deal with erosion prediction and parameter identification differently than physically-based erosion models. Based on physical laws and theoretical principles, physically-based erosion models attempt to represent the processes of erosion by mathematical equations that represent the erosion processes of soil particle detachment, transport and deposition (Lopes and Ffolliott, 1994). Two different approaches have been used in physically-based erosion modeling. The first approach assumes steady state conditions even though the processes of sediment detachment and transport are known to be unsteady (Meyer and Wischmeier, 1969; Foster and Meyer, 1972; Komura, 1976; Meyer et al. 1983; Rose, 1985). The second approach models the processes of erosion without steady-state assumptions. A kinematic-wave approximation to the dynamic flow equations is commonly used to model the hydraulics of the erosion processes, even though simplifying assumptions are required, such as constant and uniform rates of rainfall intensity and infiltration. The erosion processes are generally modeled using the continuity equation for sediment transport and empirical relationships for detachment by raindrop impact and hydraulic shear (Bennett, 1974; Singh, 1983; Lopes, 1987).

Rainfall Simulators and Rainfall Simulator Plots in Soil Erosion Research

Rainfall simulators have been used for soil erosion research and are designed to simulate precipitation occurring from a natural rainstorm over small areas. The use of rainfall simulators and rainfall simulator plots is advantageous because hydrological and soil erosion characteristics can be measured in a controlled environment. Researchers can also make measurements and observations during a simulated storm that may be difficult or impossible during a natural rainstorm (Meyer, 1994).

Rainfall simulator plots are designed to represent a micro-watershed. Like a watershed, the rainfall simulator plot can be represented by more than one element, where an element can be defined as either a plane or channel. Each element may represent changes in soil characteristics, hillslope characteristics or variations in land use. Channel elements can receive sediment inflows from upstream and lateral planes and channels. Rainfall simulator plots can also be modeled as a single plane, assuming that erosion by hydraulic shear is driven by the hydraulics of broad shallow overland flow.

Erosion Processes

The erosion processes involve the detachment, transport and deposition of soil particles by the erosive forces of raindrops and surface flow. Conceptually, hillslope erosion has been traditionally divided into two phases based on the characteristics of overland flow: interrill and rill erosion. Interrill erosion is the result of detachment induced by raindrop impact and transport by broad shallow surface flow. As the surface flow moves downslope, its flow depth increases and concentrates in rills. Soil detachment occurs in rills when the hydraulic shear of the flowing water is sufficient to overcome the binding forces between individual soil particles. These concentrated flow areas transport the detached sediment from both rill and interrill areas.

An alternative approach to modeling erosion on a hillslope is to assume that concentrated flow areas do not develop when an area is small. In this case, it is assumed that sediment entrainment is induced by two processes: raindrop impact and hydraulic shear of broad shallow overland flow.

Many physically-based erosion models conceptualize the erosion process as one of entrainment of soil particles and the detachment or deposition of sediment as a function of the flow's ability to carry the sediment load (Foster and Meyer, 1972). This is known as transport-capacity approach and basically describes a balance between entrainment and deposition rates of the sediment in flow (Nearing et al., 1994). When the transport capacity of the flow is exceeded, deposition will occur. If the transport capacity is not reached, then entrainment of detached particles will occur given the available sediment supply.

Another approach to erosion modeling is simultaneous sediment exchange. It is based on a concept of a continuous exchange of particles between the flow and soil surface and does not consider the capacity of the flow to entrain soil particles. Lopes (1987) developed a model that calculated rates of detachment and entrainment of sediment by flow, detachment and entrainment of soil by raindrop impact, and the deposition of sediment. In this model, net entrainment and detachment occur when the rates of entrainment and detachment exceed the rates of deposition.

Erosion Induced by Raindrop Impact

Generally, the hydrologic variables driving the soil erosion processes in areas where entrainment by raindrop impact predominates are obtained by applying overland flow equations. Young and Wiersma (1973) found that the detachment capacity of overland flow was negligible compared to that of raindrop splash, due to the low magnitude of the shear stresses caused by thin sheet flow. Kirkby (1980) found that when rates of erosion are high, soil loss from areas where entrainment caused by raindrop impact is usually low compared to losses from erosion caused by hydraulic shear. However, erosion induced by raindrop impact can dominate in rangelands or where slope angles are low and slope lengths are short (Nearing et al., 1989).

A common model for entrainment by raindrop impact describes the rate of sediment transport as a non-linear function of rainfall intensity. Other models describe detachment by raindrop impact as a linear function of the rainfall excess rate and rainfall intensity. Such relationships are usually developed based upon extensive rainfall simulation studies on a variety of different soils (Nearing et al., 1989).

Flow-Induced Erosion

Entrainment induced by broad shallow overland flow occurs when hydraulic forces overcome the resistance threshold for the soil. The balance between the erosive power of the flow and erosion resistance of the soil determines the entrainment rate. The hydraulic variables driving the soil erosion process are often obtained by equations developed from observations in large channels.

When employing the hydraulics of channels Hernandez (1992) found that parameter identification was a problem in rainfall simulator plots where well-defined drainage patterns did not exist. This implies that erosion caused by hydraulic shear may occur even in the absence of a well-defined rill or channel. Govers (1992) suggested that the hydraulics of overland flow are different from those of channel flow. In areas where broad shallow overland flow predominates, the hydraulics can be obtained from overland flow equations.

Flow-induced detachment is often described as a linear function of flow shear stress. The positive intercept on the shear stress axis is called the critical shear stress of the soil. Although many models describe flow-induced detachment as a linear function of hydraulic shear, flume studies have shown this relationship to be non-linear (Nearing et al., 1994). In the Water Erosion Prediction Project (WEPP) model by Lane and Nearing (1989), the critical shear stress is described as a mathematical entity that results from the linearization of the model. Nearing et al. (1994) warns that it should not be physically interpreted as a threshold level of shear stress. However, mathematically, threshold parameters can be difficult to optimize due to parameter insensitivity (Johnston and Pilgrim, 1976). A misrepresentation of the physical processes in the model can cause problems in parameter identification.

Many flow-induced models incorporate existing transport formulas that were developed based on experimental work in channels. The bedload formula of Yalin (1963) has been frequently used (Dillahah and Beasley, 1983; Kahnbilvardi et al., 1983; Park et al., 1982). Yalin's formula is of the excess-shear type, and is based on the theoretical assumption that bed-load discharge rate is a function of the range of particles in saltation rather than their number. Foster and Meyer (1972) first proposed the use of the Yalin equation for overland flow areas and Alonso et al. (1981) confirmed its ability for predicting erosion in shallow flow areas. The Water Erosion Prediction Project (WEPP) incorporates the Yalin formula into the erosion component of the model (Foster et al., 1989).

The total load formula of Yang (1973) based on the theory of stream power has been frequently used. Bagnold (1966) first proposed the concept of stream power, which is based on a balance of energy rather than a balance of forces, to determine the entrainment rate. Bagnold defined stream power as the product of bed shear stress and mean flow velocity. Sediment discharge, however, is not usually a sole function of shear stress. Consequently, Yang (1973) introduced the concept of unit stream power, which is the amount of energy dissipated per unit time and per unit weight of the flow and is equal to the product of slope and mean velocity. The total sediment concentration (not sediment discharge) is therefore directly related to unit stream power. Moore and Burch (1986) and Loch et al. (1989) have since demonstrated that the Yang formula is a good predictor of flow's transport capacity in overland flow areas.

Even though such formulas are based on physical principles, they have been calibrated utilizing experimental data. Model predictions may be erratic when these formulas are used to describe the transport capacity of flow in overland flow areas. This is due to the fact that these areas are very shallow and slopes may be much greater than those encountered in channels (Govers, 1992) where sediment transport formulas such as Yalin (1963) and Yang (1973) have been developed. However, Govers (1992) found that equations based on shear stress, unit stream power and effective stream power could be used in some cases to effectively predict the sediment transport capacity of overland flow.

Hydraulic Roughness

The identification of the magnitude of the hydraulic roughness coefficient is pertinent to modeling flow-induced erosion. Laminar flow over rough surfaces is usually characterized by a high friction factor due to turbulent friction losses around protrusions causing roughness (Phelps, 1975). In general, the resistance coefficient depends on the Reynolds number (Re) of the flow. The Darcy-Weisbach friction factor is most commonly used in hydrologic modeling, but Manning's and Chezy's coefficients may be used as well.

Soil Erodibility

Soil erodibility is defined as the resistance of the soil to both detachment and transport (Morgan, 1986). Soil erodibility, along with rainfall characteristics, topography, cover and management, is a major determinant of soil erosion and is a function of the chemical and physical properties of a soil. Particle size, aggregate stability, shear strength, infiltration capacity, organic matter and chemical content are widely accepted as the soil variables most strongly influencing a soil's erodibility.

Physically-based soil erosion models incorporate soil erodibility parameters into that part of the model dealing with soil entrainment and transport (Romkens et al., 1977; Meyer and Harmon, 1984; Musaed, 1994). Before the advent of physically-based erosion models, several researchers have related measurable physical and chemical properties to indices of soil erodibility for agricultural soils (Bennet, 1939; Barnett and Rogers, 1966; Wischmeier and Mannering, 1969; Wischmeier et al., 1971). However, the regression relationships developed require data that are not readily available for rangeland soils. Simpler relationships based on texture, organic matter and volumetric water content have been developed to evaluate soil erodibilities for physically-based models (Alberts et al., 1989; Flanagan, 1991).

Qualitatively, texture can be used as index of erodibility. In general, fine-textured soils are usually cohesive and difficult to detach. The small particles of fine textured soils are easy to transport unless the aggregates are large. Coarse-textured soils easily detach, but the large particles are difficult to transport. Medium-textured soils are both easily detached and transported and are thus classified as highly erodible soils (Wischmeier and Mannering, 1969).

Erosion modeling, however, requires a quantification of soil erodibility. Since the mechanisms differ for flow-induced and raindrop induced entrainment, erodibility parameters for each process are distinct. Considerable research has been dedicated to studying the separate processes of erosion and soil erodibility parameter identification (Meyer et al., 1975, Young and Onstad, 1978; Hussein and Laflen, 1982; Van Liew and Saxton, 1983; Bradford et al., 1987). A wide range of single parameters and combinations of parameters have been identified with varying degrees of success. When regression relationships are inappropriate, soil erodibilities can be identified by optimization.

Erosion Parameters

In order to model soil erosion by water, it is important to understand the controlling variables and parameters in the soil erosion process. Generally, physically-based erosion models are structurally defined with a set of equations based on the physical laws representing the governing processes. In order to apply an erosion model to any given watershed, the relationships have to be made specific for that watershed. Numerical values are defined for the equation's parameters that control the model's operation so that predicted sediment yields match observed sediment yields. This procedure is called model calibration. Model calibration for erosion modeling is made even more difficult by the fact that erosion components are driven by hydrological models that contain their own parameters that also have to be identified.

Two different approaches have been used to determine parameter values in physically-based erosion models. The first approach assigns parameter values based on an assumption that the model parameters have a physical meaning. Values are determined based on a knowledge of the erosion processes or on measurable properties in the watershed. The second approach utilizes an automated optimization algorithm where parameter values are determined based upon a comparison between observed and simulated sediment yields in terms of an objective function. Computers are generally used because the number of iterations involved in solving the optimization problem. Although parameters identified by automated optimization algorithms are more objective and reproducible than estimates made based on the subjective judgment of a hydrologist, automated techniques may generate unrealistic parameter values that minimize the differences between simulated and observed sediment yields, but conceptually have no meaning (Hendrickson et al., 1988).

Automated Techniques

Parameter estimation from data and prior information is an important area of research. With the advent of the digital computer, research into the use of automated techniques for hydrological modeling has increased. The automated optimization technique is comprised of three parts; 1) the objective function, 2) the optimization algorithm, and 3) the calibration data. The following presents a discussion of each of these elements.

Objective Function

For any method of optimization, there exists some objective measure; i.e. objective function, as to how closely the sediment yield data simulated by the model compares with the actual measured values (Gottfried and Weisman, 1973). The selected objective function will affect the values of the fitted parameters because each criterion of best fit places a different emphasis on the differences between measured and calculated values (Sorooshian and Dracup, 1980; Sorooshian et al., 1983).

SIMPLE LEAST SQUARES ESTIMATOR

When automatically calibrating an erosion model for a particular watershed, a nonlinear programming algorithm is used to minimize the objective function, F:

$$F = f(\theta_1, \theta_2, \theta_3, \ldots, \theta_n) \tag{2.1}$$

where θ_n = model parameters. The most frequently used objective function is the simple least squares (SLS) criterion:

$$SLS = \sum_{t=1}^{n} \left(c_{t,obs} - c_{t,sim}\right)^2 \tag{2.2}$$

where $c_{t,sim}$ is the simulated sediment concentration at time t, $c_{t,obs}$ is the observed sediment concentration at time t, and n is the total number of data points.. The simple least squares criterion assumes that model residuals are uncorrelated and homoscedastic.

MAXIMUM LIKELIHOOD ESTIMATION

Objective functions based on maximum likelihood (ML) theory have been demonstrated to provide more reliable estimates of parameter values than the SLS criterion (Sorooshian and Dracup, 1980; Sorooshian and Gupta, 1983; Sorooshian et al. 1983). This phenomena is due to the fact that if the objective function accounts for stochastic properties of the model errors, then it is easier for the optimization method to search for the best parameter values (Sorooshian and Gupta, 1983).

The selection of the objective function has been somewhat arbitrary in the erosion literature (Lopes, 1987; Page, 1988; Blau et al., 1988). The simple least squares criterion is usually employed and implies that model residuals are assumed to be uncorrelated and homoscedastic. However, violations in the aforementioned assumptions often occur in erosion modeling, where residuals are heteroscedastic and autocorrelated. If the stochastic nature of the residuals is not considered, then unsatisfactory parameter estimation can result. Biased parameter estimates will lead to unsatisfactory model predictions.

The accuracy of the maximum likelihood procedure can be highly dependent on the available information. If the data set is of sufficient length and well represents the variability, then it will be expected to produce good parameter estimates. However, if the representability of the data is questionable, then the ML approach may not produce good estimates of the parameters. To minimize such effects, Sorooshian (1981) updated the procedure so that the lack of information can be expressed through the use of Bayes' theorem. Accordingly, Bayesian theory, can be used to update the parameters using newly acquired data, if available.

HETEROSCEDASTIC MAXIMUM LIKELIHOOD ESTIMATOR (HMLE)

Stream discharge measurements are usually affected by non-homogenous variance (Aitken, 1973; Sorooshian and Dracup, 1980). This means that with increasing sediment concentrations and yields, an increase in error variance can also be expected. Sorooshian and Dracup (1980) proposed the use of the Hetereoscedastic Maximum Likelihood Error estimator (HMLE) for the case where errors are assumed to be uncorrelated and heteroscedastic (non-homogeneous variance).

The HMLE estimator is the maximum likelihood, minimum variance, asymptotically unbiased estimator when the variance of errors in the observed data is assumed to be related to the magnitude of the data (Sorooshian, 1981; Sorooshian and Dracup, 1980). The errors in the data are assumed to be Gaussian with a zero mean. The HMLE estimator is defined as:

$$\min \text{HMLE} = \frac{\frac{1}{n}\sum_{t=1}^{n} w_t \left(c_{t,obs} - c_{t,sim}\right)}{\left[\prod_{t=1}^{n} w_t\right]^{1/n}} \tag{2.3}$$

where w_t is the weight assigned to time t and is computed as:

$$w_t = f_t^{2(\lambda-1)} \tag{2.4}$$

where f_t is the expected true sediment concentration at time t and λ is the unknown transformation parameter that stabilizes the variance. The expected true sediment concentration can be approximated by either $c_{t,sim}$ or $c_{t,obs}$ (Sorooshian et al., 1983) but it is currently recommended that measured sediment concentration values be utilized since it is a more stable estimator (Sorooshian et al., 1993). However, Gupta (1984) warns that utilizing measured values may create bias in the estimate of λ.

Sorooshian (1981) proposed a two-stage method for non-linear models. In the first stage, given a set of model parameters, the residuals of the model are obtained. In the second stage, values of $\{\Theta\}$ obtained in the first stage are used to compute the most probable value of λ. This procedure is repeated until a satisfactory value of λ has been found. The optimal value of λ is one that satisfies the following equation:

$$\sum_{t=1}^{n} \ln\left(c_{t,obs}\right) - \left(n\sum_{t=1}^{n} w_t \ln\left(c_{t,obs}\right)\left(c_{t,obs} - c_{t,sim}\right)^2 \Big/ \left(\sum_{t=1}^{n} w_t \left(c_{t,obs} - c_{t,sim}\right)^2\right)\right) = 0 \tag{2.5}$$

where λ must be solved for iteratively. Once the value for λ is obtained, it is used to solve Equations (2.3) and (2.4) to compute the HMLE objective function.

Duan (1991) developed an equivalent and more stable procedure for estimating λ by rearranging Equation (2.5) to give the following:

$$R = \frac{R_n}{R_d} - 1 \tag{2.6}$$

where

$$R_d = \sum_{i=1}^{n} w_t \left(c_{t,obs} - c_{t,sim}\right)^2 \tag{2.7}$$

$$R_n = \sum_{i=1}^{n} w_t \left(c_{t,obs} - c_{t,sim}\right)^2 a_t \tag{2.8}$$

$$a_t = \frac{\ln c_{t,obs}}{a_d} \tag{2.9}$$

where a_d = the logarithmic average of the observed sediment concentration and the HMLE function is computed as:

$$\mathrm{HMLE} = \frac{\frac{1}{n} R_d}{\exp\left[(2\lambda - 1)a_d\right]} \tag{2.10}$$

where λ = 1 is used an initial value. An iterative procedure is then used to estimate λ such that R = 0 in Equation (2.6).

Parameter Optimization

When an automated technique is employed, the algorithm will attempt to minimize the objective function by varying the parameter values. If the objective function is minimized, it is considered to be a successful trial, and those values are usually retained. To track values retained during the optimization procedure, contour plots can be generated where coordinate axes correspond to parameter values. Contours represent equal values of the objective function on the response surface. If a two-parameter model is used, the procedure can be generalized by the following. Search methods begin by defining a straight line that passes through a point representing starting values for the parameters. The objective function is then evaluated at different points along that line. When an optimum value is encountered, a new search direction is defined and the process is repeated until a minimum value is found. The manner in which the search directions are defined and how each line is searched depends on the method of optimization. The minimum or optimum value of the objective function corresponds to optimized values of the parameters (Ibbitt and O'Donnell, 1971).

Direct search methods have been used to identify parameters in erosion models. Lopes (1987) and Blau et al. (1988) utilized the Simplex method for parameter identification, a direct search method developed by Nelder and Mead (1965). Convergence problems were encountered by Lopes (1987) due to parameter interaction in the Water Erosion Simulation Project (WESP) model used in this study. Parameter insensitivity was identified as a difficulty by Blau et al. (1988) for a transport capacity model developed by Shirley and Lane (1978). Although the problems identified in these studies were not directly related to the constraints of the Simplex method, such a procedure is not designed to handle the presence of multilocal optima (Gottfried and Weisman, 1973) which are commonly encountered in the calibration of erosion and hydrological models.

THE SIMPLEX ALGORITHM

The Simplex method belongs to a group of techniques that are defined as hill climbing methods. They determine a path toward an optimum by evaluating the objective function at several points rather than by calculating derivatives (Gottfried and Weisman, 1973). These iterative search techniques (which also includes Rosenbrock's (1960) technique and Hooke and Jeeves' (1961) pattern search method) have been found to be superior to gradient techniques in hydrologic modeling. This is because values of the derivatives of the model equations with respect to its parameters cannot be explicitly obtained due to the presence of threshold-type parameters in the model (Johnston and Pilgrim, 1976; Moore and Clark, 1981). Johnston and Pilgrim maintained that the response surface would have discontinuous derivatives and that these would cause the optimization algorithm to prematurely terminate. Gupta and Sorooshian (1985) compared the Simplex method to the derivative based Newton method and found the Simplex method to be more efficient.

In the Simplex method, an essential role is played by the geometric figure called a simplex that is defined as a set of $n + 1$ points in n-dimensional space. In the case of $n = 2$, the corresponding figure is an equilateral triangle; when $n = 3$, it is a tetrahedron. The method can be viewed as the moving, shrinking, and expanding of the simplex toward a minimum. To find the minimum error value, the Simplex method searches the parameter space using an initial simplex, using n corners of the eight corner points in the space of reasonable values. The function is evaluated at each of the vertices. The point with the highest errors is replaced by a point with lower error to form a new simplex. To determine the location of this new point, the worst point is reflected through the centroid of the other two points. If the function evaluated at the new point does not reduce the error, then the new point is generated by contraction toward the centroid. If neither of these approaches finds a point with lower error, then the entire simplex is contracted towards the point having the lowest error. This iterative process is continued until convergence to a minimum is found. The stopping criterion suggest by Nelder and Mead (1965) is:

$$\left\{\frac{1}{n}\sum_{i=1}^{n+1}\left(f(x_i)-f(x_o)\right)^2\right\}^{1/2} < \varepsilon \qquad (2.11)$$

where $f(x_i)$ = function of the observed data, $f(x_o)$ = function of the simulated data, and ε is some small preset number (Kowalik and Osborne, 1968).

Global Optimization

Parameter identification for hydrologic and erosion modeling can be formulated as a global optimization problem where the objective function is concave and possesses many local minima in the region of interest. Global optimization methods, however, will normally use some local procedure, which limits their ability to converge to a global minimum. Duan et al. (1992) suggests that automatic calibration procedures in current use for hydrological models are incapable of finding the globally optimal parameter estimates due to problems such as parameter interaction, non-convexity of the response surface, discontinuous derivatives and presence of multilocal optima.

THE SHUFFLED COMPLEX EVOLUTION - UNIVERSITY OF ARIZONA (SCE-UA) ALGORITHM

Duan et al. (1992) developed a new global optimization procedure called Shuffled Complex Evolution - University of Arizona (SCE-UA). The SCE-UA algorithm searches through the parameter space using the simplex geometrical shape. However, the points are periodically shuffled to avoid a convergence to a local minimum. The algorithm begins by randomly selecting s number of points where $s = p \times m$ and p = the number of complexes and m = the number of points in each complex. After computing the function value at each point, the points are sorted in order of increasing function value and are stored in an array that is partitioned into a number of communities (complexes) selected by the user. By randomly choosing $n + 1$ points from each complex, a simplex is formed according to a trapezoidal probability distribution defined as:

$$\rho_i = \frac{2(m+1-i)}{m(m+1)} \tag{3.25}$$

where the point with the highest probability is $\rho_1 = 2/m + 1$ and the point with the lowest probability is $\rho_m = 2/m(m+1)$.

New points replace points with the greatest error using two iterations of the Simplex method described earlier and the generation of random points within the feasible space. After evolving each simplex $2n + 1$ times, the simplex is then dissolved and the updated points are returned to the complex where new $n+1$ points are randomly selected to form a new simplex in the same manner as previously described. After a certain number of generations, new complexes are formed with the updated points by shuffling, a non-random action. In this way, the sharing of information about the search space is accomplished. This entire process is repeated until a minimum is reached (Duan et al., 1992).

Duan et al. (1992) tested the performance of the SCE-UA along with three other global search procedures on the model SIXPAR; the adaptive random search (ARS) method, a combined ARS/simplex method and a multistart simplex (MSX) method. Results show that both the MSX and SCE-UA methods were effective in finding the globally optimal parameters. However, the SCE-UA method was found to be three times more efficient. The efficiency of the SCE-UA method was confirmed for the Sacramento

Soil Moisture Accounting model (SAC-SMA) (Sorooshian et al., 1993). In this study, the SCE-UA achieved a 100% success rate in locating the global minimum while the MSX method had little success with more than twice the number of iterations.

Luce and Cundy (1994) compared parameter values found by the SCE-UA procedure and the (local search) Simplex method utilizing a physically-based model for studying runoff and erosion from forest roads. The authors report that both methods were successful in converging to unique optimal parameter sets for infiltration and overland flow parameters. In only three out of the 84 cases were the hydrographs improved by using parameter values estimated with the SCE-UA algorithm. These were cases where the error surface was flat and the Simplex method terminated prematurely.

Difficulties in Parameter Optimization

Despite using a systematic approach, different sets of observed data can produce very different parameter sets (Johnston and Pilgrim, 1976). Different initial parameter values can also generate distinct sets of optimum parameter values (Page, 1988). Since the accuracy of measurements is never perfect, it cannot be expected that parameter values be identical to their true values. Inevitably, random errors occur. It is desirable, however, that they be close to their true values. Although each series of measurement will obtain different values for the parameters, it is desirable that these estimators fluctuate around their mean values and that they do not vary extremely from one series of measurements to another (Schmidt, 1982).

Several factors can contribute to large fluctuations in parameter estimates, some of which have been reported in the erosion modeling literature (Lopes, 1987; Page, 1988; Page et. al, 1989; Blau et al., 1988). Ibbitt and O'Donnell (1971) and Johnston and Pilgrim (1976) have outlined the following reasons for the inability to obtain unique and conceptually realistic parameter sets for conceptual rainfall-runoff models which also play a major role in erosion modeling.

INTERDEPENDENCE BETWEEN MODEL PARAMETERS

When model parameters interact, the change in the value of one parameter can be compensated by changes by in one or more of the other parameters. For a two-parameter model, a long flat-bottomed valley in the response surface results and optimization methods will make little or no progress along the floor of a valley toward its lowest point.

INDIFFERENCE OF OBJECTIVE FUNCTION TO VALUES OF INACTIVE PARAMETERS

The objective function (and thus the simulated model output) is not affected by the changes in the value of a parameter. This may be caused by parameter redundancy or it is not activated by the calibration data set. When this occurs, zero gradients occur in some areas of the response surface and optimization methods make no progress towards a minimum.

DISCONTINUITIES IN THE RESPONSE SURFACE

Local-type direct search methods for are not designed to handle the presence of discontinuous derivatives. In such cases, the optimization method may terminate before encountering the true optimum.

PRESENCE OF LOCAL OPTIMA DUE TO NON-CONVEXITY OF THE RESPONSE SURFACE

Local optima are defined as points on the response surface that have lower values of the objective function than any surrounding points, but have greater values than another point in another region of the response surface. The optimization method may therefore terminate at a point that is not the global minimum.

Furthermore, even the most complex models may not completely represent the physical processes of erosion. Therefore, it is possible that some of the difficulties in identifying a unique set of parameter values may be due to model structure.

Data Calibration

The selection of trial model parameters is made during calibration. Data used in the calibration of an erosion model should be representative of the factors influencing the erosion processes. However, calibration is rarely straight-forward. Data come from various sources with different degrees of accuracy and levels of representativeness.

Some researchers have attempted to use longer periods of data for calibration to account for a wide variety of conditions in the watershed. Sorooshian et al. (1983) argue that it is not the length of record that is most important, but the information contained within it. They propose that the most important aspect of the calibration phase is considering the stochastic properties of the data, which relates to the appropriate selection of the objective function. Parameter estimation developed within a framework of maximum likelihood theory can aid in the selection of the appropriate objective function, which can smooth the response surface and make it more concentric. This improved concentricity increased the chances for convergence to the true parameter set (Sorooshian and Dracup, 1980).

Sorooshian et al. (1983) compared the performance of the HMLE and SLS criterion in the calibration of a soil moisture accounting model of the U.S. National Weather Service River Forecasting System (SMA-NWSRFS). The model was calibrated using daily records of variable length and then tested for a 6 year period. They found that SLS technique was better able to provide the closest reproduction of the observed hydrograph for the calibration period. However, the HMLE estimator was found to provide the best model performance for the forecasting period.

The likelihood function plays a critical role in both classical and Bayesian theories of inference. In classical theory, it is used to construct maximum likelihood estimators (MLEs) which have desirable asymptotic properties. In Bayesian theory, it is used to update the prior distribution using newly acquired data. Wilson and Haan (1991) developed a calibration procedure that combines site measurements of erodibility with those parameters already identified in the Water Erosion Prediction Project (WEPP) database. Assuming a normal distribution of interrill erodibility and a log-normal distribution of rill erodibility, theoretical relationships were derived to estimate parameters using Bayesian estimation theory. When tested, results showed that the technique worked well in combining site-specific information with prior information represented by regression equations (Wilson et al., 1991).

METHODS

The Model

The Water Erosion Simulation Program (WESP) (Lopes, 1987) was used in this study. The erosion component of the model was modified to incorporate three different flow-induced erosion equations for overland flow which were coupled with the hydrological component of the WESP model.

The Hydrological Component

Woolhiser and Ligget (1967) described the movement of water over a plane using a kinematic approximation of the spatially-varied, unsteady and one-dimensional flow equations:

$$\frac{\partial h}{\partial t} + \frac{\partial q}{\partial x} = r \tag{3.1}$$

$$q = \alpha h^{m} \tag{3.2}$$

where h = depth of flow [L], q = the discharge per unit width [L^2T^{-1}], r = the rainfall excess rate [LT^{-1}], x = the distance downslope [L], t = time [T], and α and m are parameters related to the slope and roughness of the flow. For normal flow conditions, Manning's equation yields m = 5/3 and $\alpha = (1/n)\, S_o^{1/2}$ where n = Manning's roughness coefficient and S_o = the slope of the plane [L/L] By substituting Equation (3.2) into Equation (3.1):

$$\frac{\partial h}{\partial t} + \alpha m h^{m-1} \frac{\partial h}{\partial x} = r \tag{3.3}$$

In order to solve the kinematic wave equations, the depth at the upstream boundary must be defined. For an uppermost plane, the boundary conditions are:

$$h(0,t) = 0 \quad \text{for } t \geq 0 \tag{3.4}$$

For planes where runoff is being contributed by other planes, the boundary conditions are (Woolhiser et al., 1990):

$$h(0,t) = \left[\frac{\alpha_u h_u (L_u, t)^{m_u} w_u}{\alpha w}\right]^{1/m} \tag{3.5}$$

where L_u = the length of the contributing plane, $h_u(L_u,t)$ = the depth at the lower boundary of the contributing plane at time t, w_u = the width of the contributing plane, α_u = the slope roughness parameter for the contributing plane, m_u = the exponent for the contributing plane, and α, m and w refer to the receiving plane. The initial conditions are:

$$h(x,0) = 0 \quad \text{for } x \geq 0 \tag{3.6}$$

In the kinematic approximation, the friction slope is assumed to be equal to the plane slope ($S_f = S_o$). This translates into an assumption of the water surface slope being equal to the plane slope (Lighthill and Whitham, 1955; Henderson, 1963; Woolhiser and Ligget, 1967). If the kinematic flow number is greater than 10, then solutions to the kinematic wave equations provide good approximations to the shallow water equations. The kinematic wave equations are solved numerically by a four-point implicit finite difference method:

$$\frac{\theta}{\Delta t}\left[h_{j+1}^{i+1}-h_{j+1}^{i}\right]+\frac{1-\theta}{\Delta t}\left[h_{j}^{i+1}-h_{j}^{i}\right]+\frac{\omega\alpha}{\Delta x}\left[\left(h_{j+1}^{i+1}\right)^{m}-\left(h_{j}^{i+1}\right)^{m}\right]$$
$$+\frac{(1-\omega)}{\Delta x}\alpha\left[\left(h_{j+1}^{i}\right)^{m}-\left(h_{j}^{i}\right)^{m}\right]=\omega r^{i+1}+(1-\omega)r^{i} \tag{3.7}$$

where θ and ω and are weighting factors for space and time respectively.

The Infiltration Component

The rainfall excess rate (r) is calculated in WESP by subtracting the difference between rainfall intensity and infiltration rates. When rainfall begins on an infiltrating soil, there is always an initial period where the infiltration rate (f) is equal to the rainfall rate (i) and the rainfall excess (r) is zero. The maximum infiltration rate (f_c) is described as a function (f) of the initial water content (θ_i) and the amount of water already infiltrated in the soil:

$$f_c = f(F,\theta_i) \tag{3.8}$$

The Green and Ampt (1911) infiltration equation is used in the WESP model. Two parameters are important to the infiltration model; the saturated hydraulic conductivity (Ks) and the net capillary drive (Ns):

$$f_c = Ks\left[1+\frac{Ns}{F}\right] \tag{3.9}$$

$$Ns = \varphi(S_{max} - S_i)\phi \tag{3.10}$$

where ϕ = soil porosity, $S_{max} = \theta_s/\phi$ = maximum relative saturation, θ_s = saturated water content [L^3/L^3], $S_i = \theta_i/\phi$ = initial relative saturation, and φ = the soil matric potential [L].

The Erosion Component

WESP calculates the sediment concentration in broad shallow flow areas by applying the sediment continuity equation in combination with the overland flow equations. Because the hydraulic conditions of overland flow are often totally different from those of channels and it is assumed that in small watersheds well-defined rills do not develop, the overland flow equations were also used to solve the sediment continuity equation for flow-induced detachment and transport in this study. The sediment continuity equation normally used for one-dimensional flow on hillslopes is (Bennett, 1974)

$$\frac{\partial(ch)}{\partial t} + \frac{\partial(cq)}{\partial x} = e_i + e_f \qquad (3.11)$$

where c = the sediment concentration $[ML^3]$, e_i = the input sediment flux to the flow $[ML^{-2}T^{-1}]$ by raindrop impact, e_f = the flow-induced input sediment flux to the flow $[ML^{-2}T^{-1}]$, and dispersion terms have been neglected. The first term in the continuity equation represents the rate of storage of sediment within the flow depth. The second term represents the change in sediment load with distance.

The WESP model (Lopes, 1987) utilizes a simultaneous sediment exchange approach. WESP represents the erosion/deposition process on hillslopes as two separate processes of sediment entrainment and deposition. For broad shallow flow areas, sediment entrainment is carried out by raindrop impact and hydraulic shear. Entrainment and deposition can occur simultaneously at different rates and the resultant sediment concentration is determined by the relative magnitude of these two processes. Thus,

$$\phi(x,t) = e_f - d + e_i \tag{3.12}$$

where ϕ = sediment flux to the flow [$ML^{-2}T^{-1}$], e_f = flow-induced sediment entrainment [$ML^{-2}T^{-1}$], d = rate of sediment deposition [$ML^{-2}T^{-1}$] and e_i = rate of sediment entrainment by raindrop impact [$ML^{-2}T^{-1}$].

Entrainment by Raindrop Impact

One raindrop-induced entrainment equation was selected for use in this study. Notwithstanding the successes of other raindrop-induced erosion equations, the equation selected has been proven to be effective over a wide range of conditions and is currently used in the Water Erosion Prediction Project (WEPP) (Lane and Shirley, 1982). Ulman (1994) also demonstrated its success in describing rain-drop induced erosion on forest roads.

If hydraulic shear is considered to be negligible in raindrop-induced entrainment areas and uniform rainfall intensity is assumed in the area of interest, then (Lane and Shirley, 1982):

$$e_i = K_i i^2 \left(\frac{r}{i}\right) = K_i ir \tag{3.13}$$

where K_i = raindrop induced erodibility parameter [MTL^{-4}], i = rainfall intensity [LT^{-1}], and r = rainfall excess rate [LT^{-1}]. This expression relates soil particle entrainment to rainfall erosivity and the erodibility of the soil. The transport in broad shallow flow areas is related to the ratio of the rainfall excess rate to the rate of rainfall intensity, which can be interpreted as a normalized runoff intensity for sediment transport by broad shallow flow (Lopes and Lane, 1988).

Entrainment by Flow

Three different equations describing erosion by hydraulic shear were evaluated in this study. All of the equations have been presented in Govers (1992), but have only been evaluated under steady state conditions. Since WESP is both time variant and spatially varied, the equations were implemented as fully dynamic equations. Each of the equations can be represented by the generic form of:

$$e_f = K_{fp}(x)^b \tag{3.14}$$

where K_f = a flow-induced erodibility parameter [dimensions equation dependent], p = an index used to distinguish between coefficients for each equation, x = a variable specific to the equation, and b is an exponent with a value = 1.5 (Lopes, 1987; Hernandez, 1992).

The first equation relates entrainment by flow to excess effective stream power:

$$e_{f1} = K_{f1}(\Omega_e)^{1.5} \tag{3.15}$$

where Ω_e = excess effective stream power. Bagnold (1980) defined the concept of excess effective stream power as:

$$\Omega_e = \Omega - \Omega_c \tag{3.16}$$

where Ω = the effective stream power and Ω_c = the critical stream power. These have been defined as:

$$\Omega = \frac{(\tau\bar{u})^{3/2}}{h^{2/3}} \tag{3.17}$$

$$\Omega_c = \frac{(\tau_c\bar{u})^{3/2}}{h^{2/3}} \tag{3.18}$$

where $\tau = \gamma hS$ = the hydraulic shear [$ML^{-1}T^{-2}$], γ = the fluid specific weight [$ML^{-2}T^{-2}$], h = the flow depth [L], $\bar{u}$ = the mean flow velocity [LT^{-1}], $\tau_c = \rho\bar{u}_{*c}^2$ = critical hydraulic shear [$ML^{-1}T^{-2}$], ρ = fluid density [ML^{-3}], and $\bar{u}_{*c}$ = mean critical shear velocity [LT^{-1}].

The second equation used in this study relates entrainment by flow to the shear stress of the flow:

$$e_{f2} = K_{f2}(\tau - \tau_c)^{1.5} \tag{3.19}$$

The third equation presented includes the effect of particle size on the transport capacity of the flow:

$$e_{f3} = K_{f3}\left(\frac{\tau - \tau_c}{D^{1/3}}\right)^{1.5} \tag{3.20}$$

where D = the effective particle diameter [L]. The effective particle diameter was determined by:

$$D = e^{\sum m_i \ln d_i} \tag{3.21}$$

where m_i = the weight percentage of sand, silt and clay, d_i = the geometric mean of sand, silt and clay, and e and ln represent the exponential and natural logarithm operators.

Sediment Deposition

The rate of sediment deposition (d) in WESP is determined by a relationship defined by Mehta (1983), which states that deposition is a linear function of the sediment concentration and the effective particle fall velocity:

$$d = \beta \, T_w V_s c \qquad (3.22)$$

where β = a constant [dimensionless], T_w = the top width of the flow [L], V_s = the effective particle fall velocity [LT^{-1}], and c = the sediment concentration [ML^{-3}]. For deposition in overland flow areas, β was assumed to equal 0.50 (Davis, 1978).

The Data

Three sets of data were used in this study : 1) synthetic data 2) data that were collected from rainfall simulator plots set up by the USDA-ARS WEPP team at different sites across the western United States and 3) Kendall watershed at the Walnut Gulch Experimental Watershed.

The synthetic data used was generated based on the experimental procedures and soil characteristics of the rainfall simulator plots. Three different slopes (5, 10 and 15%) were incorporated into the data set so that the effect of slope on the ability of the optimization procedure to find an optimal parameter set could be evaluated.

For the rainfall simulator plots, three rainfall simulation treatments using a V-Jet 80100 nozzle were applied to 3.05 x 10.5 m plots. When the initial conditions were dry, rainfall was applied at a rate of 60 mm/hr for 60 minutes. The wet antecedent moisture treatment was applied twenty-four hours after the dry treatment, at a rainfall rate of 60 mm/hr for 30 minutes. The very wet antecedent moisture treatment was applied when no surface water was evident on the plot by visual inspection, approximately 30 minutes after the wet treatment, at intensities of 60 mm/hr and 130 mm/hr during a 30 minute period (Simanton et al., 1985). The synthetic data were assumed to have a similar treatment.

Ten rainfall simulator plots from four different areas in the Western United States were selected for this analysis, based on a criterion of a minimum slope of 7% so that the parameters would be sufficiently activated. For both the synthetic and rainfall simulator data, sediment graphs were used to compare measured and simulated data. Characteristics of each rainfall simulator plot are given in Table 3.1.

Table 3.1. Soil Characteristics for Rainfall Simulator Plots and Kendall Watershed

Plot No. & Watershed	% Sand	% Silt	% Clay	Soil Type	Effective Particle Diameter (mm)	Slope (%)
31	16.7	14.2	69.1	Gravely Sandy Loam	1.209E-01	10.2
34	16.7	14.2	69.1	Gravely Sandy Loam	1.209E-01	10.0
56	5.0	25.5	69.5	Very Gravely Fine Sandy Loam	1.0175E-04	8.1
59	5.0	25.5	69.5	Very Gravely Fine Sandy Loam	1.0175E-04	7.5
63	7.8	28.7	63.5	Fine Sandy Loam	7.9060E-05	8.6
66	7.8	28.7	63.5	Fine Sandy Loam	7.9060E-05	8.8
102	15.1	36.0	48.9	Loam	1.0810E-04	11.2
105	15.1	36.0	48.9	Loam	1.0810E-04	9.8
120	44.2	33.4	22.4	Clay	1.0643E-05	11.2
121	44.2	33.4	22.4	Clay	1.0643E-05	11.6
Kendall	62.7	23.0	14.2	Sandy Clay	8.1047e-06	9.4

Kendall Watershed is located in the eastern part of the Walnut Gulch Experimental Watershed. The watershed has gentle hillslopes covered by grasses, an average slope of 9.4%, and is dominated by soils of a sandy clay texture (see Table 3.1). Because the runoff is small in relation to its rainfall depth due to its gentle slope, sandy soils and grass stands, Kendall Watershed has not developed a well-defined channel. Thus Kendall Watershed was selected for this study because it can be modeled as a single plane.

Three rainfall-runoff events from the years 1975-1977 were selected for this study. The events were chosen based on their maximum rainfall duration that produced measurable amount of runoff and sediment. Because the sediment graphs were unavailable for these events, parameters for the erosion equation were optimized based on the total sediment yield for each event.

Determining Values Of Hydraulic Parameters

For the natural data studies, values of the hydraulic parameters had to be determined before optimizing for the erosion parameters. The SCE-UA algorithm and the SLS objective function were used to determine the values for hydraulic roughness (Manning's n), net capillary drive (Ns), and saturated hydraulic conductivity (Ks). The Nash-Sutcliffe coefficient (r^2) was used as a measure of goodness-of-fit between simulated and observed of both the runoff rate and sediment concentration values:

$$r^2 = 1 - \frac{\sum_{t=1}^{n}\left(X_{t,obs} - X_{t,sim}\right)^2}{\sum_{i=1}^{n}\left(X_{t,obs} - \overline{X}\right)^2} \tag{3.23}$$

where $X_{t,obs}$ = the measured value, $X_{t,sim}$ = the simulated value, $\overline{X}$ = the average observed value, and n = the number of observations. When the simulated and observed correspond well, the values of the coefficient will lie between 0.5 and 1.0, where 1.0 represents a perfect comparison (Nash and Sutcliffe, 1970).

True Parameter Values

Soil parameter values that were determined for the Water Erosion Prediction Project (WEPP) model resulting from the rainfall simulator plots at Walnut Gulch provided a basis for determining the true parameter values of the synthetic data set. Since both WEPP and WESP describe entrainment by raindrop impact with the same equation, the raindrop-induced soil erodibility parameter (K_i) was assumed to be have the same value. The value for critical shear stress (τ_c) was also assumed to equivalent between the synthetic and rainfall simulator data sets. However, the values of the flow-induced erodibility parameter (K_f) had to be altered to fit each of the equations describing entrainment by hydraulic shear.

WEPP describes detachment by hydraulic shear on bare soil as (Foster et al., 1989):

$$D_r = K_f(\tau - \tau_c)\left(1 - \frac{G}{T_c}\right) \tag{3.24}$$

where D_r = the flow detachment rate [$ML^{-2}T^{-1}$] , G = the sediment load [$ML^{-2}T^{-1}$] and T_c = the transport capacity of the flow [$ML^{-2}T^{-1}$]. This equation is similar to Equation 2 of this study with the exception of the value of the exponent and the relationship describing detachment utilizing the transport capacity approach. To determine the true parameter value of K_{f2} for the synthetic data, the WEPP K_f value [TL^{-1}] was multiplied by the length of the plot to evaluate K_{f2} [T] for b = 1. To fully activate the K_f parameter, the WESP model was run using the synthetic data developed for the very wet run with a 15% slope for b = 1. The K_f for each equation was adjusted so that the sediment yield at b = 1.5 was equal to the sediment yield at b = 1 for Equation 2.

For both the rainfall simulator plot studies and the watershed events, the true values of K_{fp} were equation dependent whose true values were not known. The optimized values of τ_c, however, were compared to true values of the critical shear stress as determined by the Shields diagram. For the rainfall simulator plot studies, the optimized values of K_i assumed the value that was determined in the WEPP field experiments in the rainfall simulator studies. For the watershed events, a value of K_i could be determined by a regression equation developed by WEPP. However, because WESP does not incorporate adjustments in soil entrainment and transport due to plant and rock cover, K_i was manually calibrated for the selected events.

Treatment of Systematic Error

The error model used to synthetically generate observed sediment concentration data was a first-order autoregressive model known as a Markov model (Lipschutz, 1968). This model assumes that the additive errors are autocorrelated to a lag-one by a simple linear relationship given by:

$$\varepsilon = \rho\varepsilon_{t-1} + \eta_t \tag{3.25}$$

where ε_t = additive errors at time t, ρ = the first-lag autocorrelation coefficient that measures the degree of systematic error ($-1 < \rho < 1$), and η_t = the purely random component of measurement error, which is assumed to have a Gaussian distribution with a zero mean, constant variance, and is independently and identically distributed for all t. The variance of the independent variables σ^2 is defined as:

$$\sigma^2 = 1 - \rho^2 \tag{3.26}$$

where the standard deviation of the errors was set equal to 20% of the standard deviation of error-free sediment concentration values. This error exceeded the error generally encountered in hydrologic data series according to Sorooshian (1980). Two different levels of correlated error were created by fixing the value of ρ, the serial correlation coefficient, at 0.25 and 0.50. This error model was chosen based upon the high probability of correlated error in sediment concentration data that is also known to be present in streamflow measurements (Sorooshian and Dracup, 1980).

Parameter Identification

Erosion parameters were fitted to produce an optimal parameter set that corresponded to the actual sediment concentration graphs of both the natural and synthetic data. Search and optimization algorithms were used to find the best values of the parameters K_i, K_{fp} and τ_c. For the synthetic data, both two and three parameter problems were posed with data that was error free, as well as with data with two levels of correlated error. In the first case, the value of K_i was fixed, and K_{fp} and τ_c were determined by optimization. In the second case, K_i and K_{fp} were optimized with $\tau_c = 0$ and $\tau_c \neq 0$. In the third case, all three erosion parameters were determined by optimization.

Sum of the least squares of the error (SLS) (Equation 2.2) and the heteroscedastic maximum likelihood estimator (HMLE) (Equations 2.6 - 2.10) were used as the objective functions. The Simplex algorithm (Nelder and Mead, 1965) was used to find the optimal values of the parameters with a single start. This method is quick, but can terminate prematurely if the error surface is flat or pitted. The Shuffled Complex Evolution (SCE-UA) (Duan et al., 1992) was also used for parameter identification. The SCE-UA was designed to find the global minimum for error surfaces with multiple local optima. Both methods required a range of reasonable parameter values.

A two-parameter optimization problem (K_f-τ_c) was posed for the natural data sets, which included the rainfall simulator plots and Kendall Watershed rainfall-runoff events. Only the most successful combination of flow-induced erosion equation, optimization algorithm and objective function in the synthetic data study were used for parameter identification in the natural data sets.

WESP was run to find the optimal parameter set. To this end, the search routines submitted parameter values to WESP, which then ran the model on an event basis. Simulated and measured sediment concentrations were compared in the objective function (SLS and HMLE). If the stopping criteria were not met, the search routine submitted new parameter values to the model and the process repeated itself until acceptable values with minimal error were found.

Convergence Criteria

For the Simplex algorithm, the optimization process will terminate if one of the following stopping criteria is met; the prespecified tolerance limit for minimum change in the values of the objective function has been satisfied (function convergence), the coordinates of the simplex have changed by less than the specified amount (parameter convergence), or the maximum number of iterations has been reached. Since the SCE-UA algorithm is based on an extension of the Simplex local-search algorithm, the stopping criteria are the same. However, the SCE-UA algorithm allows the user to specify the number of shuffling loops in which the criterion value must change by the prespecified tolerance for function convergence. The SCE-UA algorithm will also terminate if the population of points converges into a sufficiently small space that will not allow the spread of the population in each parameter direction to exceed more than one thousandth of the corresponding feasible parameter range. Any further search would not result in significant improvement of the parameter estimates.

For both the Simplex and SCE-UA methods, the objective function tolerances were set at 0.001. For the SCE-UA method in the two-parameter case, 4 complexes of points were selected. For the three parameter case, 6 complexes were used. The minimum number of shuffling loops in which the criterion value must change by the pre-specified tolerance for function convergence was set to 10.

Methodology Used for Comparison

The comparison of the two search algorithms and the two objective functions was carried out by maintaining the same initial conditions, parameter bounds and starting parameter values. For the synthetic data, a comparison of the three different flow-induced erosion equations was performed by evaluating how successful the optimization algorithm and objective function were in arriving at the true parameter values under different antecedent moisture conditions.

To evaluate the performance of the search algorithms and objective functions, the following criteria were used:

1) the relative efficiency with which inactive and active parameters were estimated,
2) the relative efficiency in avoiding local optima,
3) the continuity and shape of the response surface configurations, and
4) the ability to attain the best value of the objective function.

RESULTS & DISCUSSION

Synthetic Data Case

The results for the synthetic data study were for a case where precipitation intensities and duration were based on rainfall simulator experiments at Walnut Gulch Experimental Watershed. As described earlier, soil and hydraulic variables were based on the soil description for Plots 31 and 34 (see Table 4.1). Then, for a specified set of hypothetically true parameter values, sediment concentration values were generated by the WESP model for three different values of slope (5, 10 and 15%). These data were then input as observed values for optimization. Because preliminary investigations of the rainfall simulator plots indicated that the value of critical shear stress (τ_c) approached zero, two sets of synthetic data were generated where $\tau_c = 0.0$ and $\tau_c = 0.502$.

In order to study parameter interactions and any uncertainties in the processes of erosion, four different parameter optimization problems were posed as described in the METHODS section of this thesis. These parameter optimization problems were studied when no error was present in the data and when the data were contaminated with correlated and random error. To this end, the sediment concentration values were contaminated with error according to the error model outlined earlier. The same initial conditions were used throughout to assure identical response surface configurations.

Table 4.1. Hydraulic Parameter and Soil and Plot Characteristics for the Synthetic Data Set.

Parameter/Variable	Value	Units
Effective Particle Diameter	0.1209	mm
Porosity	0.437	(dimensionless)
Saturated Hydraulic Conductivity (Ks)	5.98	mm/hr
Maximum Soil Saturation (Smax)	0.92	(dimensionless)
Initial Soil Moisture Content (Si dry)	0.31	(dimensionless)
Initial Soil Moisture Content (Si wet)	0.61	(dimensionless)
Initial Soil Moisture Content (Si very wet)	0.87	(dimensionless)
Soil Moisture Tension Parameter (ψ dry)	70	mm
Soil Moisture Tension Parameter (ψ wet)	25	mm
Soil Moisture Tension Parameter (ψ very wet)	15	mm
Plot Length	10.7	m
Plot Width	3.05	m
Hydraulic Roughness Coefficient (Manning's n)	0.04	$m^{1/6}$

RESPONSE SURFACES

To determine the boundaries and starting values of the parameters, the response surfaces for each of the three flow-induced erosion equations were generated. To this end, incremented parameter values were submitted to WESP (without the aid of the optimization algorithms) and the values of the objective function were calculated for very wet runs on plots of 15% slope where it was assumed that the parameters would be most activated. Separate response surfaces were generated for the SLS and HMLE objective functions. Figures 4.1-4.6 show the resulting response surface configurations. Upper and lower parameter bounds were determined by identifying "regions of attraction." Starting values for the parameters were defined as the midpoint between the upper and lower bounds. The true parameter values, starting values and lower and upper parameter bounds used are given in Table 4.2.

Table 4.2. Parameter Bounds and Starting Values for Synthetic Data Set

Parameter	Units	True Values	Lower Bound	Upper Bound	Starting Value
K_{f1}	M/L^2T	1.7188E-04	5.00E-05	4.00E-04	2.25E-04
K_{f2}	$T^2/L^{0.5}M^{0.5}$	3.7365E-03	1.00E-03	1.00E-02	4.25E-03
K_{f3}	$T^2/L^{0.005}M^{0.5}$	3.9685E-05	2.50E-05	1.50E-04	9.00E-05
τ_c	M/LT^2	0.502	0.3	2.0	1.15

The response surface configurations depicting the relationship between K_f and τ_c (Figures 4.1 - 4.3) show two difficulties that are related to the structure of the model. The first difficulty is that of parameter insensitivity that is identified by the shape of the response function. τ_c is less sensitive than K_f as noted by the relative sensitivity of function value in the two parameter directions. Along the K_f axis, the response surface wall is steeper than in the τ_c (inactive parameter) direction. A second difficulty is due to interactions that exist within the model. This effect is noted in the valley that has formed on the response surface that is inclined along the K_f axis.

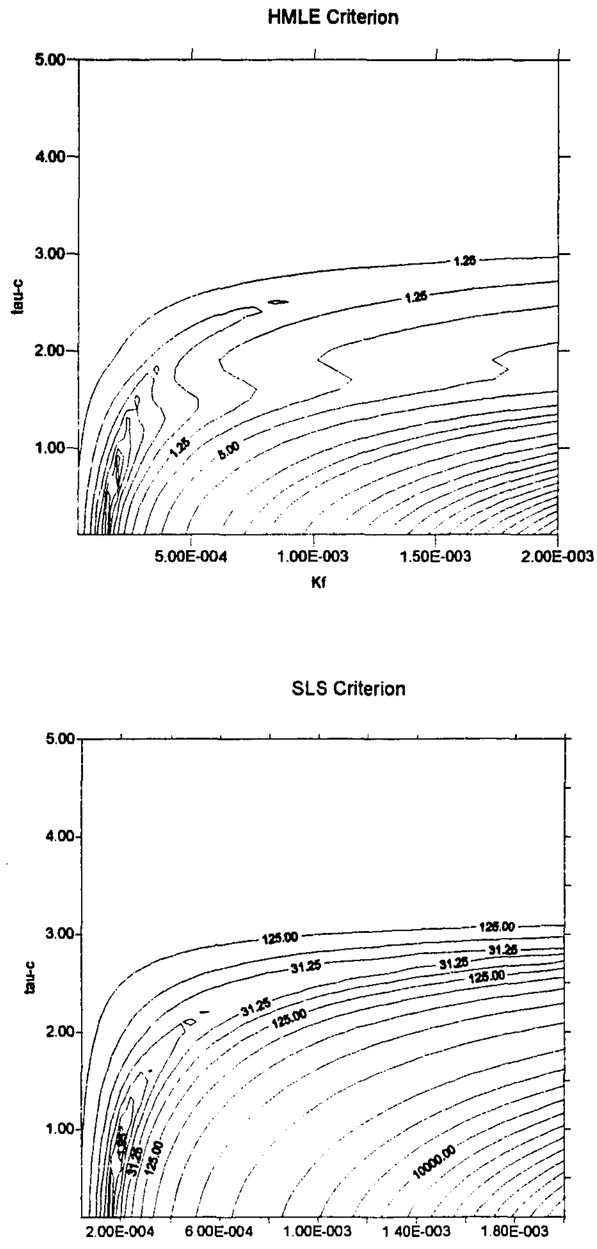
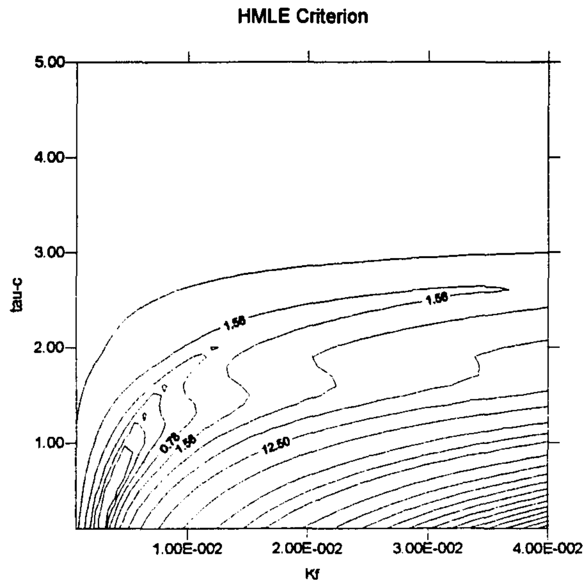


Figure 4.1. K_f -τ_c Contour Plots for Equation 1.



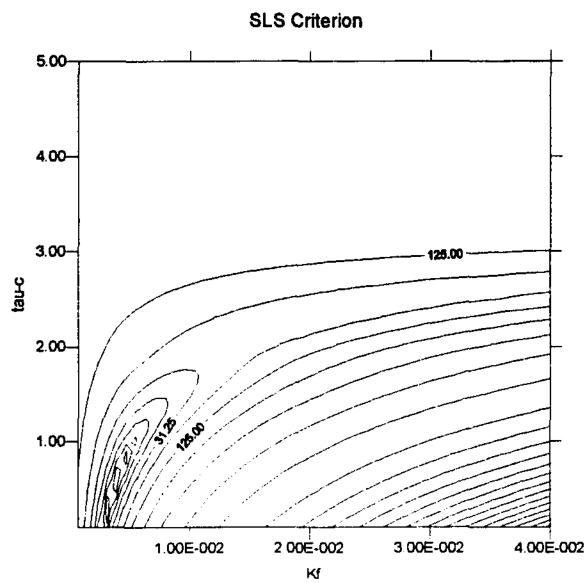


Figure 4.2. K_f -τ_c Contour Plots for Equation 2.

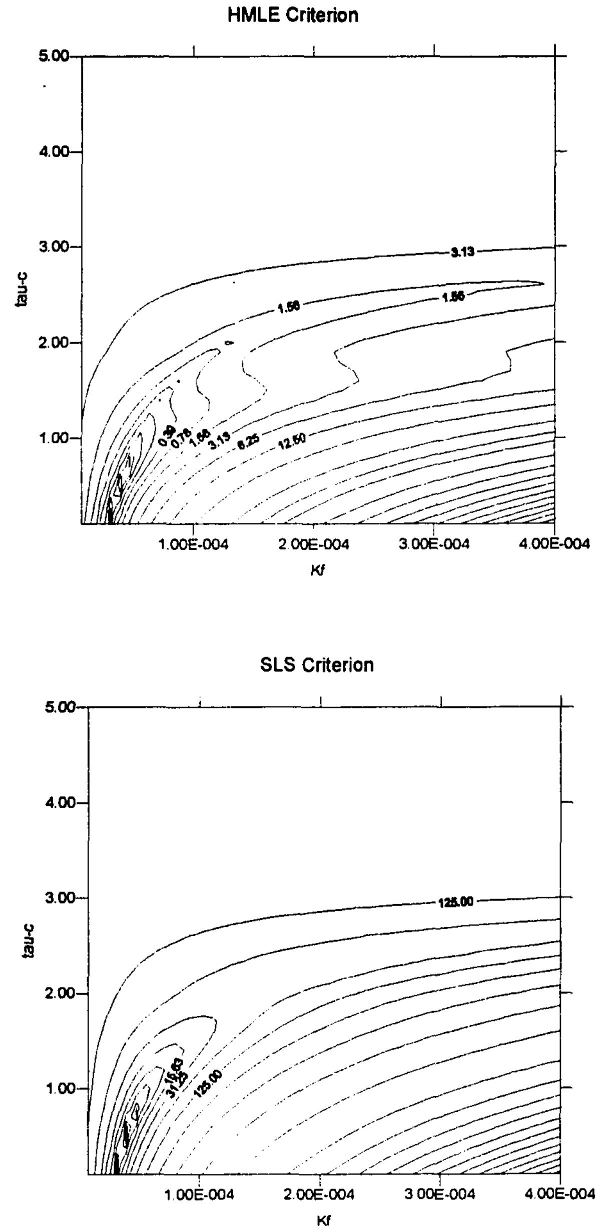


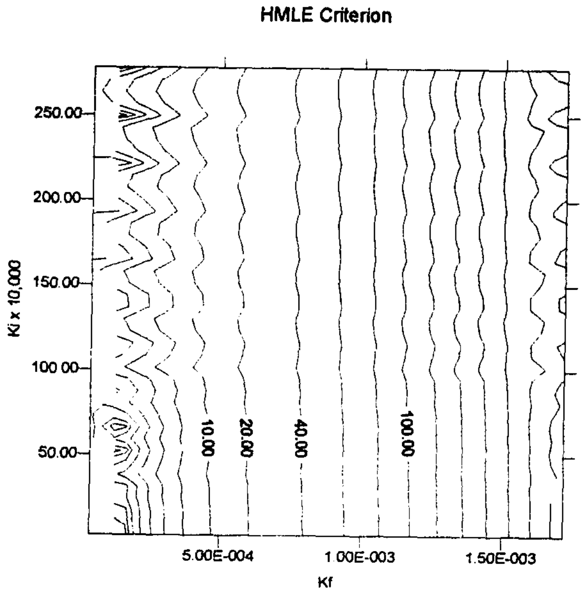
Figure 4.3. K_f -τ_c Contour Plots for Equation 3.

The response surface configurations for K_i and K_f (Figures 4.4-4.6) also demonstrate differences in the relative sensitivities of the two parameters. Very small changes in K_f could produce very large changes in the value of K_i. This observation leads to a more serious difficulty associated with the relationship between K_i-K_f. The vertical, elongated contours that are especially dominant in the contour plot of Equation 2 indicate that for any one value of K_f, an infinite number of values for K_i are possible. Another difficulty present in the contour plots of Equations 1 and 3 is the discontinuous response surface associated with extreme values of both K_i and K_f.

The response surfaces also demonstrate that the values of the SLS objective function are higher than those of the HMLE criterion for the same parameter values. This result means that the value of the SLS criterion for the same initial conditions will be higher than that of the HMLE objective function, and a direct comparison of their values cannot be made.

THE ERROR-FREE DATA CASE: THE TWO-PARAMETER PROBLEM

For the error-free data case, parameter estimates were considered to be a success if the they were not more than 1% in error of its true value. Based on this criterion, for all three cases of the two-parameter optimization problem, the synthetic error-free data study demonstrated a 100% success rate for both the Simplex and SCE-UA algorithms and for both objective functions in finding the true parameter values for plots with slopes of 10% and 15% for all three flow-induced erosion equations. However, no successful trials



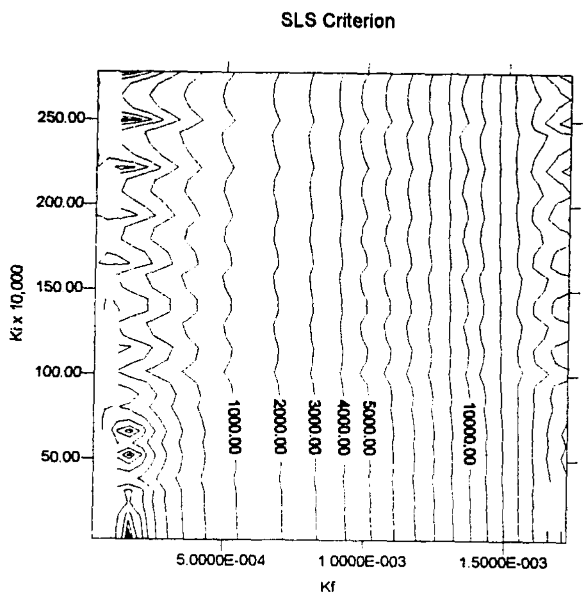
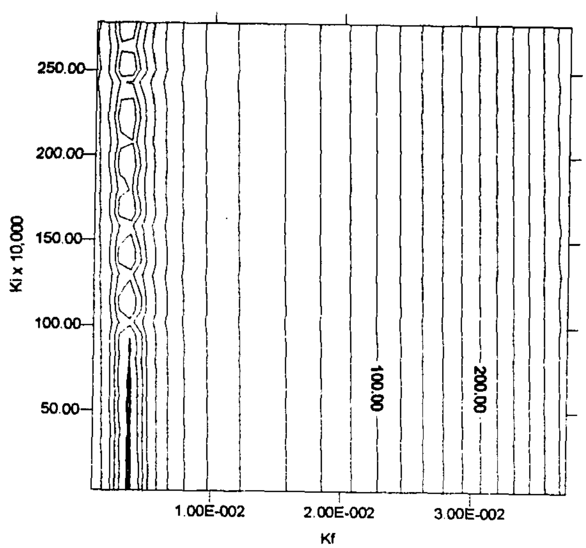


Figure 4.4. K_i - K_f Contour Plots for Equation 1.

HMLE Criterion



SLS Criterion

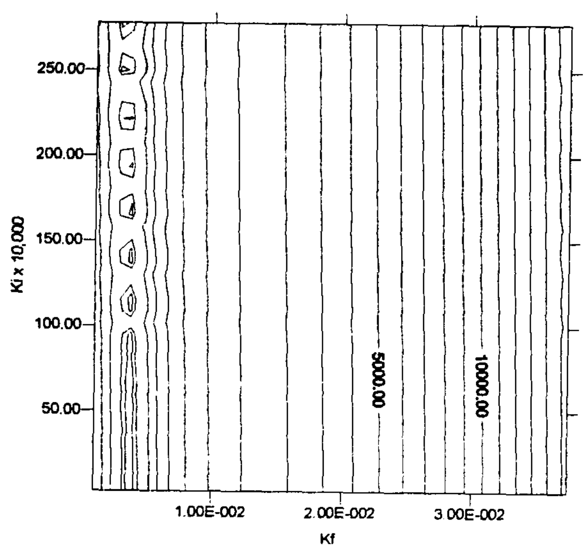
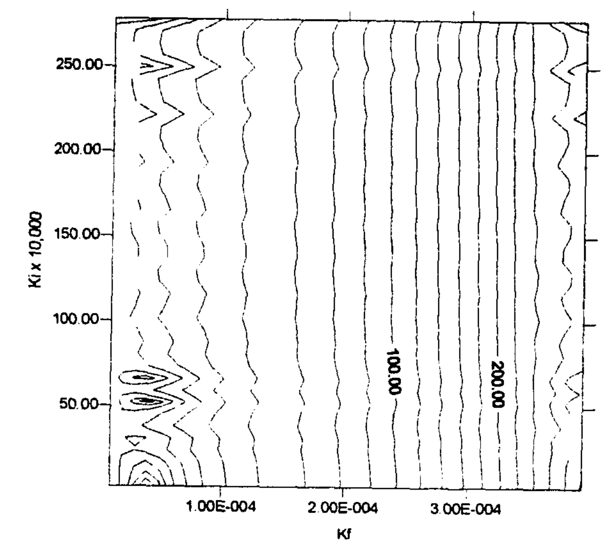


Figure 4.5. K_i - K_f Contour Plots for Equation 2.

HMLE Criterion



SLS Criterion

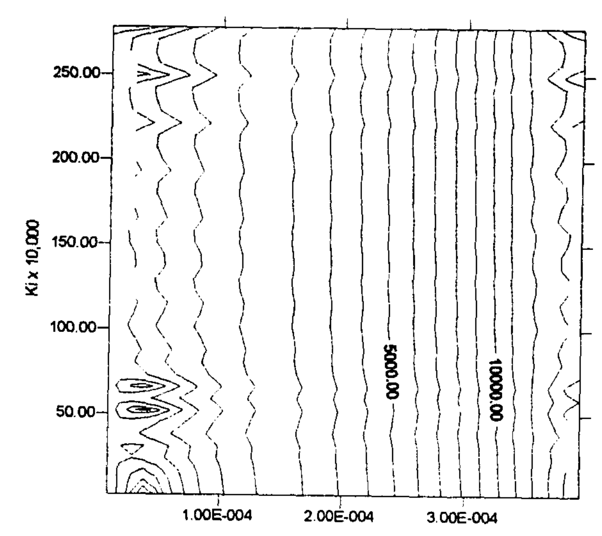


Figure 4.6. K_i - K_f Contour Plots for Equation 3.

resulted for plots with a 5% slope. This could be attributed to the assignment of a constant value for the deposition parameter (β) in broad shallow overland flow areas, which may have resulted in too much deposition occurring in areas of lower slope values. To eliminate this problem, the value of the dimensionless constant β in Equation 3.22 may have to be optimized for events where the slope is less than 10%. Because of the inability of the optimization procedure to estimate the parameter values of the error-free data for slopes of 5%, plots with these values were eliminated from the analysis.

THE ERROR-FREE DATA CASE: THE THREE-PARAMETER PROBLEM

For the three-parameter, error-free synthetic data case, only the SCE-UA algorithm with both criteria demonstrated a 100% success rate in estimating the true values of K_i, K_f, and τ_c. The Simplex in combination with the SLS criterion was entirely successful for both Equations 1 and 2, but for Equation 3, demonstrated only at 50% rate of success in cases where the parameters were most activated. Equation 1 demonstrated success with the Simplex and HMLE criterion on the very wet run with a 15% slope. Equation 2 demonstrated the same success on the very wet run on slopes of 10 and 15%. No successful HMLE events resulted with Equation 3.

The success of the Simplex and HMLE for the very wet runs may indicate a sensitivity of the optimization procedure to a variable rate of rainfall intensity. However, it is more likely that Simplex was more sensitive to the degree of activation of the parameters. On the 15% slope, the parameters would be more active than on a 10%

slope, which is why Equation 1 found success with only one of the variable intensity rainfall runs.

The K_f-τ_c contour plots (see Figures 4.1-4.3) reveal that the SLS criterion has a smoother, more elliptical response surface than that of the HMLE. This may explain why in part, for the three-parameter optimization problem, the Simplex in conjunction with the HMLE criterion is unable to estimate the true values of the parameters. However, the uncertainty involved in the estimation of K_i seems to be more pertinent to the estimation problem. For the Simplex and HMLE optimization procedure, with the exception of Equation 3, a higher estimation error is associated with runs on a 10% slope. More error is also associated with the wet runs than on the dry runs, presumably due to the fact that the dry runs are of a longer duration and better activate the threshold parameter, τ_c. If τ_c is not fully activated, then any uncertainty in the erosion processes are then incorporated into the parameter K_i when using the HMLE criterion.

Analysis of The Results for the Synthetic Data Case

The parameter values estimated in the synthetic data study have been tabulated in Tables A1-A36. The following discussion is limited to the cases where error is present in the data, given the success of the error-free data case for the two-parameter optimization problems. For the analysis of the three-parameter problem when error is present, the error-free data case will be considered since the nonsuccesses under ideal conditions will provide a basis for understanding the parameter estimation error when noise is incorporated into the data set.

A tally of the highest error associated with each of the four optimization procedures (Simplex and SLS, SCE-UA and SLS, Simplex and HMLE and SCE-UA and HMLE) was performed to evaluate the optimization procedures. The highest error determination considered only the absolute differences in percent error, regardless of the magnitude of difference. If more than one procedure was associated with the highest error, then each procedure was counted as having the highest error. This procedure implies that a small difference in the percent error in the synthetic data would translate into a significant difference in error when working with observed data in the field. Such a pattern was noted between the error-free data sets and the correlated error cases. Equation 1 in the 2-parameter cases, for example, demonstrated the highest error of estimation when no error was present in the data. This error was magnified when estimating the parameter values for the correlated error events.

The HMLE was compared to the SLS criterion only with the algorithm with which it was associated. For example, the parameter estimation error of the Simplex and HMLE was only compared to the Simplex and SLS, and differences in error between the SCE-UA and HMLE and the SCE-UA and SLS were also considered separately. However, a direct comparison of the highest estimation error associated with each of the four procedures was performed without any special consideration given to the algorithm that employed the selected objective function.

The relative amount of estimation error with respect to each flow-induced erosion equation is considered when selecting the best equation for use in the natural data studies. The selection of the best optimization procedure considered the four evaluation criteria outlined in the methodology presented in this thesis, where the two-parameter cases are evaluated separately from that of three-parameters since there were estimation problems associated with two of the four procedures in the error-free data case.

ESTIMATION OF ACTIVE & INACTIVE PARAMETERS

By incorporating error into synthetic data, uncertainties in the processes modeling erosion are created. Such uncertainties are manifested in the estimation of the parameters that are used to describe these processes. Whereas K_i is related to the erodibility of the soil by raindrop impact; K_f and τ_c are related to detachment and transport by hydraulic shear. K_f describes the transport capacity of the flow and τ_c refers to the critical shear that the flow must exceed in order for detachment to occur.

Clearly, all four of the parameter optimization problems posed demonstrated that the greatest uncertainty is incorporated into the estimates of K_i (see Tables A1-A36). Not only were large errors present in the estimates of K_i for all of the correlated error cases, but with the three-parameter, error-free data set as well. Excluding the errors in estimation for the error-free, three parameter problem, the average percent error for K_i at both levels of correlated error was 92.13% (93.77% and 90.48% for K_i-K_f and K_i-K_f-τ_c respectively). This value was much greater than the average estimation error for τ_c

(19.32% and 21.27% for K_f-τ_c and K_i-K_f-τ_c respectively) and K_f (10.37% and 4.27% for K_f-τ_c and K_i-K_f respectively) (see Tables 4.3-4.5).

Table 4.3. Error Statistics for 2-parameter problem (K_i-K_f).

Eq. No.	ρ	Fixed Value of τ_c	Avg. % Error K_f	% Error SD K_f	Avg. % Error K_i	% Error SD K_i
1	0.25	0.502	3.43	2.05	88.33	41.27
	0.50		3.66	3.07	94.99	56.16
	0.25	0.0	2.19	2.00	96.13	43.43
	0.50		3.94	3.04	91.59	50.58
2	0.25	0.502	8.82	1.07	78.70	48.33
	0.50		2.04	1.77	88.73	43.61
	0.25	0.0	4.14	9.01	117.22	43.14
	0.50		1.92	1.90	60.57	37.09
3	0.25	0.502	2.25	1.44	101.32	48.16
	0.50		3.04	1.90	92.83	51.53
	0.25	0.0	7.92	13.33	86.72	47.13
	0.50		7.90	13.36	128.14	40.33
AVG			4.27	4.50	93.77	45.90

Two factors contributed to the large error found in the estimate of K_i. For the K_i-K_f estimation problem, the value of τ_c was fixed. Because the critical shear stress is a threshold parameter and K_f is related to the transport capacity of the flow, then detachment by hydraulic shear cannot vary by a large measure. Therefore any uncertainties or changes to be accounted for in detachment, were noted in the parameter value for K_i. The nearly vertical line relationship demonstrated in the response surface configuration of the K_i-K_f plots is another contributing factor (see Figures 4.3-4.6). K_f is more sensitive to changes in the objective function than K_i, and presumably for any given value of K_f, there is more than one possible value of K_i.

Table 4.4. Error Statistics for 2-parameter Problem (K_f-τ_c)

Eq. No.	ρ	Avg. % Error K_f	% Error SD K_f	Avg. % Error τ_c	% Error SD τ_c
1	0.25	10.65	10.41	25.83	14.78
	0.50	18.96	24.60	37.55	31.43
2	0.25	5.70	5.92	9.54	8.09
	0.50	8.44	6.26	14.52	8.42
3	0.25	6.15	8.93	6.46	8.84
	0.50	12.29	5.65	22.03	11.80
AVG		10.37	10.30	19.32	13.89

Table 4.5. Error statistics for 3-parameter problem.

Eq. No.	ρ	Avg. % Error K_i	% Error SD K_i	Avg. % Error K_f	% Error SD K_f	Avg. % Error τ_c	% Error SD τ_c
1	0.25	89.44	48.54	14.11	14.57	31.69	17.44
	0.50	94.71	57.01	20.21	23.54	38.97	31.78
2	0.25	96.74	50.45	8.33	11.59	12.38	14.43
	0.50	91.02	51.06	8.08	4.40	16.86	10.87
3	0.25	84.03	59.16	6.21	6.75	6.89	6.59
	0.50	86.94	59.70	11.32	6.77	20.82	12.26
AVG		90.48	54.32	11.38	11.27	21.27	15.56

The parameter estimates resulting from the 3-parameter problem were consistent with those of the 2-parameter cases; the estimate of K_i contained the highest error and the average percent errors for both K_f and τ_c were nearly the same between the K_f-τ_c and K_i-K_f-τ_c problems (see Tables 4.3 - 4.5). In general, the error associated with the estimates of K_i was slightly higher in the 2-parameter case than in the 3-parameter problem, while the converse was true for both K_f and τ_c. This outcome meets the theoretical expectation since most of the uncertainty is incorporated in K_i when τ_c is fixed, whereas the uncertainty in the 3-parameter problem is incorporated into all of the parameter estimates.

The average estimation error, however, can be misleading. The abilities of each of the flow-induced erosion models to produce parameters close to their true values need to be evaluated separately. The generalizations stated above, therefore, are for describing the tendencies and uncertainties present in the different parameter optimization problems posed in this study.

EFFECT OF ALGORITHM & OBJECTIVE FUNCTION ON ACTIVE AND INACTIVE PARAMETERS

Tables 4.6 - 4.9 and Figures 4.7 - 4.8 show that in all of the two-parameter cases studied, the Simplex algorithm, in general, provided parameter estimates closer to the true values for both the active (K_f and K_i) and inactive (τ_c) parameters. There were only two exceptions to this rule that occurred in the K_f-τ_c optimization problem, where the estimate

Table 4.6. Optimization procedures associated with highest estimation error for 3-parameter optimization problem (K_i-K_f-τ_c).

Parameter	ρ	Simplex and SLS	SCE-UA and SLS	Simplex and HMLE	SCE-UA and HMLE
K_i	0.25	5	4	1	9
K_f		4	1	6	8
τ_c		3	1	6	9
K_i	0.50	2	7	2	8
K_f		4	7	6	2
τ_c		2	8	4	4

Table 4.7. Optimization procedures associated with highest estimation error for 2-parameter optimization problem (K_f-τ_c).

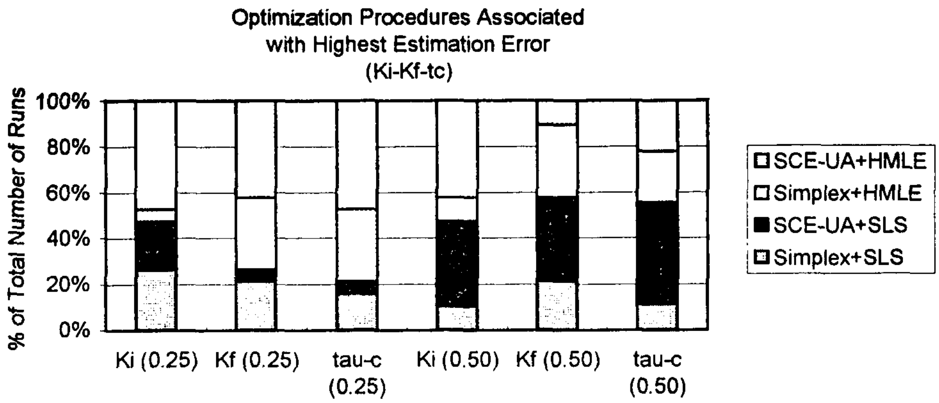
Parameter	ρ	Simplex and SLS	SCE-UA and SLS	Simplex and HMLE	SCE-UA and HMLE
K_f	0.25	3	0	8	7
τ_c		2	3	8	6
K_f	0.50	6	5	4	3
τ_c		6	7	2	4

Table 4.8. Optimization procedures associated with highest estimation error for 2-parameter optimization problem (K_i-K_f; τ_c = 0.502).

Parameter	ρ	Simplex and SLS	SCE-UA and SLS	Simplex and HMLE	SCE-UA and HMLE
K_i	0.25	1	6	5	8
K_f		1	8	1	9
K_i	0.50	3	3	3	9
K_f		2	7	1	11

Table 4.9. Optimization procedures associated with highest estimation error for 2-parameter optimization problem (K_i-K_f; τ_c = 0.0).

Parameter	ρ	Simplex and SLS	SCE-UA and SLS	Simplex and HMLE	SCE-UA and HMLE
K_i	0.25	2	2	4	10
K_f		1	8	1	9
K_i	0.50	6	6	3	7
K_f		2	11	2	6



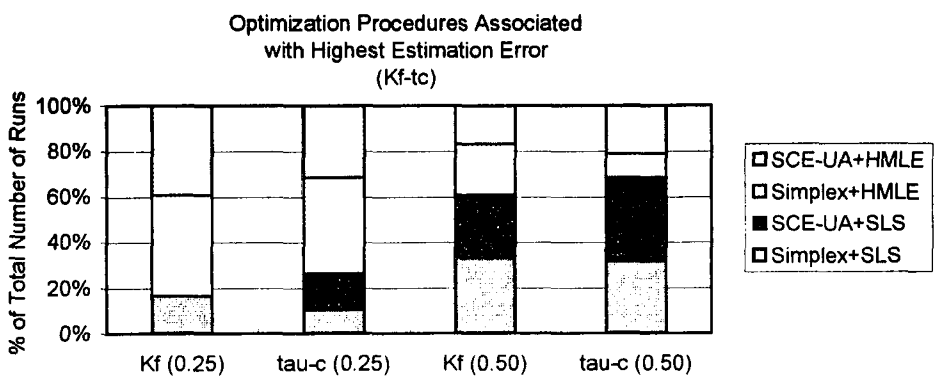
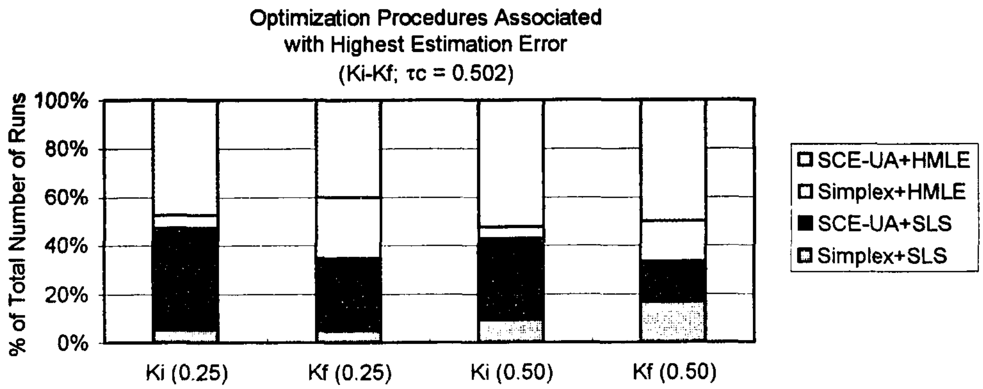


Figure 4.7. Optimization procedures associated with the highest estimation error for each parameter. Results from 3-parameter problem and 2-parameter (K_f-τ_c) optimization problems.



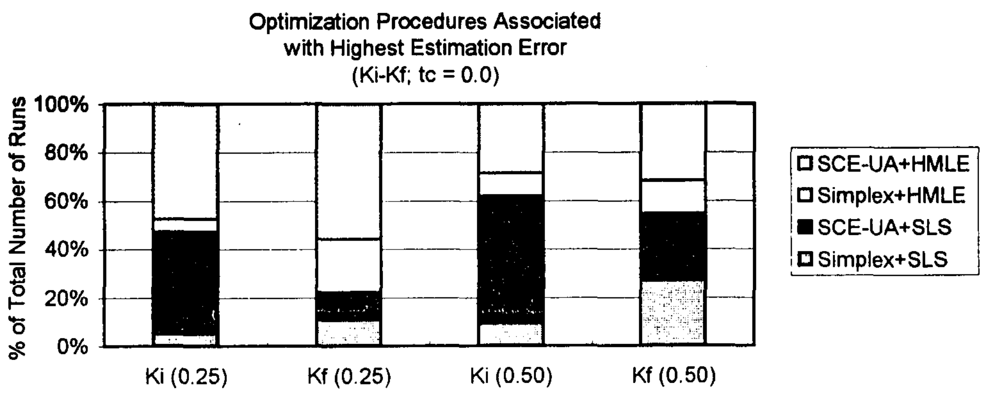


Figure 4.8. Optimization procedures associated with the highest estimation error for each parameter. Results from 2-parameter problems (K_i-K_f) shown above for τ_c = 0.502 and τ_c= 0.0.

of K_f was improved by use of the SCE-UA algorithm in both error cases. For the correlated error case $\rho = 0.25$, the SLS criterion outperformed the HMLE estimator. For the case where $\rho = 0.50$, the HMLE criterion provided better overall estimates for all of the parameters.

Gauging the success of the optimization procedures employed for the 3-parameter problem posed difficulties since it is known that sediment entrainment by raindrop impact has a behavior similar to that of entrainment by hydraulic shear, and that unique parameter identification may not be possible unless the value of K_i is determined separately (Lopes, 1987). However, few patterns of success were noted. The estimates of K_f were consistent with those of the 2-parameter problems, where the SCE-UA algorithm outperformed the Simplex, and the SLS criterion was the best estimator with lower levels of error. The behavior of τ_c with respect to the algorithm and objective function employed was less consistent; the SLS criterion provided better estimates in both error cases while the SCE-UA algorithm was most successful for $\rho = 0.25$, while the Simplex was more successful for $\rho = 0.50$. The Simplex and HMLE procedure was a notable example of success since it was the most unsuccessful procedure in the error-free data case. It better estimated the value of K_i in both error cases and provided better overall estimates for all three parameters in Equation 3 for $\rho = 0.25$.

EFFECT OF ALGORITHM & OBJECTIVE FUNCTION ON FLOW-INDUCED EROSION EQUATIONS

The effect of the algorithm and objective function employed on each of the flow-induced erosion equations showed similar trends to those previously stated (see Figures 4.7 and 4.8). For example, for ρ= 0.25 in the K_f-τ_c, and K_i-K_f (τ_c = 0.502) parameter optimization problems, the HMLE estimator was consistently associated with higher error than that of the SLS criterion. The reverse was true for ρ = 0.50 case; that is, these same optimization problems were associated with higher error when employing the SLS criterion.

The 2-parameter optimization problem for K_i-K_f (τ_c = 0.0) did not show the same trends. In fact, for both ρ = 0.25 and ρ = 0.50 the HMLE criterion performed slightly better than the SLS estimator overall. This outcome supports the hypothesis that as the error quantity was increased, the HMLE criterion provided better estimates of the parameters by reducing the number of local optima on the response surface. In the case where the value of τ_c was fixed at zero, greater error in the estimate of K_i would be expected since the structure of the equation is exponential. Less error would be expected for the case where τ_c was fixed at a value of 0.502, since this expression of excess shear stress represented a process of decay.

For the K_i-K_f optimization problems, the Simplex algorithm performed slightly better overall for all three flow-induced equations. For the K_f-τ_c case, the SCE-UA performed slightly better than the Simplex in estimating K_f. However, the differences in the highest error associated with each of the algorithms did not usually differ by more than unity, and thus were not considered to be significant differences in the abilities of the algorithms to estimate the K_f for each of the flow-induced erosion equations.

OBJECTIVE FUNCTION

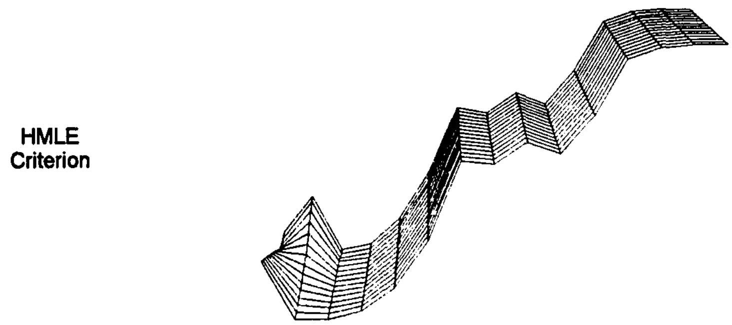
The selection of the objective function plays a major role in forming the shape of the response surface. The more elliptical in shape the response surface is, the easier it is for the optimization method to search for the best parameter values The response surface configurations for the SLS criterion for all three equations are more elliptical than those of the HMLE criterion for the K_f-τ_c case. For this reason, it may be that when the error is low, the SLS criterion provided better parameter estimates than when the HMLE objective function was used. Because the HMLE stabilizes a non-stationary variance, it would not necessarily follow that the HMLE criterion have a significant effect on a data set where correlated error was present. However, as previously noted, the HMLE provided better parameter estimates at higher levels of correlated error.

No significant differences in the shapes of the response surface configurations were noted between the two estimators for the relationship between K_i-K_f. However, differences between the flow-induced equations did exist. Equations 1 and 3 demonstrated more than one "region of attraction" as well as several discontinuities in their response surface configurations. The contour plot for Equation 2, although smoother and continuous, demonstrated a long, narrow valley that could cause difficulties in parameter identification.

The success of the HMLE criterion at a higher level of error suggests that the local minima were reduced as the degree of correlation in errors was increased. Results from parameter optimization for K_f-τ_c and Equation 2 is a notable example: for $\rho = 0.50$, the HMLE criterion resulted in better estimates of K_f, 8 out of 12 times and for τ_c, 10 out of 12 times. Figure 4.9 shows that for Equation 2, the SLS response surface configuration is flatter and has more local minimum than that of the HMLE criterion. By contrast, Figure 4.10 demonstrates that for $\rho = 0.25$, the SLS response surface is steeper than the HMLE estimator.

BEST VALUE OF OBJECTIVE FUNCTION AND AVOIDANCE OF LOCAL MINIMA

An examination of Tables A1-A36 demonstrates that in all of the parameter optimization problems posed when error was present, the SCE-UA algorithm consistently resulted in a smaller value of the objective function, except for those cases in which the comparison resulted in a tie. This observation suggests that local optima do indeed exist on the response surface. One explanation for the Simplex's lack of convergence to the global optima may be that it is located in a small crater-shaped region that lies in a relatively flat area on the response surface. Figures 4.11 and 4.12 demonstrate that the



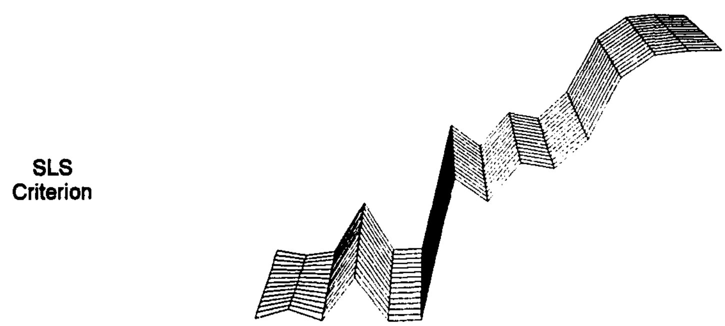


Figure 4.9. Comparison of response surfaces for HMLE and SLS criteria (Equation 2, dry run, 15% slope, $\rho = 0.50$).

SLS
Criterion

HMLE
Criterion

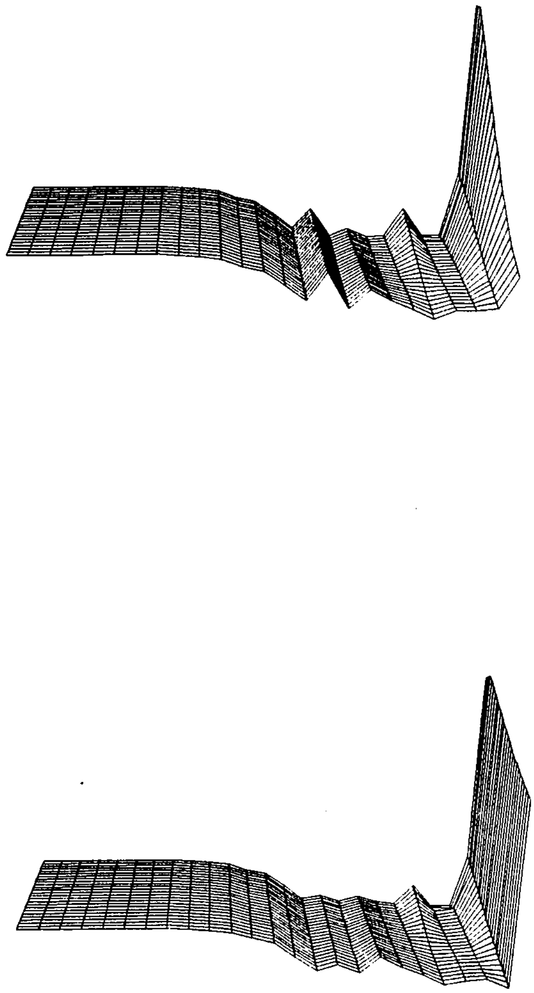
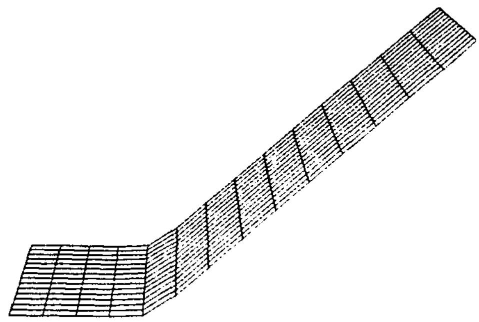


Figure 4.10. Comparison of response surfaces for HMLE and SLS criteria (Equation 2, wet run, 10% slope, $\rho = 0.25$).

Simplex
Surface



SCE-UA
Surface

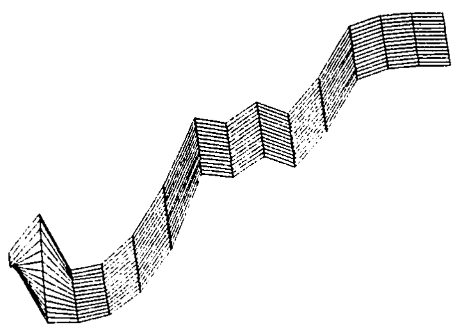


Figure 4.11. Comparison of response surfaces for SCE-UA and Simplex algorithms. (Equation 2, dry run, 10% slope, HMLE, $\rho = 0.50$).

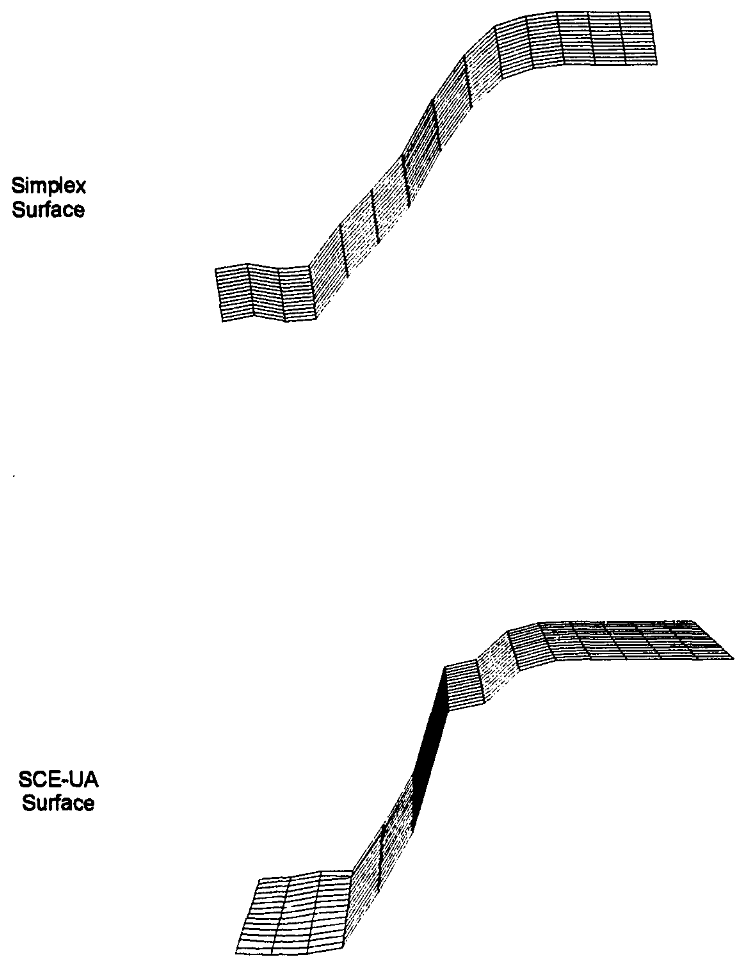


Figure 4.12. Comparison of response surfaces for SCE-UA and Simplex algorithms.
(Equation 2, dry run, 10% slope, SLS, $\rho = 0.25$).

minimum lies in a relatively flat area for the Simplex algorithm, whereas the SCE-UA response surface is steeper.

However, contrary to the theoretical expectation, Simplex usually obtained better estimates for the parameters in the 2-parameter problems even though SCE-UA was better able to converge to the global minimum. One theory that may explain this result is that when error was introduced into the sediment concentration data, the error affected the values of the hydraulic parameters as well. Fixing the values of the hydraulic parameters may have impacted the analysis in such a way that the lowest value of the objective function did not necessarily correspond to the best estimates of the erosion parameters.

Another theory that might explain why the lowest value of the objective function did not correspond to the best estimates of the parameters is the use of the four-point implicit method to numerically solve the kinematic wave equations. Although very conservative estimates of the change in time were used in this analysis, an analytical solution may perhaps lessen the uncertainty in the model processes when error is present.

In the 3-parameter problem posed, the success of the algorithms and objective functions was independent of the algorithms' abilities to locate the global minimum on the response surface. This is more than likely due to the similar behavior of the two entrainment terms (Lopes, 1987) as few patterns of success arose from this estimation problem. The success of the Simplex and HMLE procedure when error was present (given its failure with the error-free data set) supports the result that an early termination of the Simplex algorithm was likely to result in better estimates of the parameters.

In the case of the error-free data, the SCE-UA algorithm generally did not succeed in finding a lower value of the objective function for the 2-parameter problems. This was a result of the SCE-UA algorithm terminating due to the population of points converging into a sufficiently small space such that any further search would not result in a significant improvement of the parameter estimates. This was indeed the case since very small differences in parameter estimates resulted between the use of the two algorithms. This again suggests that a small crater-shaped region exists in a relatively flat area of the response surfaces.

DATA SET VARIABILITY

All three parameters demonstrated different sensitivities to the three antecedent moisture conditions tested, without any effects due to the level of correlated error. Even though the estimation procedures were sensitive to the calibration data variability, no trends were noted in the selected objective function's ability to reduce this sensitivity. According to averages in the percent error of estimation calculated for the three antecedent moisture conditions (see Tables 4.10-4.13 and Figure 4.13), the dry runs provided the best estimates for the parameter τ_c, 4 out of 6 times, for the 3-parameter problem and, 5 out of 6 times, for the 2-parameter problems. This result may be related to the length and variability of the data which are crucial factors in the activation of a threshold parameter. Data from dry runs contained more information on varying soil

Table 4.10. Average estimation error for different initial moisture conditions for 3-parameter optimization problem.

Parameter	ρ	Equation No.	Avg. % Error Dry	Avg. % Error Wet	Avg. % Error Very Wet
K_i	0.25	1	99.99	68.78	99.56
		2	119.16	97.93	73.15
		3	94.40	78.00	79.68
K_f		1	3.20	30.33	8.81
		2	5.36	18.52	2.63
		3	2.18	10.57	5.46
τ_c		1	11.39	44.84	38.85
		2	5.23	27.28	4.66
		3	3.68	10.59	6.41
K_i	0.50	1	94.86	83.96	105.31
		2	77.60	75.93	119.52
		3	84.64	96.09	80.11
K_f		1	8.14	45.20	7.31
		2	7.96	6.07	10.19
		3	10.41	16.54	7.01
τ_c		1	20.67	66.97	29.25
		2	12.95	11.86	25.76
		3	11.24	23.39	27.80

Table 4.11. Average estimation error for different initial moisture conditions for 2-parameter optimization problem (K_f-τ_c)

Parameter	ρ	Equation No.	Avg. % Error Dry	Avg. % Error Wet	Avg. % Error Very Wet
K_f	0.25	1	3.10	22.97	6.02
		2	4.32	10.35	2.41
		3	3.17	12,88	2.41
τ_c		1	6.17	33.12	38.21
		2	6.67	18.34	3.60
		3	2.40	13.20	3.78
K_f	0.50	1	7.31	44.34	5.16
		2	11.45	6.45	7.41
		3	11.35	16.20	9.31
τ_c		1	18.52	63.64	30.49
		2	9.33	12.78	21.31
		3	11.46	25.26	29.38

Table 4.12. Average estimation error for different initial moisture conditions for 2-parameter optimization problem (K_i-K_f; τ_c = 0.502)

Parameter	ρ	Equation No.	Avg. % Error Dry	Avg. % Error Wet	Avg. % Error Very Wet
K_i	0.25	1	91.93	63.08	109.99
		2	133.70	54.03	48.34
		3	122.77	104.40	76.80
K_f		1	3.55	31.42	2.82
		2	1.56	1.48	2.42
		3	1.50	1.82	3.43
K_i	0.50	1	110.68	51.29	123.00
		2	95.59	114.29	56.12
		3	55.87	118.05	104.55
K_f		1	3.31	1.94	5.75
		2	4.04	0.59	1.48
		3	2.33	2.11	37.38

Table 4.13. Average estimation error for different initial moisture conditions for 2-parameter optimization problem (K_i-K_f; τ_c = 0.0)

Parameter	ρ	Equation No.	Avg. % Error Dry	Avg. % Error Wet	Avg. % Error Very Wet
K_i	0.25	1	108.20	76.11	104.09
		2	124.01	149.73	77.93
		3	101.55	96.83	61.84
K_f		1	1.60	1.26	3.73
		2	9.05	1.26	2.10
		3	2.03	18.67	101.55
K_i	0.50	1	100.04	97.12	77.63
		2	78.64	38.44	64.65
		3	145.72	103.91	134.79
K_f		1	2.53	3.33	5.98
		2	1.05	1.60	3.12
		3	1.47	18.98	3.25

moisture contents. Moreover, dry run simulations were twice the duration of the wet and very wet runs.

Wet antecedent moisture conditions provided the best estimates for the parameter K_i, 11 out of 18 times for all four parameter optimization problems, followed by very wet runs providing the best estimates, 7 out of 18 times. The dry runs were not associated with the best estimates for the estimates of K_i. This result also may be related to the length of the data record. Given that entrainment by raindrop impact is similar to entrainment by hydraulic shear, the model cannot separate the two processes when optimizing for the appropriate parameters. The longer the simulation, the less clear the distinction becomes between the two processes of entrainment. The higher degree of success with the very wet simulations may be related to a higher rainfall intensity rate.

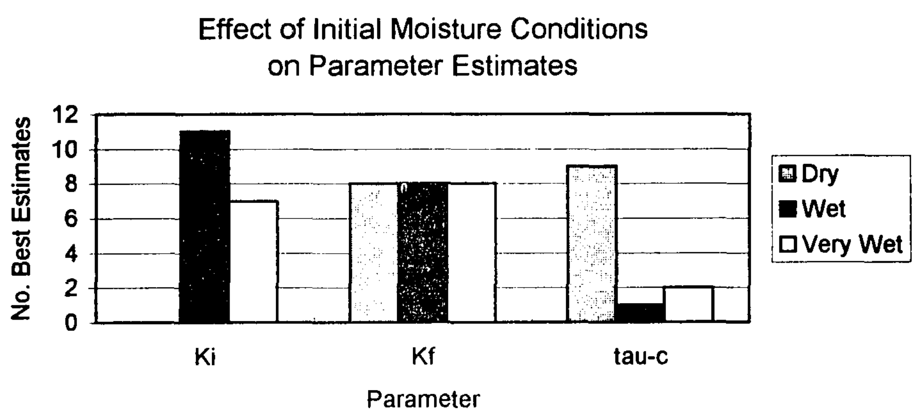


Figure 4.13. Number of best estimates associated with each initial moisture condition according to average percent estimation error for all four optimization procedures.

The effect of antecedent moisture was not as evident with respect to the parameter estimate of K_f. Each antecedent moisture condition provided the best estimates 8 out of 24 times for all of the parameter optimization problems posed. However, all estimation errors for K_f greater than 15% occurred in the wet runs. This result was not due to the effect of random error since all three flow-induced equations generated the same result, but due to the very low sediment concentration values associated with these runs. A higher flow rate would make it easier for the estimation procedure to determine the transport capacity of the flow.

EVALUATION OF FLOW-INDUCED EROSION EQUATIONS

A very high level of error was associated with Equation 1, which relates sediment entrainment to the stream power of the flow (Bagnold, 1966). Even when no error was present in the data, the error of estimation for the dry and wet runs was usually twice that of the other two erosion equations. This may have been due to an inability of Equation 1 to predict erosion under fully dynamic conditions.

In general, Equations 2 and 3 were associated with lowest estimation error for all three parameters. In the K_f-τ_c estimation problem, Equation 3 generated the best estimates of τ_c when $\rho = 0.25$ (6.46% vs. 9.54%) whereas Equation 2 performed best for the case where $\rho = 0.50$ (14.52% vs. 22.03%). Equation 2 was chosen for use in further studies because the results indicate that it would perform well regardless of the level of error. By contrast, greater inaccuracies in the estimate of τ_c may exist unless the level of error is known to be low.

Another factor considered in the selection of the best flow-induced erosion equation was the shape of the response surface for K_i-K_f. Equation 2 was the only one of the three that was unaffected by discontinuities in the response surface. Moreover, the Simplex and SLS procedure only demonstrated a 50% success rate for the error-free data case. These factors showed that Equation 2 was more robust than the other two equations.

OPTIMIZATION PROBLEM SELECTED FOR NATURAL DATA STUDIES

Four different parameter optimization problems were posed with the primary objective of studying the behavior of the erosion parameters with respect to the optimization algorithm and objective function employed. The inclusion of K_i in the optimization problem clearly resulted in a significant amount of uncertainty in the analysis. For this reason, K_i is often determined by measuring sediment yields from small plot studies. In very small areas, it is assumed that all of the erosion is induced by raindrop impact, since the area is too small to experience erosion by hydraulic shear. In the absence of plot studies, regression equations that relate soil properties to K_i have been used to determine its value.

Once the value of K_i has been estimated, it can be fixed so that the values of the parameters relating erosion by hydraulic shear can be determined. Other soil erosion studies have also indicated this to be the best approach for estimating parameter values (Lopes, 1987; Page, 1988).

The Simplex algorithm was selected for use in the rainfall simulator plot and watershed studies because it was more successful in estimating the true values of the parameters. The only relevant exception to this rule was in the K_f-τ_c optimization problem where K_f was better estimated by SCE-UA. Because τ_c is a threshold parameter and is more difficult to estimate than K_f, it was considered best to choose the algorithm that could better estimate the inactive parameter. Inaccurate estimates of τ_c would also have a greater impact on model predictions than any differences in the parameter estimates for K_f generated by Simplex or SCE-UA.

The selection of the objective function for use in the natural data studies depended on the amount of error assumed to be present in the data. The synthetic data study clearly demonstrated that higher levels of error in the sediment concentration data would be better served by the HMLE estimator. However, it was assumed that the amount of correlated error present in the natural data would not warrant the use of the HMLE criterion.

Analysis of Plot Data

To test the selected flow-induced erosion equation, data from WEPP rainfall simulator plots located in the Western United States were used. A 2-parameter optimization problem was posed by fixing the value of K_i. The value of K_i had already been determined experimentally using small plot studies by the USDA-ARS WEPP team.

ESTIMATION OF HYDRAULIC PARAMETERS

Values of the hydraulic parameters and the Nash-Sutcliffe coefficient appear in Tables 4.14 and 4.15 and their corresponding hydrographs are in Figures 4.14-4.23. With the exception of the dry run for plot 105, all of the simulations generated hydrographs fit the measured data well. This is important because the hydrology drives the erosion component of the model. If the hydraulic parameters are not well estimated, then it may not be possible to obtain good estimates of the erosion parameters.

TRUE VALUES, INITIAL VALUES AND PARAMETER BOUNDS

Because preliminary investigations of the rainfall simulator plots indicated that the value of critical shear stress (τ_c) approached zero, and that in general, most values of τ_c for rangeland soils did not exceed a value of 6.0 (Foster et al., 1989), these values were designated the minimum and maximum values of the parameter for all simulations. The range of values for the parameter K_f changed from site to site, and were determined by trial and error (see Table 4.16).

Since the value of K_f is model dependent, it's true value was unknown. Therefore, τ_c was the only parameter that could be compared to its true value as determined by the critical conditions for incipient motion to occur. After obtaining values of the Reynolds

Table 4.14. Optimized hydraulic parameters for the rainfall simulator plots.

Plot No.	Antecedent Moisture	Re	Manning's n	Ns	Ks	Objective Function	Nash-Sutcliffe Coefficient
31	Dry	57.9	2.90280e-02	4.41380e-01	5.54130e-08	240.22	0.96
	Wet	53.5	2.81550e-02	5.33810e-02		403.34	0.95
	Very Wet	53.0	3.7089e-02	5.52800e-02		410.53	0.97
34	Dry	35.1	6.32860e-02	5.38480e-02	2.96770e-07	848.78	0.88
	Wet	52.5	2.70770e-02	3.80480e-02		429.16	0.93
	Very Wet	57.6	2.70040e-02	1.01360e-02		421.81	0.98
56	Dry	30.3	3.84050e-02	3.42550e-03	3.34560e-06	174.16	0.98
	Very Wet	36.2	4.00000e-02	1.66690e-02		303.92	0.78
59	Dry	55.8	3.82490e-02	1.50470e-01	1.73860e-07	81.84	0.99
	Very Wet	40.2	4.74690e-02	1.1394e+00		1426.10	0.65
63	Dry	53.6	3.21660e-02	4.21110e-02	3.93120e-08	248.59	0.96
	Very Wet	51.6	4.90720e-02	9.11000e-01		205.43	0.92
66	Dry	47.0	4.07300e-02	2.52970e-02	9.92950e-08	231.16	0.98
	Very Wet	7.0	4.07330e-02	3.01810e-01		455.05	0.84
102	Dry	15.2	2.81580e-02	5.18280e-01	3.60950e-07	90.188	0.77
	Wet	42.9	5.99740e-02	1.27120e-01		1358.2	0.71
	Very Wet	42.0	5.99220e-02	3.39010e-02		690.77	0.92
105	Dry	55.0	5.12160e-02	1.72610e-01	1.72180e-07	3291.8	-0.39
	Wet	36.2	3.70150e-02	1.77970e-01		856.17	0.74
	Very Wet	38.3	5.99220e-02	6.46050e-02		936.53	0.92
120	Dry	58.3	5.89490e-02	1.04820e+00	7.51070e-08	703.61	0.83
	Wet	56.2	5.77280e-02	1.43670e-01		232.21	0.95
	Very Wet	59.1	5.52580e-02	8.01780e-02		213.07	0.97
121	Dry	48.7	3.73930e-02	1.75689e+00	4.73970e-08	857.57	0.66
	Wet	58.8	5.99901e-02	4.28810e-01		355.68	0.94
	Very Wet	49.4	6.67600e-02	5.04840e-02		837.64	0.92

Table 4.15. Parameter bounds and starting values for rainfall simulator plots

		τ_c [M/LT^2]			K_{f2} [$T^2/L^{0.5}M^{0.5}$]	
Plot Nos.	Lower Bound	Upper Bound	Starting Value	Lower Bound	Upper Bound	Starting Value
31, 34	0.0	6.0	1.150	5.0e-02	1.0e+00	4.25e-01
56, 59, 63, 66	0.0	6.0	0.100	1.0e-04	2.5e-01	1.25e-01
102, 105	0.0	6.0	0.875	5.0e-02	1.0e+00	1.0e-01
120, 121	0.0	6.0	0.875	5.0e-02	2.0e-02	1.0e-04

number from the overland flow at steady-state, the Shield's diagram was used to identify the value of τ_c.

SEDIMENT GRAPHS FOR RAINFALL SIMULATOR PLOTS

In only 4 of the 24 simulations did the Nash-Sutcliffe coefficient indicate a good fit between the measured and the simulated sediment graphs (see Table 4.16 and Figures 4.14 - 4.23). It was in these cases that some of the largest errors in estimation occurred for the critical shear stress parameter. Conversely, when the error of estimation was low, the Nash-Sutcliffe coefficient indicated a poor fit between the simulated and measured data.

Plots 31 and 34 are a case in point, as the synthetic data were generated based on the soil properties at these sites. The only simulation (plot 31, Wet Run) to produce a sediment graph that matched the measured data (Nash-Sutcliffe Coefficient = 0.77) was also associated with the highest estimation error for τ_c for all six runs. Two simulations generated good estimates of τ_c, (less than 11% error), however, the results showed virtually no match between the measured and simulated sediment graphs.

Because WESP generated hydrographs that provided a good fit to the measured data, these anomalies may be linked to a structural problem in the erosion component of the WESP model. The analysis of the synthetic data identified a problem early on with the interactions of the deposition parameter occurring at very low slopes. WESP assumed that entrainment and deposition occurred simultaneously. If too much deposition

Table 4.16. Erosion parameter estimates for rainfall simulator plots.

Plot No.	Antecedent Moisture	% Slope	Fixed Value K_i	Parameter Estimates: a K_f	Parameter Estimates: τ_c	b Value of τ_c	% Error of True Value τ_c	Value of Obj. Ftn.	Nash-Sutcliffe Coefficient	No. of Iterations
31	Dry	10.2	285,000	1.6899E-01	4.8227E-01	5.4042E-01	(10.76015%)	1.8823E+03	4.50E-01	71
	Wet			5.6370E-02	5.7948E-04	5.4042E-01	(99.89277%)	3.1588E+02	7.70E-01	156
	Very Wet			5.0001E-02	3.7531E-01	5.4042E-01	(30.55216%)	9.6677E+02	1.60E-01	100
34	Dry	10		6.0261E-02	3.0237E-01	4.7452E-01	(36.27877%)	2.2344E+03	4.10E-01	100
	Wet			5.0171E-02	5.6329E-01	5.2724E-01	(6.83749%)	5.3285E+03	-1.37E+00	101
	Very Wet			5.9516E-02	6.8658E-04	5.2724E-01	(99.86978%)	2.2295E+03	-8.20E-03	93
56	Dry	8.5	222,855	9.4761E-02	1.8051E-03	5.6473E-01	(99.68036%)	6.7520E+02	1.30E-01	48
	Very Wet			1.0115E-01	2.5757E-04	5.8086E-01	(99.95566%)	6.6359E+02	7.30E-01	59
59	Dry	7.1		3.4933E-02	2.5573E-02	6.4540E-01	(96.03765%)	3.9634E+02	-6.50E-01	59
	Very Wet			8.2727E-02	4.3905E-04	5.8086E-01	(99.92441%)	2.5003E+02	8.00E-01	63
63	Dry	8.6	186,445	1.5110E-02	5.9127E-05	5.0149E-01	(99.98821%)	8.1605E+01	3.90E-01	92
	Very Wet			2.1566E-02	3.6865E-04	5.0149E-01	(99.92649%)	1.1197E+01	9.50E-01	91
66	Dry	8.0		1.9131E-02	3.1051E-03	4.7641E-01	(99.34823%)	1.0836E+02	3.10E-01	60
	Very Wet			2.7595E-02	1.5909E-04	4.3880E-01	(99.96374%)	6.8785E+02	5.90E-02	77
102	Dry	11.2	315,178	1.0976E-01	2.3611E-03	5.6570E-01	(99.58262%)	4.7677E+02	-3.80E-01	64
	Wet			5.0007E-02	3.3085E-01	6.3427E-01	(47.83767%)	8.5356E+02	-7.20E-01	57
	Very Wet			5.0027E-02	7.9432E-01	6.5140E-01	(21.94044%)	6.7471E+02	-2.60E-01	65
105	Dry	9.8		5.0063E-02	6.3875E-01	6.8569E-01	(6.84566%)	3.5213E+02	1.70E-01	67
	Wet			6.4687E-02	2.0695E-03	6.1712E-01	(99.66465%)	7.4228E+02	2.90E-01	62
	Very Wet			5.0036E-02	5.3836E-01	6.1712E-01	(12.76251%)	3.8301E+02	1.20E-01	64
120	Dry	11.2	947,294	3.3447E-04	6.4087E-04	6.7510E-02	(99.05070%)	1.5280E+03	-2.20E-01	45
	Wet			1.8990E-04	6.1951E-03	6.7510E-02	(90.82343%)	3.5753E+02	1.30E-01	39
	Very Wet			7.1875E-04	3.5684E+00	6.7510E-02	(5185.73545%)	2.9100E+02	-3.10E+00	20
121	Dry	11.6		9.1398E-04	8.7357E-03	6.5820E-02	(86.72789%)	3.7593E+03	-1.02E+00	74
	Wet			3.8742E-04	3.5665E-03	6.7510E-02	(94.71708%)	2.3602E+03	-1.70E-01	55
	Very Wet			3.1719E-04	3.4180E-03	6.7510E-02	(94.93705%)	7.5927E+02	2.20E-01	39

[a] True value of K_f is unknown [b] True value of τ_c was determined using Shield's diagram

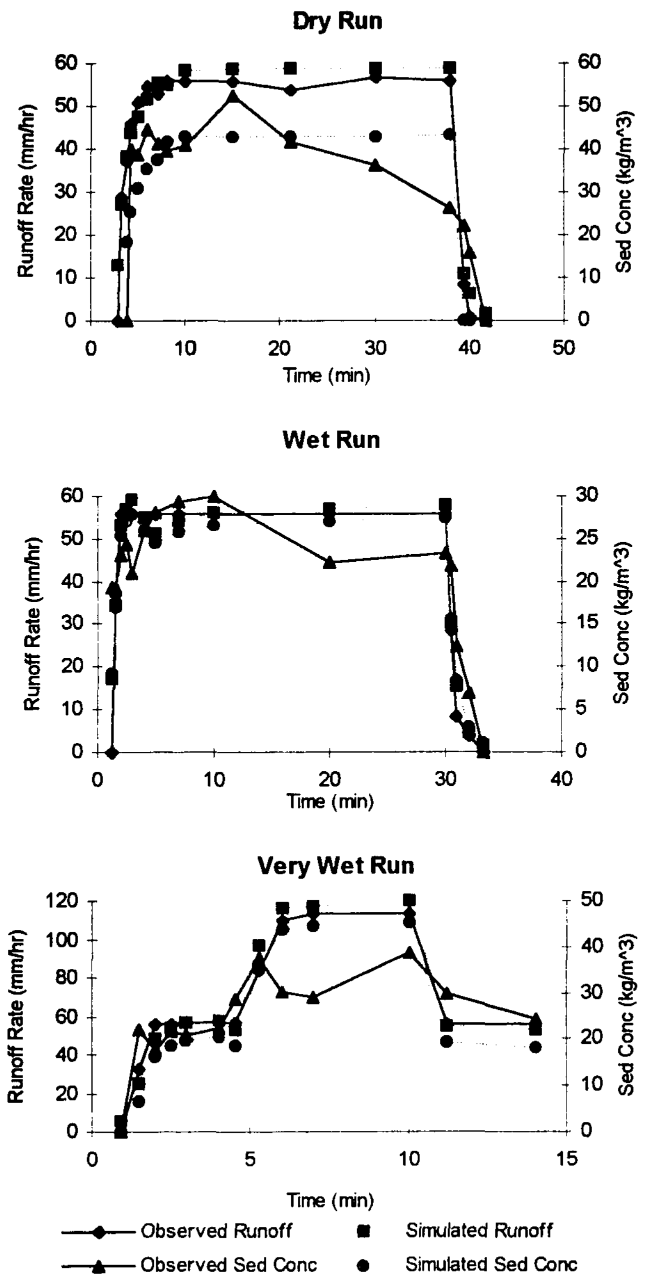


Figure 4.14. Hydrographs and sediment graphs for plot number 31.

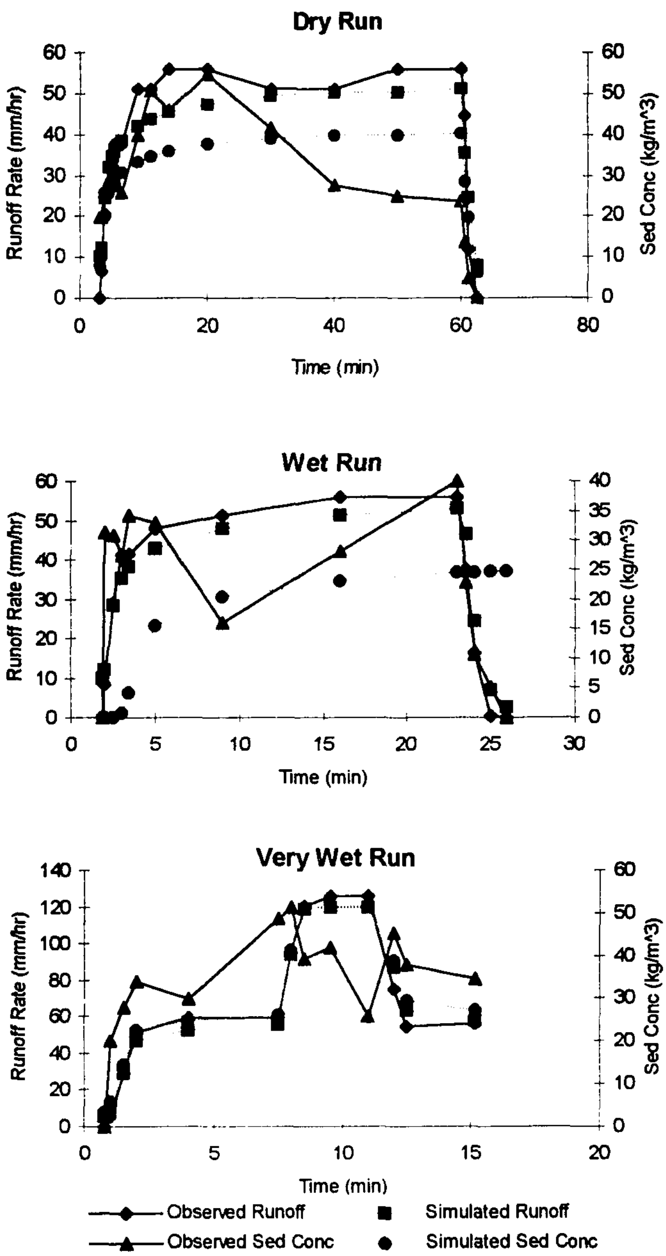


Figure 4.15. Hydrographs and sediment graphs for plot number 34.

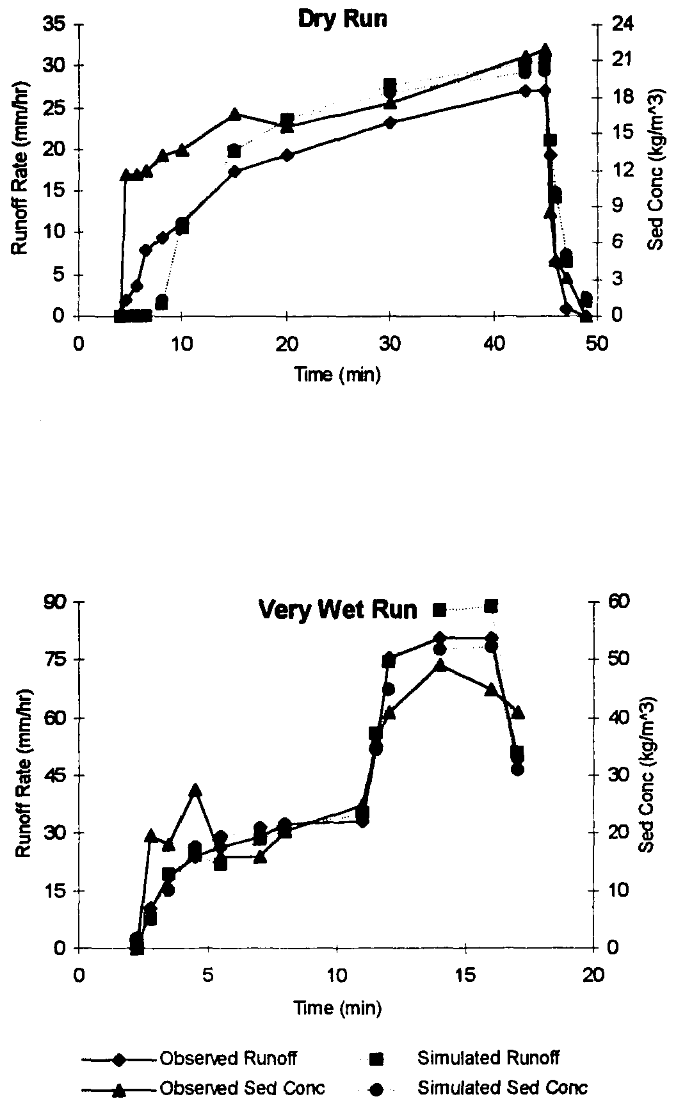


Figure 4.16. Hydrographs and sediment graphs for plot number 56.

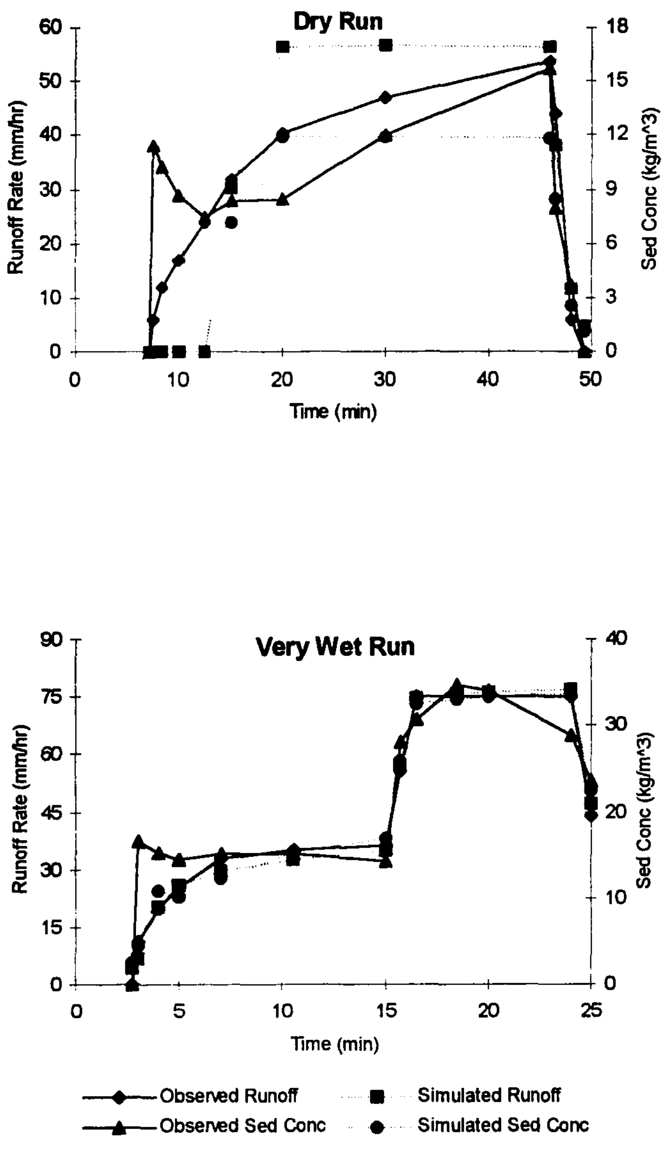


Figure 4.17. Hydrographs and sediment graphs for plot number 59.

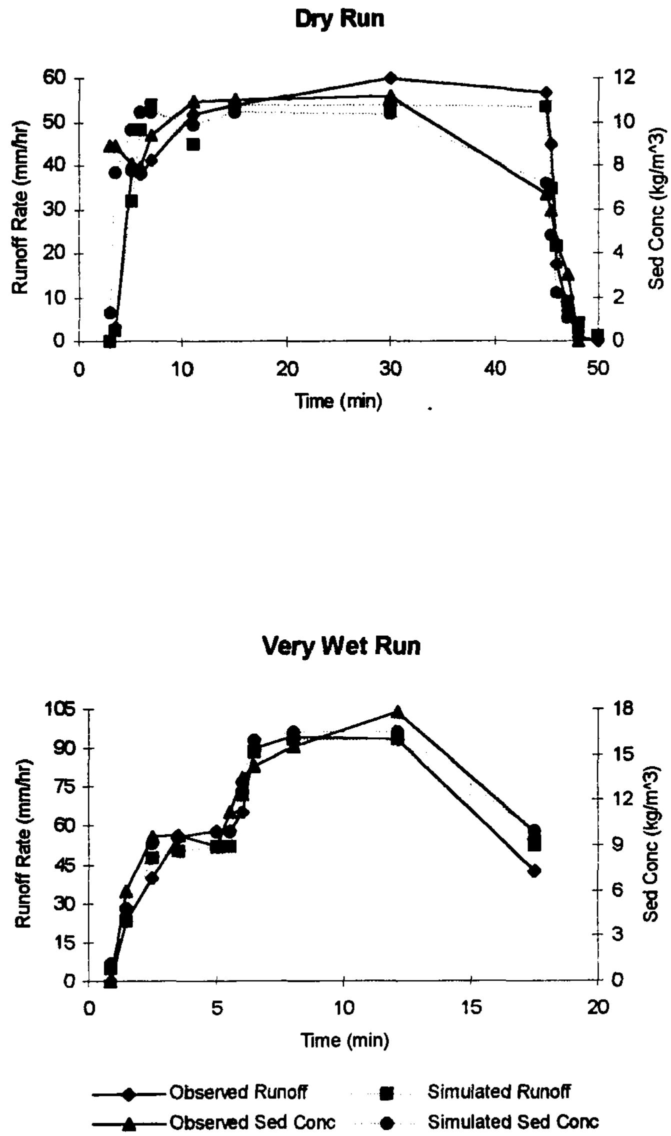


Figure 4.18. Hydrographs and sediment graphs for plot number 63.

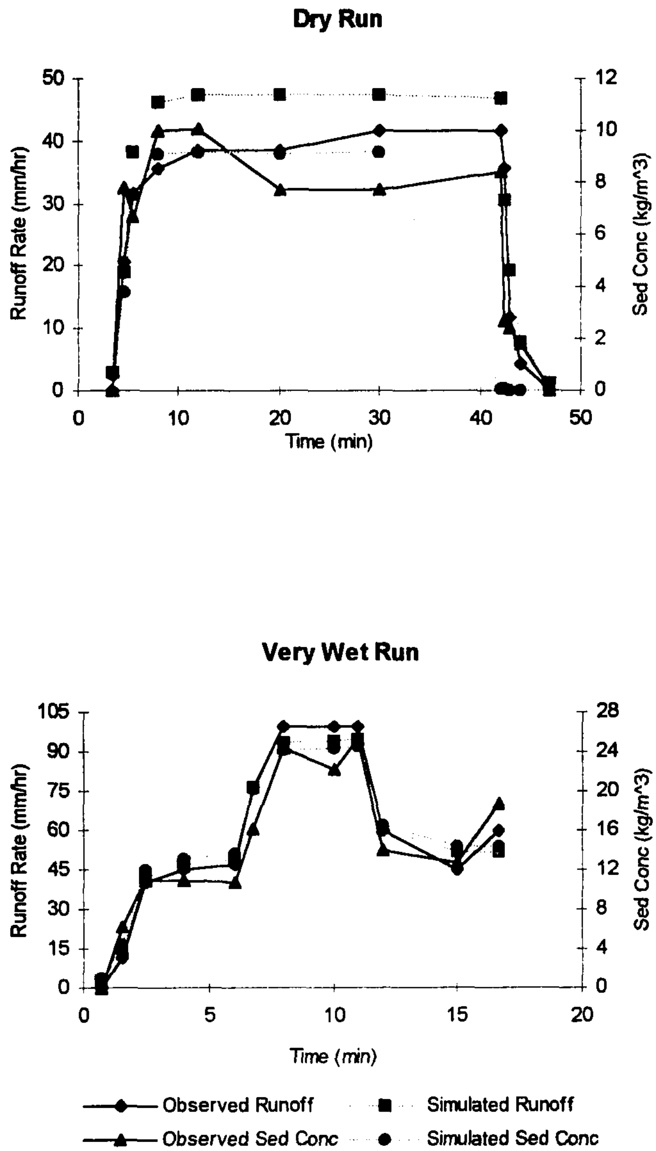


Figure 4.19. Hydrographs and sediment graphs for plot number 66.

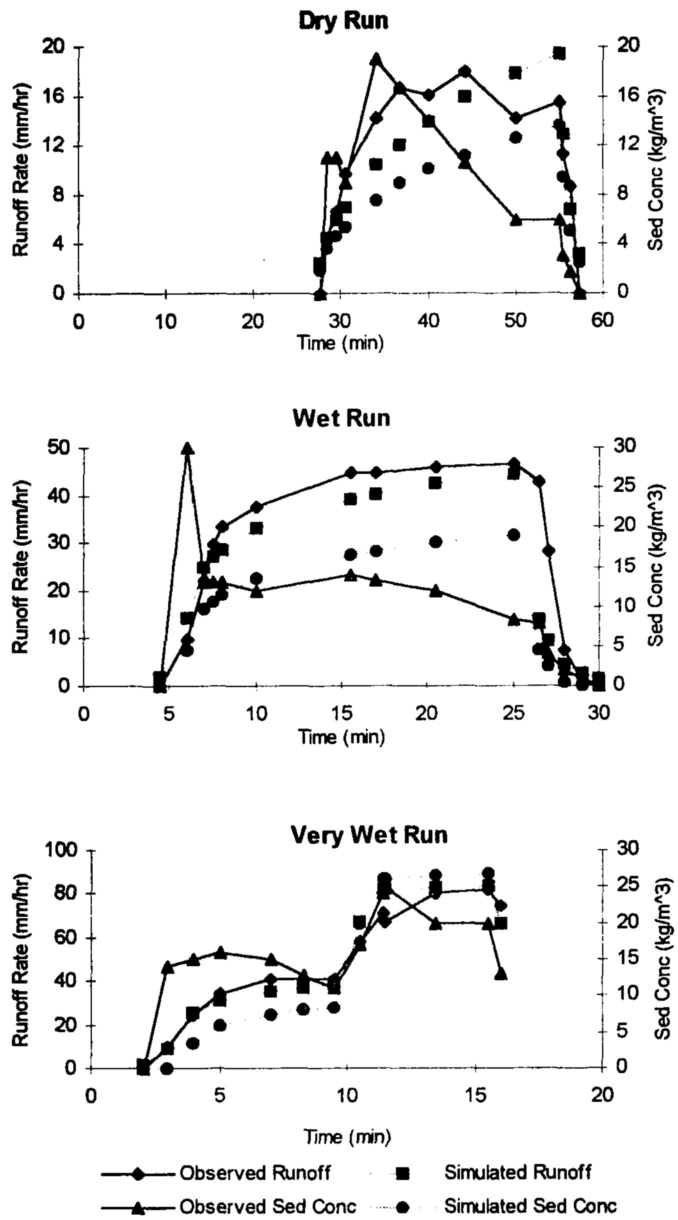


Figure 4.20. Hydrographs and sediment graphs for plot number 102.

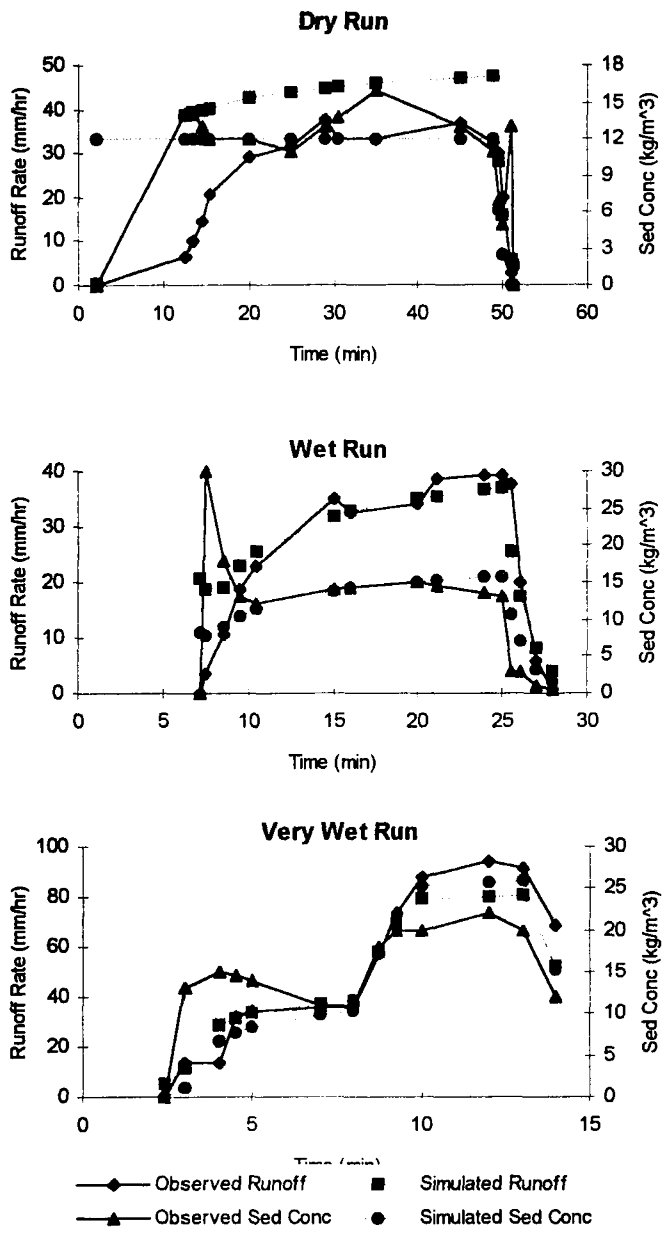


Figure 4.21. Hydrographs and sediment graphs for plot number 105.

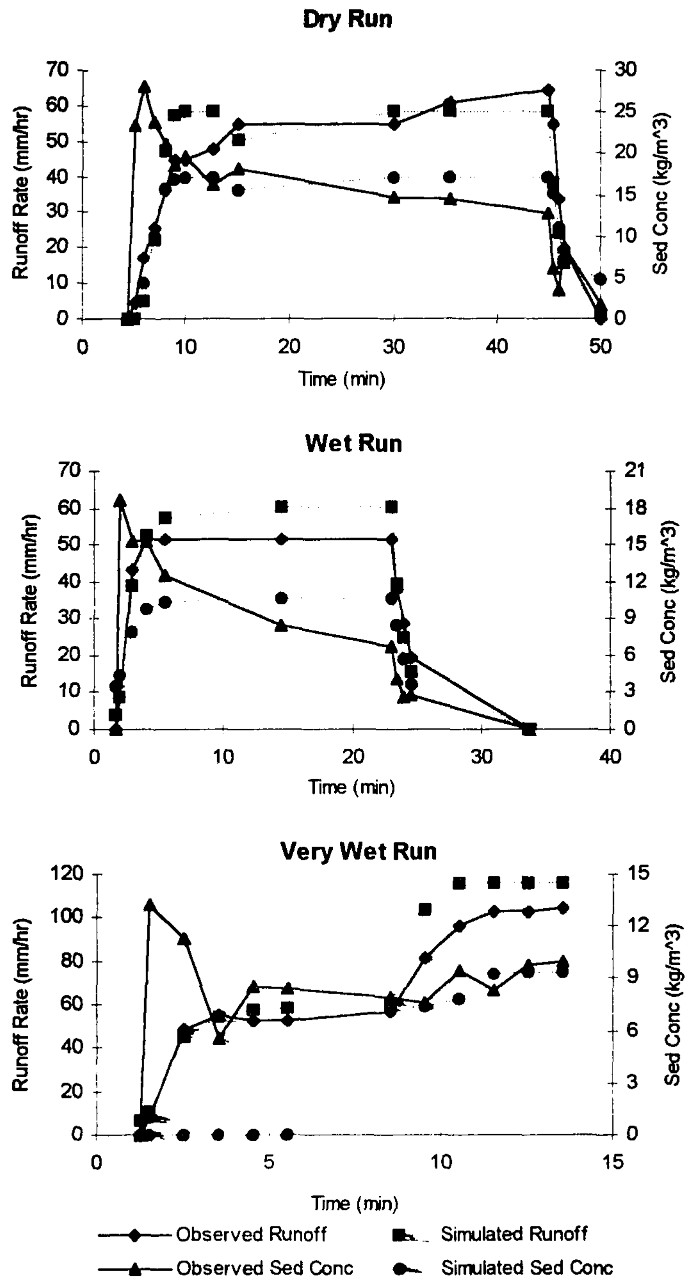


Figure 4.22. Hydrographs and sediment graphs for plot number 120.

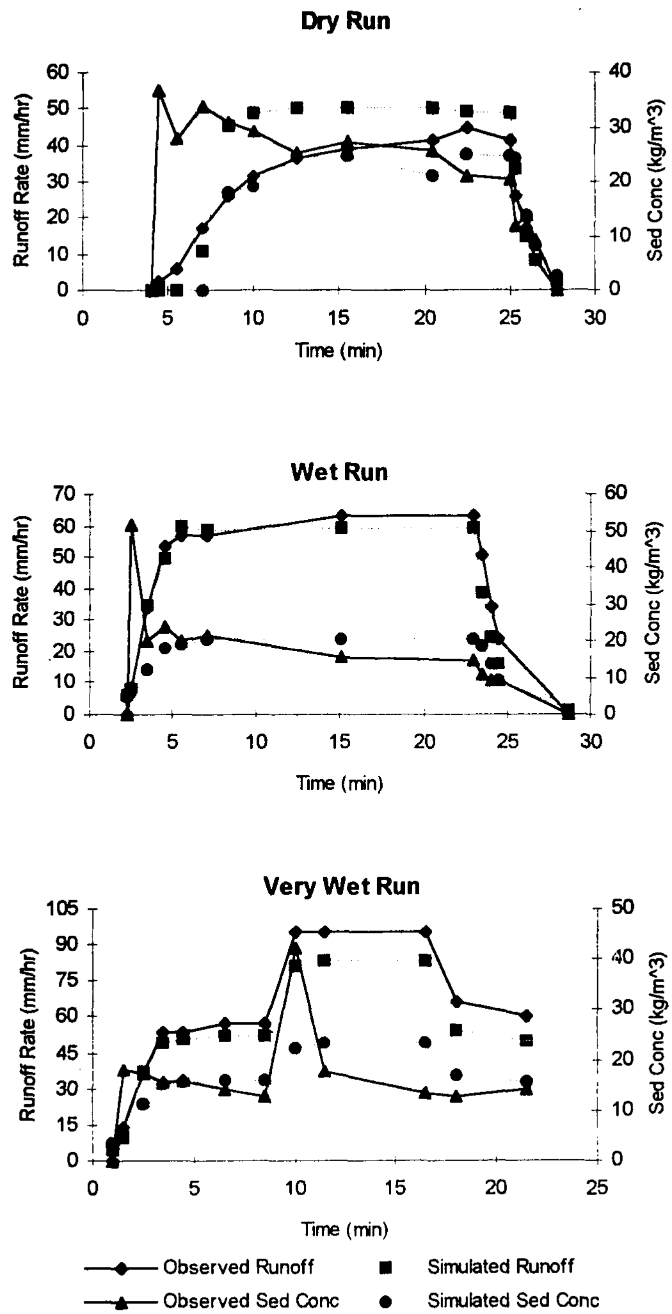


Figure 4.23. Hydrographs and sediment graphs for plot number 121.

occurred in the simulated event, then simulated sediment concentrations would have been too low. This was in fact the case where the simulated sediment concentrations were severely underestimated on the rising limb of nearly all of the sediment graphs and overestimated on the falling limb.

PROCESSES OF DEPOSITION & ENTRAINMENT

To ascertain the effects that different values of the deposition parameter would have on parameter estimates, β was assigned a value of 0.25 and 0.75. Very small changes in the value of the objective function and estimates of τ_c were noted, while the estimates of K_f showed the greatest fluctuation. Since lower values of β reflect turbulent flow conditions, the transport capacity of the flow (K_f) was increased. For higher values of β, estimates of K_f were decreased.

This outcome indicates that the equation describing the downward sediment flux may be inappropriate for the WESP model. However, there may be other confounding factors. For example, all of the successful sediment graphs estimated the critical shear stress parameter at a value close to zero. Such a low value for critical shear stress is not realistic. Sediment particles are entrained by flow whenever the magnitude of instantaneous fluid force acting on the sediment particle exceeds the resistance force for the particle to be moved. A greater force will be needed to initially detach a sediment particle from the soil matrix than one that will be required to re-entrain that same particle once it has been deposited on the soil surface. Presently, WESP cannot account for any processes of re-entrainment, which may explain the very low estimates of the critical shear stress parameter. Moreover, the true effective particle diameter is unknown and small errors in its estimate may adversely effect the parameter estimation procedure.

ACTIVATION OF EROSION BY HYDRAULIC SHEAR

Equation 2 was selected as the best model of the three tested for describing flow-induced erosion. However, the synthetic data used in this analysis were also generated by the same flow-induced erosion model, and may not be appropriate for describing entrainment by hydraulic shear in broad-shallow overland flow areas under natural conditions. All of the equations tested in this analysis incorporated existing transport formulas that were developed based on experimental work in channels. Equation 2, for example, incorporated the bedload formula of Yalin (1963). Although it was assumed that the hydraulics of overland flow were different than those of a channel in this analysis, it may be that different equations and parameters are necessary for describing erosion by hydraulic shear.

It is also not known if entrainment by hydraulic shear actually occurred on the rainfall simulator plots studies. Bare soil conditions do not normally occur in rangeland environment, and had to be artificially created to conduct these plot studies (Simanton et al., 1985). Below ground biomass was left undisturbed, while all of the vegetation was clipped and rocks were removed from the soil surface. Under these circumstances, infiltration was enhanced, thereby reducing runoff and entrainment than what might have normally occurred under natural bare soil conditions. If erosion by hydraulic shear did not occur, then this would have also accounted for very low values in the estimates of τ_c.

Analysis of Watershed Events

To test the effect of scale on the selected flow-induced erosion equation, data were used from a small experimental watershed located in the USDA-ARS Walnut Gulch Experimental Watershed near Tombstone, Arizona. A 2-parameter optimization problem was posed by fixing the value of K_i. Because the WESP model does not currently incorporate any adjustment factors for the erosion parameters when cover is present, the value of K_i was adjusted so that the detachment by raindrop impacted accounted for approximately 80% of the total sediment yield. This value was arbitrarily selected in accordance with erosion studies that have shown that sediment entrainment by raindrop impact predominates in rangeland environments (Nearing et al., 1989).

PARAMETER ESTIMATES

Before optimizing for the erosion parameters, the values of the hydraulic parameters were determined for each event (see Table 4.17). Parameter bounds and starting values for the watershed events are shown in Table 4.18. The agreement between the simulated and the observed watershed responses for both runoff and sediment yield indicate that WESP satisfactorily described the sedimentation processes occurring in

Kendall Watershed (see Table 4.19). Estimates of the critical shear stress parameter confirmed this result in at least 2 of the 3 events studies. Even the highest estimation error (138%) associated with τ_c accurately estimated the sediment yield for that event. Moreover, this estimate was at least on the same order of magnitude as to its true value, a result that was contrary to the successful sediment graphs generated by the rainfall simulator events.

The difficulty of calibration was eased for the watershed events inasmuch as the sediment yield instead of sediment concentration values was used as a basis for comparing simulated to measured data. Typically with the rainfall simulator plots, simulated sediment concentrations were under predicted on the rising limb of the sediment graph, and over predicted on the falling limb due to the problems previously discussed. This imbalance may have been equilibrated by the comparison of a single value in the objective function. However, WESP may be better able to describe the processes of sedimentation when they occur on a larger scale.

Table 4.17. Hydraulic parameters for selected Kendall Watershed events.

Event Date	Re	Manning's n	Ns	Ks	Objective Function	Nash-Sutcliffe Coefficient
13-Sep-75	24.2	4.46700e-02	1.36050e-01	1.06300e-06	194.03	0.90
28-Jul-76	18.6	2.50060e-02	1.05400e-01	1.65350e-06	7.403	0.99
5-Sep-76	16.8	4.63320e-02	5.23160e-03	2.94730e-06	547.88	0.71

Table 4.18. Parameter bounds and starting values for selected Kendall Watershed events.

	τ_c $[M/LT^2]$			K_{f2} $[T^2/L^{0.5}M^{0.5}]$		
Event Date	Lower Bound	Upper Bound	Starting Value	Lower Bound	Upper Bound	**Starting Value**
13-Sep-75	0.0	6.0	1.150	1.00e-13	1.00e-06	**1.00e-08**
28-Jul-76	0.0	6.0	0.100	1.00e-13	1.00e-06	**1.00e-08**
5-Sep-76	0.0	6.0	0.875	1.00e-13	1.00e-06	**1.00e-08**

Table 4.19. Erosion parameter estimates for selected Kendall Watershed events.

Event Date	Fixed Value of K_i	*a* K_f	τ_c	*b* Value of τ_c	% Error of True Value of τ_c	Value of the Objective Function	No. of iterations
13-Sep-75	105000	6.1311e-07	0.03856	0.04241	(9.08041%)	1.3805e-12	108
28-Jul-76		4.5648e-06	0.03099	0.04113	(24.64381%)	2.0354e-16	116
5-Sep-76		2.0037e-07	0.09504	0.03984	(138.55924%)	2.9381e-13	98

[a] True value of K_f is unknown [b] True value of τ_c was determined using Shield's diagram

CONCLUSIONS AND FUTURE RESEARCH

Summary and Conclusions

The primary goal of this study was to determine the adequacy of the optimization procedures in identifying unique, optimal parameter values. In the first phase of this study, synthetic error-free data, as well as data contaminated with correlated and random error, provided the means for determining the effectiveness of the four optimization procedures evaluated. Four different optimization problems were posed so that the behavior the erosion parameters could be fully studied. Using a fully-dynamic process-based approach, three sediment transport equations describing flow-induced erosion were compared.

Based on the synthetic data analysis, the most successful optimization procedure and flow-induced erosion equation were selected for use in the second phase of the study. Ten rainfall simulator events from four different areas in the Western United States were selected for analysis. Three rainfall-runoff events for a small watershed were also examined.

From the evaluation of the synthetic and natural data studies, the following conclusions can be made:

(1) The Simplex algorithm was more successful than the SCE-UA in estimating the parameters. This result was contrary to the theoretical expectation since the SCE-UA algorithm achieved a 100% success rate in finding a lower value of the objective function. Although the outcome may be attributed to the fact

that the hydraulic parameters were fixed even after error was introduced into the analysis or to the use of the finite difference scheme, it was assumed that the behavior of the model was such that the global minimum on the response surface was located in areas that produced more extreme values of the parameters.

(2) The SLS criterion generated the best estimates of the parameter when the error level was low, whereas the HMLE estimator performed better when a higher level of correlated error was present in the data.

(3) Of the three flow-induced erosion equations studied, Equation 1, which was related to the stream power of the flow (Bagnold, 1966), was the only equation that was consistently associated with a high amount of estimation error. This may be due to an inability to predict erosion under fully dynamic conditions.

(4) Equation 2 was determined to be the best model describing flow-induced erosion. Although Equation 3 generated better estimates of the parameters at a lower level of error, the difference in performance between the two equations was small. Moreover, at a higher level of error, the performance of Equation 2 surpassed that of Equation 3.

(5) All four of the estimation procedures demonstrated the same sensitivities to calibration data variability. The parameter for critical shear stress (τ_c) was better estimated for dry runs. K_i, which describes entrainment by raindrop

impact, was better estimated in the wet and very wet runs. The parameter related to the transport capacity of the flow, K_f, was unaffected by calibration data variability.

(6) The selected flow-induced erosion equation did not succeed in reproducing sediment graphs with physically, realistic parameter values for the rainfall simulator plots studied. This outcome may have been the result of an inappropriate equation used to describe deposition, an inactivation of the process of entrainment by hydraulic shear and/or the use of a flow-induced erosion equation that was developed from observations in channels and was not appropriate for describing erosion in broad-shallow overland flow areas.

(7) The agreement between the simulated and the observed hydrographs and sediment yields indicate that the WESP model is able to describe the sedimentation processes occurring in small watersheds. However, because only one value for total sediment yield is used for comparison in the objective function, problems in under and over prediction at different points on the sediment graph are not at issue.

(8) Although the Simplex and HMLE optimization procedure was found to be more sensitive to very wet runs in the 3-parameter problem, it was determined that this sensitivity was more likely the result of a greater degree of parameter activation rather than a sensitivity to a variable rainfall rate.

Recommendations for Future Research

The verification of the processes in an erosion model is a critical step in developing a valid erosion prediction tool. In the WESP model, a detailed evaluation of the process of deposition is needed so that the model can accurately represent the physical system it simulates. In the synthetic data analysis, it became clear that the equation used to describe deposition was problematic, whereas in the natural data analysis, the effects of deposition were more obscured. This uncertainty must be resolved before confidence can be placed in the predictive capabilities of the WESP model.

Research into deriving flow-induced erosion equations is also needed. The equations studied in this analysis were developed from observations in channels and therefore their use outside the domain from which they were developed could lead to erroneous results. If the equation were applied to a channel, the parameter K_f could be related to entrainment by way of shear stress acting at the fluid/soil interface, headcutting and sidewall sloughing. The latter two of these mechanisms are clearly not appropriate for broad-shallow overland flow. A need exists for the development and verification of universal, fundamentally derived equations for relating erosion by hydraulic shear in broad-shallow overland flow areas.

Research into the effects of using a numerical technique to solve the continuity equation for sediment transport is necessary to determine if the noise introduced is negatively impacting parameter identification. The reason for the global minimum to be consistently located in an area that corresponded to poorer estimates of the parameters still remains unresolved. This result may have been related to the use of the implicit, four-point finite difference scheme, or even possibly to errors in the formulation of the basic equations that were discussed above.

To date, no erosion tests have been performed to relate the soil and cover properties to erodibility using statistical regression techniques for the WESP model. This approach can be problematic since the results are questionable for applications outside the range for which they were derived. However, the current methodology requires that a large number of varied data sets be evaluated to decide how the parameters are affected by a wide variety of soil and cover characteristics.

The study presented herein was confined to an analysis of erosion in overland flow areas. A similar investigation into the methods of parameter identification in areas of channel flow is necessary to the development of the WESP model. Results of such a study might indicate where the problems of parameter identification exist in broad-shallow overland flow areas.

APPENDIX A

Tables A1 - A36

Results of Parameter Optimization for Synthetic Data

Table A1. Results of K_i -Kf-τ_c parameter optimization problem with error-free data, Equation 1.

					Parameter Estimates	(% of Error from True Values)						
a	Antecedent	%	Search	Objective	*b*		*c*		*d*		Value of	No.
ρ	Moisture	Slope	Algorithm	Function	Ki		Kf		tauc		Obj. Ftn.	Iterations
0	Dry	10	Simplex	SLS	28.575	(0.26316%)	1.7190E-04	(0.01164%)	.50225	(0.04980%)	5.9059E-08	186
			SCE-UA		28.500	(0.00000%)	1.7194E-04	(0.03491%)	.50232	(0.06375%)	5.8872E-08	1554
			Simplex	HMLE	65.817	(130.93684%)	1.7349E-04	(0.93670%)	.57411	(14.36454%)	3.2616E-09	162
			SCE-UA		28.588	(0.30877%)	1.7192E-04	(0.02327%)	.50235	(0.06972%)	9.3542E-10	1720
		15	Simplex	SLS	28.635	(0.47368%)	1.7186E-04	(0.01164%)	.50202	(0.00398%)	6.7305E-08	165
			SCE-UA		28.618	(0.41404%)	1.7187E-04	(0.00582%)	.50203	(0.00598%)	6.7219E-08	1393
			Simplex	HMLE	36.003	(26.32632%)	1.7195E-04	(0.04073%)	.50968	(1.52988%)	1.5863E-09	128
			SCE-UA		28.637	(0.48070%)	1.7187E-04	(0.00582%)	.50204	(0.00797%)	1.0825E-06	1681
	Wet	10	Simplex	SLS	28.403	(0.34035%)	1.7189E-04	(0.00582%)	.50183	(0.03386%)	2.0331E-08	268
			SCE-UA		28.397	(0.36140%)	1.7189E-04	(0.00582%)	.50184	(0.03187%)	2.6321E-08	1536
			Simplex	HMLE	57.573	(102.01053%)	1.7361E-04	(1.00652%)	.56037	(11.62749%)	6.5169E-09	114
			SCE-UA		28.405	(0.33333%)	1.7191E-04	(0.01745%)	.50194	(0.01195%)	6.8692E-10	1961
		15	Simplex	SLS	69.022	(142.18246%)	1.7559E-04	(2.15848%)	.56785	(13.11753%)	1.7373E-04	150
			SCE-UA		28.538	(0.13333%)	1.7191E-04	(0.01745%)	.50230	(0.05976%)	2.1479E-08	1411
			Simplex	HMLE	74.563	(161.62456%)	1.7240E-04	(0.30254%)	.54353	(8.27291%)	1.1334E-08	231
			SCE-UA		28.502	(0.00702%)	1.7190E-04	(0.01164%)	.50213	(0.02590%)	5.5804E-10	1706
	Very Wet	10	Simplex	SLS	28.517	(0.05965%)	1.7183E-04	(0.02909%)	.50199	(0.00199%)	2.2875E-08	225
			SCE-UA		28.518	(0.06316%)	1.7187E-04	(0.00582%)	.50200	(0.00000%)	2.2925E-08	1303
			Simplex	HMLE	44.378	(55.71228%)	2.5956E-04	(51.01233%)	.80276	(59.91235%)	3.2388E-04	98
			SCE-UA		28.531	(0.10877%)	1.7187E-04	(0.00582%)	.50200	(0.00000%)	7.6016E-10	1354
		15	Simplex	SLS	28.483	(0.05965%)	1.7188E-04	(0.00000%)	.50199	(0.00199%)	2.3046E-08	233
			SCE-UA		28.483	(0.05965%)	1.7188E-04	(0.00000%)	.50200	(0.00000%)	2.3018E-08	1406
			Simplex	HMLE	28.481	(0.06667%)	1.7188E-04	(0.00000%)	.50200	(0.00000%)	7.6715E-09	217
			SCE-UA		28.477	(0.08070%)	1.7188E-04	(0.00000%)	.50200	(0.00000%)	7.9847E-10	1269

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A2. Results of K_i -Kf-τ_c parameter optimization problem with error-free data, Equation 2.

a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Ki	Parameter Estimates	(% of Error from True Values) *c* Kf		*d* tauc		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	28.560	(0.21053%)	3.7366E-03	(0.00268%)	.50204	(0.00797%)	4.7347E-08	273
			SCE-UA		28.536	(0.12632%)	3.7366E-03	(0.00268%)	.50203	(0.00598%)	4.7447E-08	1472
			Simplex	HMLE	14.235	(50.05263%)	3.7565E-03	(0.53526%)	.49892	(0.61355%)	2.3846E-09	172
			SCE-UA		28.563	(0.22105%)	3.7366E-03	(0.00268%)	.50204	(0.00797%)	7.1169E-10	1632
		15	Simplex	SLS	29.055	(1.94737%)	3.7362E-03	(0.00803%)	.50210	(0.01992%)	6.7749E-08	165
			SCE-UA		28.618	(0.41404%)	3.7364E-03	(0.00268%)	.50202	(0.00398%)	6.0946E-08	1515
			Simplex	HMLE	39.562	(38.81404%)	3.7272E-03	(0.24890%)	.50353	(0.30478%)	2.0538E-09	191
			SCE-UA		28.723	(0.78246%)	3.7364E-03	(0.00268%)	.50206	(0.01195%)	9.2029E-10	1694
	Wet	10	Simplex	SLS	28.450	(0.17544%)	3.7359E-03	(0.01606%)	.50189	(0.02191%)	1.5559E-08	370
			SCE-UA		28.536	(0.12632%)	3.7366E-03	(0.00268%)	.50203	(0.00598%)	4.7447E-08	1472
			Simplex	HMLE	61.108	(114.41404%)	3.7015E-03	(0.93671%)	.51029	(1.65139%)	9.6494E-09	244
			SCE-UA		28.406	(0.32982%)	3.7356E-03	(0.02409%)	.50181	(0.03785%)	4.3201E-10	1606
		15	Simplex	SLS	28.541	(0.14386%)	3.7363E-03	(0.00535%)	.50197	(0.00598%)	2.0133E-08	255
			SCE-UA		28.527	(0.09474%)	3.7363E-03	(0.00535%)	.50196	(0.00797%)	2.0130E-08	1652
			Simplex	HMLE	45.423	(59.37895%)	3.7231E-03	(0.35862%)	.50459	(0.51594%)	3.9103E-09	195
			SCE-UA		28.504	(0.01404%)	3.7362E-03	(0.00803%)	.50194	(0.01195%)	4.4843E-10	1734
	Very Wet	10	Simplex	SLS	28.531	(0.10877%)	3.7363E-03	(0.00535%)	.50198	(0.00398%)	1.9403E-08	230
			SCE-UA		28.539	(0.13684%)	3.7362E-03	(0.00803%)	.50198	(0.00398%)	1.9763E-08	1335
			Simplex	HMLE	28.534	(0.11930%)	3.7363E-03	(0.00535%)	.50198	(0.00398%)	6.4762E-10	216
			SCE-UA		28.531	(0.10877%)	3.7363E-03	(0.00535%)	.50199	(0.00199%)	6.4908E-10	1493
		15	Simplex	SLS	28.500	(0.00000%)	3.7365E-03	(0.00000%)	.50199	(0.00199%)	2.8262E-08	188
			SCE-UA		28.497	(0.01053%)	3.7365E-03	(0.00000%)	.50199	(0.00199%)	2.8308E-08	1461
			Simplex	HMLE	28.561	(0.21404%)	3.7362E-03	(0.00803%)	.50196	(0.00797%)	1.3702E-09	154
			SCE-UA		28.503	(0.01053%)	3.7365E-03	(0.00000%)	.50199	(0.00199%)	9.4509E-10	1481

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A3. Results of K_i -Kf-τ_c parameter optimization problem with error-free data, Equation 3.

[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	[b] Ki	Parameter Estimates	[c] Kf	(% of Error from True Values)	[d] tauc		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	35.153	(23.34386%)	3.9630E-05	(0.13859%)	.50393	(0.38446%)	3.3798E-06	137
			SCE-UA		28.558	(0.20351%)	3.9684E-05	(0.00252%)	.50201	(0.00199%)	5.5114E-08	1329
			Simplex	HMLE	74.996	(163.14386%)	4.2010E-05	(5.85864%)	.55255	(10.06972%)	1.4855E-05	168
			SCE-UA		28.564	(0.22456%)	3.9686E-05	(0.00252%)	.50204	(0.00797%)	8.2215E-10	1980
		15	Simplex	SLS	50.489	(77.15439%)	3.9561E-05	(0.31246%)	.50656	(0.90837%)	2.2236E-05	153
			SCE-UA		28.652	(0.53333%)	3.9683E-05	(0.00504%)	.50200	(0.00000%)	6.2682E-08	1549
			Simplex	HMLE	74.970	(163.05263%)	5.5614E-05	(40.13859%)	.77582	(54.54582%)	1.2197E-03	161
			SCE-UA		28.646	(0.51228%)	3.9684E-05	(0.00252%)	.50202	(0.00398%)	9.9707E-10	1775
	Wet	10	Simplex	SLS	74.982	(163.09474%)	4.0136E-05	(1.13645%)	.52847	(5.27291%)	2.3237E-04	261
			SCE-UA		28.469	(0.10877%)	3.9679E-05	(0.01512%)	.50191	(0.01793%)	1.9111E-08	1569
			Simplex	HMLE	36.335	(27.49123%)	3.9598E-05	(0.21923%)	.50402	(0.40239%)	1.9291E-09	346
			SCE-UA		28.418	(0.28772%)	3.9677E-05	(0.02016%)	.50185	(0.02988%)	5.6308E-10	2130
		15	Simplex	SLS	28.492	(0.02807%)	3.9684E-05	(0.00252%)	.50196	(0.00797%)	2.4085E-08	268
			SCE-UA		28.531	(0.10877%)	3.9684E-05	(0.00252%)	.50199	(0.00199%)	2.4316E-08	1415
			Simplex	HMLE	32.149	(12.80351%)	3.9684E-05	(0.00252%)	.50259	(0.11753%)	2.1964E-09	220
			SCE-UA		28.506	(0.02105%)	3.9685E-05	(0.00000%)	.50199	(0.00199%)	6.0122E-10	1907
	Very Wet	10	Simplex	SLS	28.516	(0.05614%)	3.9684E-05	(0.00252%)	.50198	(0.00398%)	2.5454E-08	218
			SCE-UA		28.509	(0.03158%)	3.9684E-05	(0.00252%)	.50198	(0.00398%)	2.6064E-08	1260
			Simplex	HMLE	64.342	(125.76140%)	3.7152E-05	(6.38276%)	.47459	(5.46016%)	4.0288E-05	99
			SCE-UA		28.531	(0.10877%)	3.9682E-05	(0.00756%)	.50197	(0.00598%)	8.6428E-10	1327
		15	Simplex	SLS	28.514	(0.04912%)	3.9685E-05	(0.00000%)	.50201	(0.00199%)	1.6427E-08	208
			SCE-UA		28.504	(0.01404%)	3.9686E-05	(0.00252%)	.50204	(0.00797%)	1.8361E-08	1246
			Simplex	HMLE	11.336	(60.22456%)	3.9469E-05	(0.54429%)	.49057	(2.27689%)	2.6470E-06	255
			SCE-UA		28.512	(0.04211%)	3.9685E-05	(0.00000%)	.50202	(0.00398%)	5.3448E-10	1347

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A4. Results of K_i-K_f-τ_c parameter optimization problem for ρ = 0.25, Equation 1.

[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	Parameter Estimates [b] Ki*		(% of Error from True Values) [c] Kf		[d] tauc		Value of Obj. Fn.	No. Iterations
0.25	Dry	10	Simplex	SLS	60.937	(113.81404%)	1.8566E-04	(8.01722%)	.61311	(22.13347%)	4.7627E-03	91
			SCE-UA		10.002	(64.90526%)	1.7941E-04	(4.38096%)	.50537	(0.67131%)	4.4972E-03	1388
			Simplex	HMLE	58.039	(103.64561%)	1.7899E-04	(4.13661%)	.58397	(16.32869%)	7.1661E-05	108
			SCE-UA		10.004	(64.89825%)	1.7515E-04	(1.90249%)	.48659	(3.06972%)	7.0619E-05	1603
		15	Simplex	SLS	47.796	(67.70526%)	1.7141E-04	(0.27345%)	.53373	(6.32072%)	9.9575E-02	72
			SCE-UA		74.977	(163.07719%)	1.7287E-04	(0.57598%)	.56058	(11.66932%)	9.9374E-02	1408
			Simplex	HMLE	45.179	(58.52281%)	1.7673E-04	(2.82174%)	.56263	(12.07769%)	1.5306E-03	62
			SCE-UA		75.060	(163.36842%)	1.7783E-04	(3.46172%)	.59672	(18.86853%)	1.4992E-03	1458
	Wet	10	Simplex	SLS	50.659	(77.75088%)	2.5003E-04	(45.46777%)	.76312	(52.01594%)	3.8926E-03	59
			SCE-UA		37.793	(32.60702%)	2.3265E-04	(35.35606%)	.70999	(41.43227%)	3.8126E-03	1289
			Simplex	HMLE	51.190	(79.61404%)	2.4887E-04	(44.79288%)	.76182	(51.75697%)	1.1590E-04	59
			SCE-UA		61.271	(114.98596%)	2.4239E-04	(41.02281%)	.76293	(51.97809%)	1.0592E-04	1707
		15	Simplex	SLS	36.781	(29.05614%)	1.8989E-04	(10.47824%)	.62453	(24.40837%)	3.5515E-02	109
			SCE-UA		29.947	(5.07719%)	1.9192E-04	(11.65930%)	.63025	(25.54781%)	3.5482E-02	1220
			Simplex	HMLE	42.200	(48.07018%)	2.0716E-04	(20.52595%)	.72402	(44.22709%)	1.1088E-03	106
			SCE-UA		74.999	(163.15439%)	2.2927E-04	(33.38957%)	.83997	(67.32470%)	1.0505E-03	1491
	Very Wet	10	Simplex	SLS	45.608	(60.02807%)	1.5670E-04	(8.83174%)	.30055	(40.12948%)	4.8371E-01	86
			SCE-UA		74.978	(163.08070%)	1.4814E-04	(13.81196%)	.30002	(40.23506%)	4.8118E-01	1200
			Simplex	HMLE	71.419	(150.59298%)	1.4907E-04	(13.27089%)	.30222	(39.79681%)	1.5834E-02	84
			SCE-UA		74.995	(163.14035%)	1.4759E-04	(14.13195%)	.30001	(40.23705%)	1.5818E-02	1112
		15	Simplex	SLS	10.001	(64.90877%)	1.6375E-04	(4.73004%)	.33326	(33.61355%)	1.6943E+00	219
			SCE-UA		10.003	(64.90175%)	1.6320E-04	(5.05003%)	.31964	(36.32669%)	1.6942E+00	1223
			Simplex	HMLE	10.002	(64.90526%)	1.6264E-04	(5.37584%)	.30002	(40.23506%)	5.5249E-02	213
			SCE-UA		10.003	(64.90175%)	1.6278E-04	(5.29439%)	.30002	(40.23506%)	5.5244E-02	1287

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A5. Results of K_i-K_f-τ_c parameter optimization problem for ρ = 0.25, Equation 2.

a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Ki	Parameter Estimates	(% of Error from True Values) *c* Kf		*d* tauc		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	35.497	(24.55088%)	3.4363E-03	(8.03426%)	.45495	(9.37251%)	1.0394E-01	137
			SCE-UA		74.999	(163.15439%)	3.3964E-03	(9.10210%)	.46583	(7.20518%)	1.0347E-01	1348
			Simplex	HMLE	27.869	(2.21404%)	3.3736E-03	(9.71230%)	.44273	(11.80677%)	1.5771E-03	143
			SCE-UA		74.994	(163.13684%)	3.3006E-03	(11.66600%)	.45167	(10.02590%)	1.5164E-03	1586
		15	Simplex	SLS	72.722	(155.16491%)	3.7037E-03	(0.87783%)	.50037	(0.32470%)	2.0055E-01	101
			SCE-UA		74.988	(163.11579%)	3.6908E-03	(1.22307%)	.49801	(0.79482%)	2.0049E-01	1516
			Simplex	HMLE	62.357	(118.79649%)	3.6907E-03	(1.22575%)	.49338	(1.71713%)	3.2153E-03	104
			SCE-UA		74.988	(163.11579%)	3.6985E-03	(1.01699%)	.49921	(0.55578%)	3.2125E-03	1512
	Wet	10	Simplex	SLS	69.897	(145.25263%)	3.8553E-03	(3.17945%)	.55796	(11.14741%)	2.1080E-02	171
			SCE-UA		10.000	(64.91228%)	3.8081E-03	(1.91623%)	.52588	(4.75697%)	2.0206E-02	1618
			Simplex	HMLE	74.996	(163.14386%)	5.4826E-03	(46.73090%)	.73766	(46.94422%)	1.0374E-03	153
			SCE-UA		46.711	(63.89825%)	4.0727E-03	(8.99773%)	.57978	(15.49402%)	3.3806E-04	2029
		15	Simplex	SLS	74.590	(161.71930%)	4.4796E-03	(19.88760%)	.69323	(38.09363%)	7.6516E-02	104
			SCE-UA		45.125	(58.33333%)	4.4796E-03	(19.88760%)	.66232	(31.93625%)	7.6150E-02	1380
			Simplex	HMLE	10.553	(62.97193%)	5.0611E-03	(35.45029%)	.74669	(48.74303%)	2.6174E-03	125
			SCE-UA		10.485	(63.21053%)	4.1902E-03	(12.14238%)	.60827	(21.16932%)	1.7600E-03	2276
	Very Wet	10	Simplex	SLS	54.938	(92.76491%)	3.6448E-03	(2.45417%)	.49106	(2.17928%)	6.6409E-01	75
			SCE-UA		10.002	(64.90526%)	3.9508E-03	(5.73531%)	.52373	(4.32869%)	6.5411E-01	1268
			Simplex	HMLE	47.453	(66.50175%)	3.7700E-03	(0.89656%)	.51987	(3.55976%)	2.1922E-02	72
			SCE-UA		10.086	(64.61053%)	3.9809E-03	(6.54088%)	.53416	(6.40637%)	2.1644E-02	1258
		15	Simplex	SLS	57.506	(101.77544%)	3.5576E-03	(4.78790%)	.50869	(1.33267%)	1.7104E+00	83
			SCE-UA		10.001	(64.90877%)	3.7312E-03	(0.14184%)	.53455	(6.48406%)	1.6546E+00	1308
			Simplex	HMLE	10.039	(64.77544%)	3.7244E-03	(0.32383%)	.53323	(6.22112%)	5.5101E-02	138
			SCE-UA		10.001	(64.90877%)	3.7290E-03	(0.20072%)	.53590	(6.75299%)	5.5096E-02	1369

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365e-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A6. Results of K_i-K_f-τ_c parameter optimization problem for $\rho = 0.25$, Equation 3.

					Parameter Estimates	(% of Error from True Values)						
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Ki		*c* Kf		*d* tauc		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	31.092	(9.09474%)	4.1063E-05	(3.47234%)	.51556	(2.70120%)	7.9436E-02	81
			SCE-UA		74.998	(163.15088%)	4.0594E-05	(2.29054%)	.52733	(5.04582%)	7.8138E-02	1467
			Simplex	HMLE	23.292	(18.27368%)	4.1287E-05	(4.03679%)	.51558	(2.70518%)	1.2600E-03	94
			SCE-UA		74.999	(163.15439%)	4.0580E-05	(2.25526%)	.52716	(5.01195%)	1.2403E-03	1404
		15	Simplex	SLS	73.601	(158.24912%)	4.0532E-05	(2.13431%)	.53039	(5.65538%)	1.8504E-01	116
			SCE-UA		40.223	(41.13333%)	4.0230E-05	(1.37331%)	.51416	(2.42231%)	1.8481E-01	1355
			Simplex	HMLE	39.608	(38.97544%)	4.0101E-05	(1.04826%)	.51133	(1.85857%)	2.9492E-03	130
			SCE-UA		74.996	(163.14386%)	4.0013E-05	(0.82651%)	.52225	(4.03386%)	2.9351E-03	1336
	Wet	10	Simplex	SLS	24.160	(15.22807%)	4.7698E-05	(20.19151%)	.60646	(20 80876%)	2.9156E-02	149
			SCE-UA		18.774	(34.12632%)	4.7589E-05	(19.91685%)	.60307	(20.13347%)	2.9151E-02	1353
			Simplex	HMLE	14.743	(48.27018%)	4.6577E-05	(17.36676%)	.59533	(18.59163%)	7.8505E-04	136
			SCE-UA		10.009	(64.88070%)	4.8566E-05	(22.37873%)	.59140	(17.80876%)	7.2810E-04	1912
		15	Simplex	SLS	61.138	(114.51930%)	3.8821E-05	(2.17715%)	.50383	(0.36454%)	1.0137E-01	123
			SCE-UA		74.999	(163.15439%)	3.9097E-05	(1.48167%)	.51510	(2.60956%)	1.0098E-01	1432
			Simplex	HMLE	34.524	(21.13684%)	3.9262E-05	(1.06589%)	.50565	(0.72709%)	3.2838E-03	139
			SCE-UA		74.885	(162.75439%)	3.8314E-05	(3.45471%)	.52038	(3.66135%)	3.2105E-03	1677
	Very Wet	10	Simplex	SLS	35.337	(23.98947%)	3.9368E-05	(0.79879%)	.51416	(2.42231%)	5.4046E-01	63
			SCE-UA		74.999	(163.15439%)	3.6758E-05	(7.37558%)	.48835	(2.71912%)	5.3129E-01	1218
			Simplex	HMLE	54.903	(92.64211%)	3.7409E-05	(5.73516%)	.47179	(6.01793%)	1.5363E-02	69
			SCE-UA		66.811	(134.42456%)	3.6758E-05	(7.37558%)	.46069	(8.22908%)	1.5356E-02	1286
		15	Simplex	SLS	39.021	(36.91579%)	4.0147E-05	(1.16417%)	.49691	(1.01394%)	1.5987E+00	68
			SCE-UA		10.012	(64.87018%)	4.1630E-05	(4.90110%)	.52394	(4.37052%)	1.5719E+00	1237
			Simplex	HMLE	12.381	(56.55789%)	4.3333E-05	(9.19239%)	.57851	(15.24104%)	5.1405E-02	116
			SCE-UA		10.005	(64.89474%)	4.2518E-05	(7.13872%)	.55854	(11.26295%)	5.0967E-02	1281

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A7. Results of K_i-K_f-τ_c parameter optimization problem for $\rho = 0.50$, Equation 1.

[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	[b] Ki	Parameter Estimates	(% of Error from True Values) [c] Kf		[d] tauc		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	36.745	(28.92982%)	1.6179E-04	(5.87037%)	.51077	(1.74701%)	6.2797E-03	104
			SCE-UA		63.052	(121.23509%)	1.6685E-04	(2.92646%)	.55765	(11.08566%)	6.2419E-03	1357
			Simplex	HMLE	42.576	(49.38947%)	1.6450E-04	(4.29369%)	.51166	(1.92430%)	9.7054E-05	84
			SCE-UA		35.562	(24.77895%)	1.6385E-04	(4.67186%)	.49498	(1.39841%)	9.6933E-05	1437
		15	Simplex	SLS	41.434	(45.38246%)	1.5342E-04	(10.74005%)	.30160	(39.92032%)	1.9481E-01	86
			SCE-UA		75.000	(163.15789%)	1.5221E-04	(11.44403%)	.33260	(33.74502%)	1.3373E-01	1387
			Simplex	HMLE	74.921	(162.88070%)	1.4967E-04	(12.92181%)	.30503	(39.23705%)	2.1424E-03	94
			SCE-UA		74.997	(163.14737%)	1.5086E-04	(12.22946%)	.31943	(36.36853%)	2.1455E-03	1354
	Wet	10	Simplex	SLS	44.297	(55.42807%)	2.1841E-04	(27.07121%)	.70960	(41.35458%)	2.2242E-03	93
			SCE-UA		40.169	(40.94386%)	2.1106E-04	(22.79497%)	.68467	(36.38845%)	2.2161E-03	1529
			Simplex	HMLE	53.102	(86.32281%)	2.1689E-04	(26.18687%)	.71786	(43.00000%)	7.2536E-03	83
			SCE-UA		17.710	(37.85965%)	1.5625E-04	(9.09355%)	.44403	(11.54781%)	3.3113E-05	1971
		15	Simplex	SLS	46.299	(62.45263%)	2.7685E-04	(61.07168%)	.96980	(93.18725%)	3.0411E-02	52
			SCE-UA		74.990	(163.12281%)	3.0821E-04	(79.31697%)	1.05510	(110.17928%)	3.0821E-04	1519
			Simplex	HMLE	46.282	(62.39298%)	2.7651E-04	(60.87387%)	.96824	(92.87649%)	9.7577E-04	60
			SCE-UA		74.998	(163.15088%)	3.0115E-04	(75.20945%)	1.04020	(107.21116%)	9.2587E-04	1569
	Very Wet	10	Simplex	SLS	16.344	(42.65263%)	1.8867E-04	(9.76844%)	.54230	(8.02789%)	3.2846E-01	63
			SCE-UA		10.003	(64.90175%)	1.9231E-04	(11.88620%)	.55606	(10.76892%)	3.2768E-01	1156
			Simplex	HMLE	35.566	(24.79298%)	1.6765E-04	(2.46102%)	.34081	(32.10956%)	9.3066E-03	74
			SCE-UA		10.005	(64.89474%)	1.7539E-04	(2.04212%)	.34261	(31.75100%)	9.2673E-03	1304
		15	Simplex	SLS	74.939	(162.94386%)	1.5794E-04	(8.11031%)	.30992	(38.26295%)	2.3084E+00	83
			SCE-UA		74.995	(163.14035%)	1.5744E-04	(8.40121%)	.30006	(40.22709%)	2.3072E+00	1192
			Simplex	HMLE	72.959	(155.99649%)	1.5924E-04	(7.35397%)	.33820	(32.62948%)	7.7294E-02	108
			SCE-UA		74.999	(163.15439%)	1.5739E-04	(8.43030%)	.30009	(40.22112%)	7.6895E-02	1183

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10.000

Table A8. Results of K_i-K_r-τ_c parameter optimization problem for $\rho = 0.50$, Equation 2.

[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	Parameter Estimates (% of Error from True Values) [b] Ki		[c] Kf		[d] tauc		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	36.908	(29.50175%)	3.3446E-03	(10.48842%)	.45871	(8.62351%)	6.3853E-02	127
			SCE-UA		10.002	(64.90526%)	3.3502E-03	(10.33855%)	.44389	(11.57570%)	6.3434E-02	1479
			Simplex	HMLE	31.694	(11.20702%)	3.3280E-03	(10.93269%)	.44927	(10.50398%)	1.0105E-03	148
			SCE-UA		10.000	(64.91228%)	3.3494E-03	(10.35996%)	.44378	(11.59761%)	1.0068E-03	1479
		15	Simplex	SLS	45.408	(59.32632%)	3.8384E-03	(2.72715%)	.55811	(11.17729%)	2.5694E-01	117
			SCE-UA		74.994	(163.13684%)	3.8403E-03	(2.77800%)	.56736	(13.01992%)	2.5648E-01	1408
			Simplex	HMLE	10.087	(64.60702%)	4.2688E-03	(14.24595%)	.62982	(25.46215%)	4.2773E-03	121
			SCE-UA		74.998	(163.15088%)	3.8058E-03	(1.85468%)	.56052	(11.65737%)	4.1112E-03	1544
	Wet	10	Simplex	SLS	45.021	(57.96842%)	3.6158E-03	(3.23030%)	.47828	(4.72510%)	4.7657E-02	127
			SCE-UA		10.000	(64.91228%)	3.5362E-03	(5.36063%)	.44970	(10.41833%)	4.7355E-02	1400
			Simplex	HMLE	44.595	(56.47368%)	3.6822E-03	(1.45323%)	.49336	(1.72112%)	1.4739E-03	196
			SCE-UA		11.437	(59.87018%)	3.6173E-03	(3.19015%)	.46928	(6.51793%)	1.4525E-03	1977
		15	Simplex	SLS	72.806	(155.45965%)	3.4363E-03	(8.03426%)	.43091	(14.16135%)	8.0968E-02	130
			SCE-UA		10.046	(64.75088%)	3.3587E-03	(10.11107%)	.38628	(23.05179%)	8.0036E-02	1419
			Simplex	HMLE	52.210	(83.19298%)	3.4258E-03	(8.31527%)	.42601	(15.13745%)	1.6654E-03	165
			SCE-UA		10.004	(64.89825%)	3.4043E-03	(8.89067%)	.40582	(19.15936%)	1.6151E-03	1832
	Very Wet	10	Simplex	SLS	56.776	(99.21404%)	3.3675E-03	(9.87555%)	.41126	(18.07570%)	4.7238E-01	88
			SCE-UA		62.240	(118.38596%)	3.3301E-03	(10.87649%)	.40890	(18.54582%)	4.7215E-01	1309
			Simplex	HMLE	21.058	(26.11228%)	3.5798E-03	(4.19376%)	.43650	(13.04781%)	1.5423E-02	83
			SCE-UA		11.437	(59.87018%)	3.6173E-03	(3.19015%)	.46929	(6.51594%)	1.4525E-03	1377
		15	Simplex	SLS	74.999	(163.15439%)	3.1849E-03	(14.76248%)	.31173	(37.90239%)	1.2809E+00	244
			SCE-UA		74.999	(163.15439%)	3.1845E-03	(14.77318%)	.31147	(37.95418%)	1.2809E+00	1244
			Simplex	HMLE	74.994	(163.13684%)	3.3909E-03	(9.24930%)	.31717	(36.81873%)	4.2692E-02	216
			SCE-UA		74.993	(163.13333%)	3.1903E-03	(14.61796%)	.31503	(37.24502%)	4.2691E-02	1232

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A9. Results of K_i-K_f-τ_c parameter optimization problem for ρ = 0.50, Equation 3.

a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Ki	Parameter Estimates	(% of Error from True Values) *c* Kf		*d* tauc		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	25.534	(10.40702%)	4.5160E-05	(13.79614%)	.56664	(12.87649%)	6.0723E-02	86
			SCE-UA		74.993	(163.13333%)	4.5004E-05	(13.40305%)	.58289	(16.11355%)	5.9338E-02	1394
			Simplex	HMLE	25.534	(10.40702%)	4.5160E-05	(13.79614%)	.56664	(12.87649%)	9.6386E-04	86
			SCE-UA		74.998	(163.15088%)	4.5072E-05	(13.57440%)	.58379	(16.29283%)	9.4023E-04	1564
		15	Simplex	SLS	16.426	(42.36491%)	4.2973E-05	(8.28525%)	.54620	(8.80478%)	1.8502E-01	142
			SCE-UA		10.000	(64.91228%)	4.3126E-05	(8.67078%)	.54622	(8.80876%)	1.8489E-01	1488
			Simplex	HMLE	11.403	(59.98947%)	4.2252E-05	(6.46844%)	.53260	(6.09562%)	2.9236E-03	143
			SCE-UA		74.886	(162.75789%)	4.1781E-05	(5.28159%)	.54249	(8.06574%)	2.9205E-03	1477
	Wet	10	Simplex	SLS	35.053	(22.99298%)	3.0956E-05	(21.99572%)	.33811	(32.64741%)	4.8774E-02	170
			SCE-UA		74.985	(163.10526%)	3.0445E-05	(23.28336%)	.34677	(30.92231%)	4.7281E-02	1491
			Simplex	HMLE	51.563	(80.92281%)	3.0285E-05	(23.68653%)	.33131	(34.00199%)	1.5490E-03	164
			SCE-UA		74.999	(163.15439%)	3.0409E-05	(23.37407%)	.34601	(31.07371%)	1.5252E-03	1976
		15	Simplex	SLS	63.033	(121.16842%)	3.7196E-05	(6.27189%)	.46856	(6.66135%)	6.4836E-02	139
			SCE-UA		74.986	(163.10877%)	3.7256E-05	(6.12070%)	.47486	(5.40637%)	6.4745E-02	1555
			Simplex	HMLE	38.351	(34.56491%)	3.5078E-05	(11.60892%)	.40717	(18.89044%)	1.6669E-03	181
			SCE-UA		34.107	(19.67368%)	3.3341E-05	(15.98589%)	.36372	(27.54582%)	6.5782E-04	1896
	Very Wet	10	Simplex	SLS	36.040	(26.45614%)	4.1786E-05	(5.29419%)	.58684	(16.90040%)	4.8326E-01	67
			SCE-UA		47.750	(67.54386%)	4.1099E-05	(3.56306%)	.58399	(16.33267%)	4.8301E-01	1119
			Simplex	HMLE	69.993	(145.58947%)	3.9500E-05	(0.46617%)	.57358	(14.25896%)	1.5843E-02	71
			SCE-UA		74.999	(163.15439%)	3.9330E-05	(0.89454%)	.57425	(14.39243%)	1.5834E-02	1321
		15	Simplex	SLS	32.355	(13.52632%)	3.5095E-05	(11.56608%)	.30167	(39.90637%)	1.2555E+00	113
			SCE-UA		10.133	(64.44561%)	3.5521E-05	(10.49263%)	.30000	(40.23904%)	1.2452E+00	1119
			Simplex	HMLE	55.641	(95.23158%)	3.4498E-05	(13.07043%)	.30028	(40.18327%)	4.0979E-02	85
			SCE-UA		10.005	(64.89474%)	3.5429E-05	(10.72446%)	.30014	(40.21116%)	4.0209E-02	1215

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

d True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A10. Results of Kf-τ_c parameter optimization problem with error-free data, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* tauc		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	1.7190E-04	(0.01164%)	.50212	(0.02390%)	5.9222E-08	96
			SCE-UA		1.7191E-04	(0.01745%)	.50214	(0.02789%)	5.9184E-08	634
			Simplex	HMLE	1.7191E-04	(0.01745%)	.50213	(0.02590%)	1.4089E-01	79
			SCE-UA		1.7190E-04	(0.01164%)	.50210	(0.01992%)	9.4199E-10	542
		15	Simplex	SLS	1.7187E-04	(0.00582%)	.50190	(0.01992%)	6.8309E-08	86
			SCE-UA		1.7187E-04	(0.00582%)	.50190	(0.01992%)	6.8481E-08	544
			Simplex	HMLE	1.7186E-04	(0.01164%)	.50190	(0.01992%)	1.4354E-01	78
			SCE-UA		1.7186E-04	(0.01164%)	.50185	(0.02988%)	1.1015E-09	601
	Wet	10	Simplex	SLS	1.7192E-04	(0.02327%)	.50218	(0.03586%)	2.7545E-08	114
			SCE-UA		1.7190E-04	(0.01164%)	.50217	(0.03386%)	2.7556E-08	642
			Simplex	HMLE	1.7193E-04	(0.02909%)	.50221	(0.04183%)	1.3935E-01	100
			SCE-UA		1.7192E-04	(0.02327%)	.50219	(0.03785%)	8.8865E-10	585
		15	Simplex	SLS	1.7191E-04	(0.01745%)	.50223	(0.04582%)	2.1481E-08	118
			SCE-UA		1.7190E-04	(0.01164%)	.50212	(0.02390%)	2.7556E-08	642
			Simplex	HMLE	1.7193E-04	(0.02909%)	.50213	(0.02590%)	1.2872E-01	140
			SCE-UA		1.7190E-04	(0.01164%)	.50219	(0.03785%)	6.0297E-10	569
	Very Wet	10	Simplex	SLS	1.7188E-04	(0.00000%)	.50200	(0.00000%)	2.3099E-08	92
			SCE-UA		1.7188E-04	(0.00000%)	.50200	(0.00000%)	2.3326E-08	535
			Simplex	HMLE	1.7188E-04	(0.00000%)	.50198	(0.00398%)	1.3544E-01	85
			SCE-UA		1.7188E-04	(0.00000%)	.50199	(0.00199%)	7.7244E-10	563
		15	Simplex	SLS	1.7188E-04	(0.00000%)	.50199	(0.00199%)	2.3099E-08	92
			SCE-UA		1.7188E-04	(0.00000%)	.50203	(0.00598%)	2.6522E-08	528
			Simplex	HMLE	1.7188E-04	(0.00000%)	.50203	(0.00598%)	1.4021E-01	74
			SCE-UA		1.7188E-04	(0.00000%)	.50199	(0.00199%)	8.1667E-10	618

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A11. Results of Kf-τ_c parameter optimization problem with error-free data, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* tauc		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	3.7367E-03	(0.00535%)	.50202	(0.00398%)	4.7698E-08	86
			SCE-UA		3.7370E-03	(0.01338%)	.50199	(0.00199%)	6.2210E-08	629
			Simplex	HMLE	3.7367E-03	(0.00535%)	.50203	(0.00598%)	1.3419E-01	84
			SCE-UA		3.7369E-03	(0.01071%)	.50206	(0.01195%)	7.6014E-10	504
		15	Simplex	SLS	3.7364E-03	(0.00268%)	.50199	(0.00199%)	6.3105E-08	88
			SCE-UA		3.7364E-03	(0.00268%)	.50199	(0.00199%)	6.2210E-08	629
			Simplex	HMLE	3.7364E-03	(0.00268%)	.50198	(0.00398%)	1.4180E-01	91
			SCE-UA		3.7364E-03	(0.00268%)	.50198	(0.00398%)	1.0104E-09	549
	Wet	10	Simplex	SLS	3.7359E-03	(0.01606%)	.50191	(0.01793%)	1.6010E-08	91
			SCE-UA		3.7362E-03	(0.00803%)	.50195	(0.00996%)	1.6409E-08	514
			Simplex	HMLE	3.7361E-03	(0.01071%)	.50193	(0.01394%)	1.2686E-01	99
			SCE-UA		3.7359E-03	(0.01606%)	.50191	(0.01793%)	5.1506E-10	595
		15	Simplex	SLS	3.7365E-03	(0.00000%)	.50200	(0.00000%)	2.0885E-08	85
			SCE-UA		3.7363E-03	(0.00535%)	.50195	(0.00996%)	2.0157E-08	575
			Simplex	HMLE	3.7362E-03	(0.00803%)	.50193	(0.01394%)	1.2720E-01	92
			SCE-UA		3.7364E-03	(0.00268%)	.50199	(0.00199%)	6.4399E-10	510
	Very Wet	10	Simplex	SLS	3.7365E-03	(0.00000%)	.50200	(0.00000%)	2.0885E-08	85
			SCE-UA		3.7366E-03	(0.00268%)	.50203	(0.00598%)	2.6814E-08	441
			Simplex	HMLE	3.7365E-03	(0.00000%)	.50202	(0.00398%)	1.3327E-01	82
			SCE-UA		3.7365E-03	(0.00000%)	.50201	(0.00199%)	7.3187E-10	498
		15	Simplex	SLS	3.7365E-03	(0.00000%)	.50198	(0.00398%)	2.9058E-08	82
			SCE-UA		3.7363E-03	(0.00535%)	.50187	(0.02590%)	2.1989E-07	385
			Simplex	HMLE	3.7365E-03	(0.00000%)	.50199	(0.00199%)	1.4101E-01	98
			SCE-UA		3.7365E-03	(0.00000%)	.50199	(0.00199%)	1.1814E-09	443

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A12. Results of Kf-τ_c parameter optimization problem with error-free data, Equation 3.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* tauc		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	3.9687E-05	(0.00504%)	.50203	(0.00598%)	5.4527E-08	121
			SCE-UA		3.9685E-05	(0.00000%)	.50200	(0.00000%)	5.5368E-08	579
			Simplex	HMLE	3.9686E-05	(0.00252%)	.50202	(0.00398%)	1.3792E-01	123
			SCE-UA		3.9686E-05	(0.00252%)	.50202	(0.00398%)	8.4665E-10	563
		15	Simplex	SLS	3.9684E-05	(0.00252%)	.50197	(0.00598%)	6.3439E-08	126
			SCE-UA		3.9684E-05	(0.00252%)	.50197	(0.00598%)	6.4531E-08	582
			Simplex	HMLE	3.9683E-05	(0.00504%)	.50196	(0.00797%)	1.4218E-01	148
			SCE-UA		3.9682E-05	(0.00756%)	.50192	(0.01594%)	1.0774E-09	555
	Wet	10	Simplex	SLS	3.9680E-05	(0.01260%)	.50194	(0.01195%)	1.9352E-08	130
			SCE-UA		3.9681E-05	(0.01008%)	.50195	(0.00996%)	1.9477E-08	527
			Simplex	HMLE	3.9681E-05	(0.01008%)	.50195	(0.00996%)	1.3030E-01	143
			SCE-UA		3.9680E-05	(0.01260%)	.50194	(0.01195%)	6.2143E-10	721
		15	Simplex	SLS	3.9684E-05	(0.00252%)	.50198	(0.00398%)	2.4184E-08	133
			SCE-UA		3.9684E-05	(0.00252%)	.50197	(0.00598%)	2.4269E-08	590
			Simplex	HMLE	3.9684E-05	(0.00252%)	.50196	(0.00797%)	1.3046E-01	159
			SCE-UA		3.9684E-05	(0.00252%)	.50197	(0.00598%)	6.6268E-10	686
	Very Wet	10	Simplex	SLS	3.9685E-05	(0.00000%)	.50199	(0.00199%)	2.6225E-08	87
			SCE-UA		3.9684E-05	(0.00252%)	.50198	(0.00398%)	2.9370E-08	448
			Simplex	HMLE	3.9684E-05	(0.00252%)	.50199	(0.00199%)	1.3873E-01	91
			SCE-UA		3.9686E-05	(0.00252%)	.50198	(0.00398%)	5.1408E-09	434
		15	Simplex	SLS	3.9686E-05	(0.00252%)	.50203	(0.00598%)	1.7655E-08	93
			SCE-UA		3.9686E-05	(0.00252%)	.50204	(0.00797%)	1.9244E-08	502
			Simplex	HMLE	3.9686E-05	(0.00252%)	.50203	(0.00598%)	1.2934E-01	86
			SCE-UA		3.9686E-05	(0.00126%)	.50201	(0.00199%)	7.1185E-09	538

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A13. Results of Kf-τ_c parameter optimization problem for $\rho = 0.25$, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	[b] Kf		[c] tauc		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	1.8167E-04	(5.69583%)	.54394	(8.35458%)	4.5690E-03	80
			SCE-UA		1.8101E-04	(5.31185%)	.54314	(8.19522%)	4.5620E-03	578
			Simplex	HMLE	1.7064E-04	(0.72143%)	.54025	(7.61952%)	5.7323E-01	65
			SCE-UA		1.7652E-04	(2.69956%)	.52483	(4.54781%)	7.0922E-05	593
		15	Simplex	SLS	1.7391E-04	(1.18106%)	.52378	(4.33865%)	9.9754E-02	39
			SCE-UA		1.7154E-04	(0.19781%)	.50768	(1.13147%)	9.9709E-02	720
			Simplex	HMLE	1.8613E-04	(8.29067%)	.55826	(11.20717%)	8.8676E-01	34
			SCE-UA		1.7310E-04	(0.70980%)	.52175	(3.93426%)	1.5454E-03	505
	Wet	10	Simplex	SLS	2.2462E-04	(30.68420%)	.67820	(35.09960%)	3.8232E-03	57
			SCE-UA		2.2455E-04	(30.64347%)	.67757	(34.97410%)	3.8224E-03	595
			Simplex	HMLE	2.2950E-04	(33.52339%)	.69084	(37.61753%)	6.2403E-01	50
			SCE-UA		2.2444E-04	(30.57947%)	.67731	(34.92231%)	1.2101E-04	729
		15	Simplex	SLS	1.9250E-04	(11.99849%)	.63201	(25.89841%)	3.5487E-02	57
			SCE-UA		1.9181E-04	(11.59530%)	.62840	(25.17928%)	3.5482E-02	602
			Simplex	HMLE	1.9999E-04	(16.35443%)	.67677	(34.81474%)	8.2172E-01	36
			SCE-UA		2.0170E-04	(17.34931%)	.68499	(36.45219%)	1.1195E-03	562
	Very Wet	10	Simplex	SLS	1.6248E-04	(5.46893%)	.30958	(38.33068%)	4.8662E-01	58
			SCE-UA		1.6163E-04	(5.96346%)	.30000	(40.23904%)	4.8582E-01	417
			Simplex	HMLE	1.6251E-04	(5.45148%)	.33300	(33.66534%)	1.1287E+00	48
			SCE-UA		1.6111E-04	(6.26600%)	.30001	(40.23705%)	1.6012E-02	475
		15	Simplex	SLS	1.6133E-04	(6.13800%)	.31966	(36.32271%)	1.7073E+00	118
			SCE-UA		1.6131E-04	(6.14964%)	.31928	(36.39841%)	1.7073E+00	474
			Simplex	HMLE	1.6095E-04	(6.35909%)	.30001	(40.23705%)	1.3482E+00	112
			SCE-UA		1.6090E-04	(6.38818%)	.30002	(40.23506%)	5.5809E-02	449

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A14. Results of Kf-τ_c parameter optimization problem for ρ = 0.25, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* tauc		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	3.4678E-03	(7.19122%)	.45753	(8.85857%)	1.0406E-01	49
			SCE-UA		3.8383E-03	(2.72447%)	.45290	(9.78088%)	1.0403E-01	550
			Simplex	HMLE	3.3171E-03	(11.22441%)	.43406	(13.53386%)	8.5087E-01	45
			SCE-UA		3.3648E-03	(9.94781%)	.44187	(11.97809%)	1.5748E-03	484
		15	Simplex	SLS	3.7191E-03	(0.46568%)	.48945	(2.50000%)	2.0151E-01	57
			SCE-UA		3.7082E-03	(0.75739%)	.48677	(3.03386%)	2.0150E-01	550
			Simplex	HMLE	3.8113E-03	(2.00187%)	.50891	(1.37649%)	9.1560E-01	48
			SCE-UA		3.7260E-03	(0.28101%)	.49032	(2.32669%)	3.2158E-03	603
	Wet	10	Simplex	SLS	3.8053E-03	(1.84130%)	.53361	(6.29681%)	2.0394E-02	54
			SCE-UA		3.8231E-03	(2.31768%)	.53600	(6.77291%)	2.0387E-02	622
			Simplex	HMLE	3.9652E-03	(6.12070%)	.56325	(12.20120%)	7.1091E-01	81
			SCE-UA		3.9703E-03	(6.25719%)	.56337	(12.22510%)	3.1789E-04	641
		15	Simplex	SLS	4.5319E-03	(21.28730%)	.66655	(32.77888%)	7.6247E-02	43
			SCE-UA		4.4746E-03	(19.75378%)	.65632	(30.74104%)	7.6181E-02	559
			Simplex	HMLE	4.2132E-03	(12.75793%)	.61720	(22.94821%)	8.6366E-01	58
			SCE-UA		4.2039E-03	(12.50903%)	.61646	(22.80080%)	1.7681E-03	686
	Very Wet	10	Simplex	SLS	3.8298E-03	(2.49699%)	.51257	(2.10558%)	6.5759E-01	47
			SCE-UA		3.8305E-03	(2.51572%)	.51216	(2.02390%)	6.5757E-01	527
			Simplex	HMLE	3.8363E-03	(2.67095%)	.51391	(2.37251%)	1.1742E+00	38
			SCE-UA		3.8623E-03	(3.36679%)	.52361	(4.30478%)	2.1755E-02	549
		15	Simplex	SLS	3.6614E-03	(2.00990%)	.52415	(4.41235%)	1.6738E+00	85
			SCE-UA		3.6614E-03	(2.00990%)	.52407	(4.39641%)	1.6738E+00	551
			Simplex	HMLE	3.6565E-03	(2.14104%)	.52542	(4.66534%)	1.3479E+00	38
			SCE-UA		3.6594E-03	(2.06343%)	.52488	(4.55777%)	5.5695E-02	508

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A15. Results of Kf-τ_c parameter optimization problem for $\rho = 0.25$, Equation 3.

					Parameter Estimates	(% of Error from True Values)				
ρ [a]	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	Kf [b]		tauc [c]		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	4.0797E-05	(2.80207%)	.51097	(1.78685%)	7.9542E-02	71
			SCE-UA		4.1024E-05	(3.37407%)	.51448	(2.48606%)	7.9503E-02	616
			Simplex	HMLE	4.1480E-05	(4.52312%)	.51953	(3.49203%)	8.3058E-01	72
			SCE-UA		4.0888E-05	(3.03137%)	.51254	(2.09960%)	1.2574E-03	582
		15	Simplex	SLS	4.0212E-05	(1.32796%)	.51024	(1.64143%)	1.8483E-01	91
			SCE-UA		4.0275E-05	(1.48671%)	.51133	(1.85857%)	1.8482E-01	674
			Simplex	HMLE	4.0095E-05	(1.03314%)	.50819	(1.23307%)	9.0694E-01	90
			SCE-UA		3.6594E-05	(7.78884%)	.52488	(4.55777%)	5.5695E-02	508
	Wet	10	Simplex	SLS	4.7908E-05	(20.72068%)	.61025	(21.56375%)	2.9160E-02	89
			SCE-UA		4.7753E-05	(20.33010%)	.60855	(21.22510%)	2.9162E-02	678
			Simplex	HMLE	5.4167E-05	(36.49238%)	.67701	(34.86255%)	8.1624E-01	57
			SCE-UA		4.7421E-05	(19.49351%)	.60765	(21.04582%)	7.9923E-04	644
		15	Simplex	SLS	3.8936E-05	(1.88736%)	.49480	(1.43426%)	1.0240E-01	95
			SCE-UA		3.9076E-05	(1.53458%)	.49824	(0.74900%)	1.0239E-01	713
			Simplex	HMLE	4.0185E-05	(1.25992%)	.52451	(4.48406%)	9.1820E-01	96
			SCE-UA		3.9173E-05	(1.29016%)	.50067	(0.26494%)	3.2925E-03	735
	Very Wet	10	Simplex	SLS	3.9624E-05	(0.15371%)	.51261	(2.11355%)	5.4274E-01	47
			SCE-UA		3.9983E-05	(0.75091%)	.52099	(3.78287%)	5.4225E-01	445
			Simplex	HMLE	3.8928E-05	(1.90752%)	.48441	(3.50398%)	1.1216E+00	48
			SCE-UA		3.9152E-05	(1.34308%)	.48957	(2.47610%)	1.5401E-02	540
		15	Simplex	SLS	4.0848E-05	(2.93058%)	.51281	(2.15339%)	1.5875E+00	49
			SCE-UA		4.0874E-05	(2.99609%)	.51337	(2.26494%)	1.5875E+00	488
			Simplex	HMLE	4.1358E-05	(4.21570%)	.52989	(5.55578%)	1.5401E-02	540
			SCE-UA		4.1647E-05	(4.94393%)	.54429	(8.42430%)	5.1658E-02	565

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A16. Results of Kf-τ_c parameter optimization problem for $\rho = 0.50$, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* tauc		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	1.6193E-04	(5.78892%)	.47280	(5.81673%)	6.3024E-03	50
			SCE-UA		1.6333E-04	(4.97440%)	.47784	(4.81275%)	6.2963E-04	593
			Simplex	HMLE	1.6313E-04	(5.09076%)	.48045	(4.29283%)	5.9972E-01	41
			SCE-UA		1.6290E-04	(5.22458%)	.47747	(4.88645%)	9.7285E-05	551
		15	Simplex	SLS	1.5631E-04	(9.05865%)	.31814	(36.62550%)	1.3541E-01	61
			SCE-UA		1.5469E-04	(10.00116%)	.30000	(40.23904%)	1.3530E-01	540
			Simplex	HMLE	1.8613E-04	(8.29067%)	.55826	(11.20717%)	9.0675E-01	34
			SCE-UA		1.5461E-04	(10.04771%)	.30003	(40.23307%)	2.1792E-03	627
	Wet	10	Simplex	SLS	2.0599E-04	(19.84524%)	.65375	(30.22908%)	2.2380E-03	54
			SCE-UA		2.0552E-04	(19.57179%)	.65215	(29.91036%)	2.2378E-07	521
			Simplex	HMLE	2.0196E-04	(17.50058%)	.64259	(28.00598%)	5.7251E-01	46
			SCE-UA		1.9049E-04	(10.82732%)	.60297	(20.11355%)	7.0034E-05	548
		15	Simplex	SLS	2.9280E-04	(70.35141%)	.99852	(98.90837%)	3.0528E-02	39
			SCE-UA		2.9419E-04	(71.16011%)	1.00245	(99.69124%)	3.0512E-02	555
			Simplex	HMLE	2.9502E-04	(71.64301%)	1.00640	(100.47809%)	8.1319E-01	32
			SCE-UA		2.9879E-04	(73.83640%)	1.01295	(101.78287%)	9.8180E-04	657
	Very Wet	10	Simplex	SLS	1.8613E-04	(8.29067%)	.55258	(10.07570%)	3.2960E-01	67
			SCE-UA		1.8681E-04	(8.68629%)	.56168	(11.88845%)	3.2950E-01	507
			Simplex	HMLE	1.7115E-04	(0.42471%)	.35622	(29.03984%)	1.0238E+00	45
			SCE-UA		1.6986E-04	(1.17524%)	.34167	(31.93825%)	9.2912E-03	497
		15	Simplex	SLS	1.6214E-04	(5.66674%)	.30000	(40.23904%)	2.4453E+00	99
			SCE-UA		1.6220E-04	(5.63184%)	.30004	(40.23108%)	2.4453E+00	440
			Simplex	HMLE	1.6205E-04	(5.71911%)	.30002	(40.23506%)	1.4130E+00	105
			SCE-UA		1.6216E-04	(5.65511%)	.30000	(40.23904%)	8.1509E-02	431

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A17. Results of Kf-τ_c parameter optimization problem for $\rho = 0.50$, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* tauc		Value of Obj. Fn.	No. Iterations
0.50	Dry	10	Simplex	SLS	4.4276E-03	(18.49592%)	.44637	(11.08167%)	6.3662E-02	49
			SCE-UA		4.4237E-03	(18.39154%)	.44650	(11.05578%)	6.3634E-02	547
			Simplex	HMLE	4.6484E-03	(24.40519%)	.48516	(3.35458%)	8.1897E-01	29
			SCE-UA		4.4768E-03	(19.81266%)	.45492	(9.37849%)	9.7505E-03	587
		15	Simplex	SLS	3.8841E-03	(3.95022%)	.56052	(11.65737%)	2.5719E-01	47
			SCE-UA		3.8684E-03	(3.53004%)	.55807	(11.16932%)	2.5711E-01	585
			Simplex	HMLE	3.7488E-03	(0.32919%)	.53752	(7.07570%)	9.3817E-01	38
			SCE-UA		3.8357E-03	(2.65489%)	.55163	(9.88645%)	3.9360E-03	625
	Wet	10	Simplex	SLS	3.5491E-03	(5.01539%)	.46085	(8.19721%)	4.7485E-02	55
			SCE-UA		3.5478E-03	(5.05018%)	.45985	(8.39641%)	4.7461E-02	561
			Simplex	HMLE	3.6750E-03	(1.64593%)	.48394	(3.59761%)	8.4498E-01	49
			SCE-UA		3.6493E-03	(2.33373%)	.48191	(4.00199%)	1.4593E-03	631
		15	Simplex	SLS	3.3608E-03	(10.05486%)	.39494	(21.32669%)	8.0255E-02	57
			SCE-UA		3.3560E-03	(10.18333%)	.39233	(21.84661%)	8.0170E-02	580
			Simplex	HMLE	3.4114E-03	(8.70066%)	.41439	(17.45219%)	8.5521E-01	88
			SCE-UA		3.4132E-03	(8.65248%)	.41459	(17.41235%)	1.6351E-03	689
	Very Wet	10	Simplex	SLS	3.5722E-03	(4.39716%)	.44111	(12.12948%)	4.7407E-01	50
			SCE-UA		3.5616E-03	(4.68085%)	.43818	(12.71315%)	4.7402E-01	542
			Simplex	HMLE	3.5568E-03	(4.80931%)	.43612	(13.12351%)	1.1216E+00	44
			SCE-UA		3.5290E-03	(5.55466%)	.42810	(14.72112%)	1.5390E-02	546
		15	Simplex	SLS	3.3584E-03	(10.11910%)	.34927	(30.42430%)	1.3112E+00	105
			SCE-UA		3.3584E-03	(10.11910%)	.34924	(30.43028%)	1.3112E+00	547
			Simplex	HMLE	3.3733E-03	(9.72033%)	.35805	(28.67530%)	1.2993E+00	100
			SCE-UA		3.3684E-03	(9.85147%)	.35508	(29.26693%)	4.3577E-02	535

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A18. Results of Kf-τ_c parameter optimization problem for $\rho = 0.50$, Equation 3.

ρ [a]	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	Parameter Estimates (% of Error from True Values) Kf [b]		tauc [c]		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	4.5501E-05	(14.65541%)	.57114	(13.77291%)	6.0609E-02	77
			SCE-UA		4.5350E-05	(14.27491%)	.56939	(13.42430%)	6.0605E-02	519
			Simplex	HMLE	4.5303E-05	(14.15648%)	.56866	(13.27888%)	8.1064E-01	71
			SCE-UA		4.5353E-05	(14.28247%)	.56943	(13.43227%)	9.6199E-04	586
		15	Simplex	SLS	4.3359E-05	(9.25791%)	.55486	(10.52988%)	1.8522E-01	86
			SCE-UA		4.3021E-05	(8.40620%)	.54987	(9.53586%)	1.8495E-01	601
			Simplex	HMLE	4.3427E-05	(9.42926%)	.55684	(10.92430%)	5.0675E-01	74
			SCE-UA		4.2205E-05	(6.35001%)	.53600	(6.77291%)	2.9258E-03	635
	Wet	10	Simplex	SLS	3.0474E-05	(23.21028%)	.32436	(35.38645%)	4.8998E-02	97
			SCE-UA		3.0264E-05	(23.73945%)	.31893	(36.46813%)	4.8985E-02	653
			Simplex	HMLE	3.0979E-05	(21.93776%)	.33485	(33.29681%)	8.5059E-01	98
			SCE-UA		3.0348E-05	(23.52778%)	.32056	(36.14343%)	1.5703E-03	660
		15	Simplex	SLS	3.7238E-05	(6.16606%)	.45643	(9.07769%)	6.5275E-02	76
			SCE-UA		3.7227E-05	(6.19378%)	.45723	(8.91833%)	6.5206E-02	652
			Simplex	HMLE	3.4558E-05	(12.91924%)	.38978	(22.35458%)	8.5943E-01	95
			SCE-UA		3.4951E-05	(11.92894%)	.39948	(20.42231%)	1.7044E-03	650
	Very Wet	10	Simplex	SLS	4.2758E-05	(7.74348%)	.60111	(19.74303%)	4.8377E-01	50
			SCE-UA		4.2452E-05	(6.97241%)	.59451	(18.42829%)	4.8343E-01	542
			Simplex	HMLE	4.2386E-05	(6.80610%)	.60248	(20.01594%)	1.1279E+00	53
			SCE-UA		4.2723E-05	(7.65529%)	.60350	(20.21912%)	1.5910E-02	507
		15	Simplex	SLS	3.5147E-05	(11.43505%)	.30162	(39.91633%)	1.2531E+00	87
			SCE-UA		3.5100E-05	(11.55348%)	.30004	(40.23108%)	1.2518E+00	397
			Simplex	HMLE	3.5446E-05	(10.68162%)	.32022	(36.21116%)	1.2879E+00	52
			SCE-UA		3.5069E-05	(11.63160%)	.30007	(40.22510%)	4.0380E-02	421

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 0.502 and starting value of 1.15

* Values of Ki are multiplied by 10,000

Table A19. Results of K_i-Kf (τ_c = 0.502) parameter optimization problem with error-free data, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Fn.	No. Iterations
0	Dry	10	Simplex	SLS	1.7189E-04	(0.00582%)	28.454	(0.16140%)	5.9781E-08	76
			SCE-UA		1.7189E-04	(0.00582%)	28.471	(0.10175%)	5.9640E-08	523
			Simplex	HMLE	1.7189E-04	(0.00582%)	28.443	(0.20000%)	9.5534E-10	88
			SCE-UA		1.7189E-04	(0.00582%)	28.473	(0.09474%)	9.4637E-10	548
		15	Simplex	SLS	1.7187E-04	(0.00582%)	28.607	(0.37544%)	6.7285E-08	93
			SCE-UA		1.7186E-04	(0.01164%)	28.612	(0.39298%)	6.7266E-08	603
			Simplex	HMLE	1.7186E-04	(0.01164%)	28.620	(0.42105%)	1.0783E-09	87
			SCE-UA		1.7186E-04	(0.01164%)	28.624	(0.43509%)	1.0766E-09	546
	Wet	10	Simplex	SLS	1.7191E-04	(0.01745%)	28.425	(0.26316%)	2.6467E-08	92
			SCE-UA		1.7191E-04	(0.01745%)	28.425	(0.26316%)	2.6482E-08	483
			Simplex	HMLE	1.7192E-04	(0.02327%)	28.406	(0.32982%)	7.2034E-10	92
			SCE-UA		1.7192E-04	(0.02327%)	28.409	(0.31930%)	7.0814E-10	601
		15	Simplex	SLS	1.7189E-04	(0.00582%)	28.420	(0.28070%)	2.3121E-08	122
			SCE-UA		1.7189E-04	(0.00582%)	28.441	(0.20702%)	2.2957E-08	614
			Simplex	HMLE	1.7188E-04	(0.00000%)	28.503	(0.01053%)	6.5906E-10	118
			SCE-UA		1.7188E-04	(0.00000%)	28.499	(0.00351%)	6.6260E-10	602
	Very Wet	10	Simplex	SLS	1.7187E-04	(0.00582%)	28.515	(0.05263%)	2.2908E-08	91
			SCE-UA		1.7187E-04	(0.00582%)	28.515	(0.05263%)	2.2868E-08	822
			Simplex	HMLE	1.7187E-04	(0.00582%)	28.520	(0.07018%)	7.5964E-10	92
			SCE-UA		1.7188E-04	(0.00000%)	28.511	(0.03860%)	7.6111E-10	505
		15	Simplex	SLS	1.7188E-04	(0.00000%)	28.483	(0.05965%)	2.3086E-08	111
			SCE-UA		1.7188E-04	(0.00000%)	28.483	(0.05965%)	2.3396E-08	522
			Simplex	HMLE	1.7188E-04	(0.00000%)	28.482	(0.06316%)	7.6718E-10	110
			SCE-UA		1.7188E-04	(0.00000%)	28.480	(0.07018%)	7.6630E-10	417

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A20. Results of K_i-K_f (τ_c = 0.502) parameter optimization problem with error-free data, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	3.7366E-03	(0.00268%)	28.475	(0.08772%)	4.8187E-08	99
			SCE-UA		3.7365E-03	(0.00000%)	28.491	(0.03158%)	4.7982E-08	838
			Simplex	HMLE	3.7364E-03	(0.00268%)	28.529	(0.10175%)	7.3938E-10	98
			SCE-UA		3.7364E-03	(0.00268%)	28.533	(0.11579%)	7.3957E-10	532
		15	Simplex	SLS	3.7363E-03	(0.00535%)	28.606	(0.37193%)	6.1381E-08	77
			SCE-UA		3.7364E-03	(0.00268%)	28.588	(0.30877%)	6.1282E-08	634
			Simplex	HMLE	3.7363E-03	(0.00535%)	28.639	(0.48772%)	9.5570E-10	131
			SCE-UA		3.7363E-03	(0.00535%)	28.641	(0.49474%)	9.5564E-10	636
	Wet	10	Simplex	SLS	3.7364E-03	(0.00268%)	28.552	(0.18246%)	1.7935E-08	101
			SCE-UA		3.7364E-03	(0.00268%)	28.543	(0.15088%)	1.7906E-08	598
			Simplex	HMLE	3.7362E-03	(0.00803%)	28.607	(0.37544%)	5.4925E-10	118
			SCE-UA		3.7362E-03	(0.00803%)	28.605	(0.36842%)	5.4967E-10	525
		15	Simplex	SLS	3.7364E-03	(0.00268%)	28.571	(0.24912%)	2.0533E-08	97
			SCE-UA		3.7364E-03	(0.00268%)	28.574	(0.25965%)	2.0506E-08	593
			Simplex	HMLE	3.7365E-03	(0.00000%)	28.508	(0.02807%)	6.3015E-10	119
			SCE-UA		3.7365E-03	(0.00000%)	28.508	(0.02807%)	6.2898E-10	653
	Very Wet	10	Simplex	SLS	3.7364E-03	(0.00268%)	28.513	(0.04561%)	2.0042E-08	84
			SCE-UA		3.7364E-03	(0.00268%)	28.521	(0.07368%)	2.0002E-08	550
			Simplex	HMLE	3.7364E-03	(0.00268%)	28.518	(0.06316%)	6.6372E-10	100
			SCE-UA		3.7364E-03	(0.00268%)	28.514	(0.04912%)	6.6189E-10	854
		15	Simplex	SLS	3.7365E-03	(0.00000%)	28.493	(0.02456%)	2.8579E-08	95
			SCE-UA		3.7365E-03	(0.00000%)	28.495	(0.01754%)	2.8531E-08	667
			Simplex	HMLE	3.7365E-03	(0.00000%)	28.493	(0.02456%)	9.4745E-10	85
			SCE-UA		3.7365E-03	(0.00000%)	28.494	(0.02105%)	9.5404E-10	597

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A21. Results of K_i-K_f ($\tau_c = 0.502$) parameter optimization problem with error-free data, Equation 3.

ρ[a]	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	Parameter Estimates Kf[b]	(% of Error from True Values)	Ki*[c]		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	3.9686E-05	(0.00252%)	28.472	(0.09825%)	5.4899E-08	112
			SCE-UA		3.9685E-05	(0.00000%)	28.477	(0.08070%)	5.4823E-08	595
			Simplex	HMLE	3.9684E-05	(0.00252%)	28.538	(0.13333%)	8.5125E-10	89
			SCE-UA		3.9684E-05	(0.00252%)	28.540	(0.14035%)	8.5498E-10	609
		15	Simplex	SLS	3.9683E-05	(0.00504%)	28.638	(0.48421%)	6.2729E-08	125
			SCE-UA		3.9683E-05	(0.00504%)	28.628	(0.44912%)	6.2719E-08	632
			Simplex	HMLE	3.9683E-05	(0.00504%)	28.640	(0.49123%)	9.9533E-10	99
			SCE-UA		3.9683E-05	(0.00504%)	28.629	(0.45263%)	9.9492E-10	592
	Wet	10	Simplex	SLS	3.9683E-05	(0.00504%)	28.532	(0.11228%)	2.0513E-08	111
			SCE-UA		3.9683E-05	(0.00504%)	28.552	(0.18246%)	2.0539E-08	526
			Simplex	HMLE	3.9683E-05	(0.00504%)	28.552	(0.18246%)	6.4503E-10	123
			SCE-UA		3.9682E-05	(0.00756%)	28.573	(0.25614%)	6.4519E-10	566
		15	Simplex	SLS	3.9685E-05	(0.00000%)	28.527	(0.09474%)	2.4453E-08	107
			SCE-UA		3.9685E-05	(0.00000%)	28.539	(0.13684%)	2.4355E-08	593
			Simplex	HMLE	3.9685E-05	(0.00000%)	28.504	(0.01404%)	5.7563E-10	90
			SCE-UA		3.9685E-05	(0.00000%)	28.504	(0.01404%)	5.8939E-10	627
	Very Wet	10	Simplex	SLS	3.9685E-05	(0.00000%)	28.495	(0.01754%)	2.6143E-08	112
			SCE-UA		3.9685E-05	(0.00000%)	28.498	(0.00702%)	2.6071E-08	652
			Simplex	HMLE	3.9685E-05	(0.00000%)	28.500	(0.00000%)	8.4940E-10	111
			SCE-UA		3.9685E-05	(0.00000%)	28.498	(0.00702%)	8.4709E-10	644
		15	Simplex	SLS	3.9684E-05	(0.00252%)	28.519	(0.06667%)	1.7629E-08	115
			SCE-UA		3.9685E-05	(0.00000%)	28.524	(0.08421%)	1.7547E-08	622
			Simplex	HMLE	3.9685E-05	(0.00000%)	28.521	(0.07368%)	5.8003E-10	112
			SCE-UA		3.9685E-05	(0.00000%)	28.523	(0.08070%)	5.8237E-10	612

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A22. Results of K_i-K_f (τ_c = 0.502) parameter optimization problem for ρ = 0.25, Equation 1.

[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	[b] Kf	Parameter Estimates (% of Error from True Values)	[c] Ki*		Value of Obj. Fn.	No. Iterations
0.25	Dry	10	Simplex	SLS	1.7809E-04	(3.61299%)	10.103	(64.55088%)	4.5071E-03	40
			SCE-UA		1.7862E-04	(3.92134%)	10.002	(64.90526%)	4.4975E-03	467
			Simplex	HMLE	1.7781E-04	(3.45008%)	12.244	(57.03860%)	7.0809E-05	40
			SCE-UA		1.7765E-04	(3.35699%)	12.585	(55.84211%)	7.0693E-05	560
		15	Simplex	SLS	1.6590E-04	(3.47917%)	65.442	(129.62105%)	9.9731E-02	38
			SCE-UA		1.6845E-04	(1.99558%)	46.275	(62.36842%)	9.9644E+00	501
			Simplex	HMLE	1.6497E-04	(4.02025%)	67.826	(137.98596%)	1.5270E-03	36
			SCE-UA		1.6400E-04	(4.58401%)	74.977	(163.07719%)	1.5261E-03	566
	Wet	10	Simplex	SLS	1.8149E-04	(5.59111%)	10.823	(62.02456%)	4.1292E-03	58
			SCE-UA		1.8175E-04	(5.74238%)	10.000	(64.91228%)	4.1248E-03	440
			Simplex	HMLE	1.8149E-04	(5.59111%)	10.823	(62.02456%)	1.3287E-04	47
			SCE-UA		1.8181E-04	(5.77729%)	10.003	(64.90175%)	1.3232E-04	472
		15	Simplex	SLS	1.7556E-04	(2.14103%)	11.251	(60.52281%)	3.6136E-02	43
			SCE-UA		1.7571E-04	(2.22830%)	10.002	(64.90526%)	3.6121E-02	533
			Simplex	HMLE	1.7556E-04	(2.14103%)	11.251	(60.52281%)	1.1658E-03	43
			SCE-UA		1.7569E-04	(2.21666%)	10.000	(64.91228%)	1.1653E-03	507
	Very Wet	10	Simplex	SLS	1.6370E-04	(4.75913%)	67.508	(136.87018%)	5.1474E-01	34
			SCE-UA		1.6167E-04	(5.94019%)	74.996	(163.14386%)	5.1357E-01	478
			Simplex	HMLE	1.6213E-04	(5.67256%)	73.278	(157.11579%)	1.6614E-02	43
			SCE-UA		1.6139E-04	(6.10310%)	74.995	(163.14035%)	1.6605E-02	432
		15	Simplex	SLS	1.7187E-04	(0.00582%)	10.000	(64.91228%)	1.7406E+00	134
			SCE-UA		1.7185E-04	(0.01745%)	10.000	(64.91158%)	1.7406E+00	455
			Simplex	HMLE	1.7194E-04	(0.03491%)	10.001	(64.90877%)	5.7334E-02	106
			SCE-UA		1.7194E-04	(0.03491%)	10.001	(64.90877%)	5.7334E-02	499

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A23. Results of K_i-K_f (τ_c = 0.502) parameter optimization problem for ρ = 0.25, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	3.6951E-03	(1.10799%)	49.633	(74.15088%)	1.0528E-01	37
			SCE-UA		3.6210E-03	(3.09113%)	74.993	(163.13333%)	1.0443E-01	462
			Simplex	HMLE	3.6135E-03	(3.29185%)	74.979	(163.08421%)	1.5589E-03	57
			SCE-UA		3.6115E-03	(3.34538%)	74.999	(163.15439%)	1.5587E-03	407
		15	Simplex	SLS	3.7338E-03	(0.07226%)	55.076	(93.24912%)	2.0104E-01	35
			SCE-UA		3.7082E-03	(0.75739%)	74.997	(163.14737%)	2.0051E-01	507
			Simplex	HMLE	3.7440E-03	(0.20072%)	53.181	(86.60000%)	3.2182E-03	33
			SCE-UA		3.7106E-03	(0.69316%)	74.998	(163.15088%)	3.2125E-03	528
	Wet	10	Simplex	SLS	3.6232E-03	(3.03225%)	20.063	(29.60351%)	2.0644E-02	34
			SCE-UA		3.6576E-03	(2.11160%)	10.001	(64.90877%)	2.0393E-02	442
			Simplex	HMLE	3.6527E-03	(2.24274%)	10.614	(62.75789%)	6.5504E-04	50
			SCE-UA		3.6563E-03	(2.14639%)	10.000	(64.91228%)	6.5445E-04	475
		15	Simplex	SLS	3.7580E-03	(0.57540%)	11.434	(59.88070%)	8.8096E-02	62
			SCE-UA		3.7605E-03	(0.64231%)	10.003	(64.90175%)	8.8030E-02	441
			Simplex	HMLE	3.7515E-03	(0.40145%)	22.685	(20.40351%)	2.8562E-03	35
			SCE-UA		3.7633E-03	(0.71725%)	10.003	(64.90175%)	2.8366E-03	519
	Very Wet	10	Simplex	SLS	3.8225E-03	(2.30162%)	23.885	(16.19298%)	6.5806E-01	32
			SCE-UA		3.8623E-03	(3.36679%)	12.204	(57.17895%)	6.5718E-01	543
			Simplex	HMLE	3.8093E-03	(1.94835%)	22.828	(19.90175%)	2.1831E-02	31
			SCE-UA		3.8275E-03	(2.43543%)	18.865	(33.80702%)	2.1825E-02	486
		15	Simplex	SLS	3.6523E-03	(2.25345%)	10.003	(64.90175%)	1.6627E+00	114
			SCE-UA		3.6524E-03	(2.25077%)	10.003	(64.90175%)	1.6627E+00	454
			Simplex	HMLE	3.6470E-03	(2.39529%)	10.001	(64.90877%)	5.5366E-02	109
			SCE-UA		3.6470E-03	(2.39529%)	10.003	(64.90175%)	5.5366E-02	459

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A24. Results of K_i-K_f ($\tau_c = 0.502$) parameter optimization problem for $\rho = 0.25$, Equation 3.

[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	Parameter Estimates (% of Error from True Values) [b] Kf		[c] Ki*		Value of Obj. Fn.	No. Iterations
0.25	Dry	10	Simplex	SLS	3.8954E-05	(1.84201%)	66.690	(134.00000%)	7.8892E-02	42
			SCE-UA		3.8751E-05	(2.35353%)	74.985	(163.10526%)	7.8757E-02	483
			Simplex	HMLE	3.9046E-05	(1.61018%)	67.035	(135.21053%)	1.2500E-03	42
			SCE-UA		3.8763E-05	(2.32330%)	74.998	(163.15088%)	1.2482E-03	498
		15	Simplex	SLS	4.0073E-05	(0.97770%)	14.537	(48.99298%)	1.8493E-01	50
			SCE-UA		4.0109E-05	(1.06841%)	10.410	(63.47368%)	1.8489E-01	504
			Simplex	HMLE	3.9178E-05	(1.27756%)	66.445	(133.14035%)	2.9480E-03	44
			SCE-UA		3.9481E-05	(0.51405%)	68.704	(141.06667%)	2.9481E-03	531
	Wet	10	Simplex	SLS	4.0037E-05	(0.88699%)	10.214	(64.16140%)	3.2584E-02	60
			SCE-UA		4.0048E-05	(0.91470%)	10.004	(64.89825%)	3.2576E-02	468
			Simplex	HMLE	3.9963E-05	(0.70052%)	13.163	(53.81404%)	1.0201E-03	53
			SCE-UA		4.0074E-05	(0.98022%)	10.009	(64.88070%)	1.0472E-03	461
		15	Simplex	SLS	3.8645E-05	(2.62064%)	65.731	(130.63509%)	1.0129E-01	45
			SCE-UA		3.8537E-05	(2.89278%)	74.959	(163.01404%)	1.0105E-01	386
			Simplex	HMLE	3.8645E-05	(2.62064%)	65.731	(130.63509%)	3.2328E-03	45
			SCE-UA		3.8514E-05	(2.95074%)	74.996	(163.14386%)	3.2174E-03	431
	Very Wet	10	Simplex	SLS	3.7892E-05	(4.51808%)	58.718	(106.02807%)	5.3468E-01	43
			SCE-UA		3.7225E-05	(6.19882%)	74.999	(163.15439%)	5.3224E-01	407
			Simplex	HMLE	3.8137E-05	(3.90072%)	59.820	(109.89474%)	1.5547E-02	45
			SCE-UA		3.9637E-05	(0.12095%)	26.834	(5.84561%)	1.5426E-02	507
		15	Simplex	SLS	4.0962E-05	(3.21784%)	14.060	(50.66667%)	1.5784E+00	47
			SCE-UA		4.1035E-05	(3.40179%)	10.001	(64.90877%)	1.5759E+00	498
			Simplex	HMLE	4.0850E-05	(2.93562%)	14.520	(49.05263%)	5.1789E-02	51
			SCE-UA		4.0934E-05	(3.14728%)	10.020	(64.84211%)	5.1709E-02	428

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A25. Results of K_i-K_f (τ_c = 0.502) parameter optimization problem for ρ = 0.50, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	1.5339E-04	(10.75751%)	66.097	(131.91930%)	6.3364E-03	38
			SCE-UA		1.6156E-04	(6.00419%)	45.474	(59.55789%)	6.2615E-03	519
			Simplex	HMLE	1.6518E-04	(3.89807%)	36.467	(27.95439%)	3.6963E-05	41
			SCE-UA		1.6477E-04	(4.13661%)	37.035	(29.94737%)	9.6949E-05	516
		15	Simplex	SLS	1.7161E-04	(0.15709%)	70.512	(147.41053%)	1.3662E-01	38
			SCE-UA		1.7108E-04	(0.46544%)	74.998	(163.15088%)	1.3628E-01	424
			Simplex	HMLE	1.7097E-04	(0.52944%)	74.778	(162.37895%)	2.1938E-03	48
			SCE-UA		1.7106E-04	(0.47708%)	74.998	(163.15088%)	2.1934E-03	489
	Wet	10	Simplex	SLS	1.7332E-04	(0.83779%)	11.125	(60.96491%)	2.4740E-03	44
			SCE-UA		1.7367E-04	(1.04142%)	10.018	(64.84912%)	2.4730E-03	467
			Simplex	HMLE	1.6945E-04	(1.41378%)	19.174	(32.72281%)	6.6505E-05	46
			SCE-UA		1.6933E-04	(1.48359%)	19.446	(31.76842%)	6.6261E-05	669
		15	Simplex	SLS	1.7634E-04	(2.59483%)	11.828	(58.49825%)	5.4202E-02	46
			SCE-UA		1.7663E-04	(2.76356%)	10.001	(64.90877%)	5.4085E-02	462
			Simplex	HMLE	1.7615E-04	(2.48429%)	12.668	(55.55088%)	1.7478E-03	38
			SCE-UA		1.7690E-04	(2.92064%)	16.799	(41.05614%)	1.7411E-03	525
	Very Wet	10	Simplex	SLS	1.8463E-04	(7.41797%)	10.004	(64.89825%)	3.3064E-01	35
			SCE-UA		1.8696E-04	(8.77356%)	17.238	(39.51579%)	2.9910E-01	479
			Simplex	HMLE	1.8551E-04	(7.92995%)	10.007	(64.88772%)	9.5511E-03	40
			SCE-UA		1.8771E-04	(9.20991%)	74.697	(162.09474%)	9.5473E-03	542
		15	Simplex	SLS	1.6626E-04	(3.26972%)	74.999	(163.15439%)	2.3888E+00	61
			SCE-UA		1.6654E-04	(3.10682%)	74.999	(163.15439%)	2.3872E+00	467
			Simplex	HMLE	1.6647E-04	(3.14754%)	74.999	(163.15439%)	7.9543E-02	39
			SCE-UA		1.6650E-04	(3.13009%)	74.999	(163.15439%)	7.9533E-02	452

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A26. Results of K_i-Kf (τ_c = 0.502) parameter optimization problem for ρ = 0.50, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Fn.	No. Iterations
0.50	Dry	10	Simplex	SLS	3.6017E-03	(3.60765%)	49.166	(72.51228%)	6.5904E-02	32
			SCE-UA		3.5633E-03	(4.63535%)	62.892	(120.67368%)	6.5875E-02	466
			Simplex	HMLE	3.6017E-03	(3.60765%)	49.160	(72.49123%)	1.0425E-03	31
			SCE-UA		3.5304E-03	(5.51586%)	74.984	(163.10175%)	1.0415E-03	471
		15	Simplex	SLS	3.6232E-03	(3.03225%)	20.063	(29.60351%)	2.6089E-01	35
			SCE-UA		3.6409E-03	(2.55854%)	10.038	(64.77895%)	2.6076E-01	454
			Simplex	HMLE	3.5803E-03	(4.18038%)	51.375	(80.26316%)	4.1734E-03	32
			SCE-UA		3.5438E-03	(5.15723%)	74.473	(161.30877%)	4.1700E-03	406
	Wet	10	Simplex	SLS	3.7329E-03	(0.09635%)	52.005	(82.47368%)	4.8016E-02	30
			SCE-UA		3.7497E-03	(0.35327%)	49.165	(72.50877%)	4.7985E-02	380
			Simplex	HMLE	3.7115E-03	(0.66908%)	54.000	(89.47368%)	1.4777E-03	37
			SCE-UA		3.7059E-03	(0.81895%)	54.691	(91.89825%)	1.4771E-03	571
		15	Simplex	SLS	3.7354E-03	(0.02944%)	54.248	(90.34386%)	8.4566E-02	37
			SCE-UA		3.7043E-03	(0.86177%)	74.992	(163.12982%)	8.2850E-02	460
			Simplex	HMLE	3.7001E-03	(0.97417%)	74.944	(162.96140%)	2.6136E-03	61
			SCE-UA		3.7023E-03	(0.91530%)	74.983	(163.09825%)	2.6116E-03	444
	Very Wet	10	Simplex	SLS	3.8228E-03	(2.30965%)	20.014	(29.77544%)	4.9532E-01	34
			SCE-UA		3.8514E-03	(3.07507%)	10.004	(64.89825%)	4.9170E-01	468
			Simplex	HMLE	3.8228E-03	(2.30965%)	20.014	(29.77544%)	1.6321E-02	34
			SCE-UA		3.8517E-03	(3.08310%)	10.004	(64.89825%)	1.6225E-02	463
		15	Simplex	SLS	3.7447E-03	(0.21946%)	10.007	(64.88772%)	1.4637E+00	109
			SCE-UA		3.7445E-03	(0.21410%)	10.009	(64.88070%)	1.4637E+00	451
			Simplex	HMLE	3.7494E-03	(0.34524%)	10.002	(64.90526%)	4.7748E-02	103
			SCE-UA		3.7489E-03	(0.33186%)	10.000	(64.91228%)	4.7748E-02	439

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A27. Results of K_i-Kf (τ_c = 0.502) parameter optimization problem for ρ = 0.50, Equation 3.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	4.0399E-05	(1.79917%)	15.293	(46.34035%)	6.5937E-02	46
			SCE-UA		4.0479E-05	(2.00076%)	10.003	(64.90175%)	6.5448E-02	493
			Simplex	HMLE	4.0342E-05	(1.65554%)	14.442	(49.32632%)	1.0347E-03	52
			SCE-UA		4.0504E-05	(2.06375%)	10.002	(64.90526%)	1.0334E-03	510
		15	Simplex	SLS	4.0841E-05	(2.91294%)	14.037	(50.74737%)	1.8767E-01	51
			SCE-UA		4.0883E-05	(3.01877%)	10.006	(64.89123%)	1.8755E-01	483
			Simplex	HMLE	4.0668E-05	(2.47701%)	16.830	(40.94737%)	2.9552E-03	50
			SCE-UA		4.0766E-05	(2.72395%)	10.010	(64.87719%)	2.9536E-03	551
	Wet	10	Simplex	SLS	3.8748E-05	(2.36109%)	66.523	(133.41404%)	5.4626E-02	38
			SCE-UA		3.8648E-05	(2.61308%)	74.996	(163.14386%)	5.3711E-02	517
			Simplex	HMLE	3.8885E-05	(2.01588%)	66.360	(132.84211%)	1.7216E-03	43
			SCE-UA		3.8669E-05	(2.56016%)	74.999	(163.15439%)	1.7065E-03	471
		15	Simplex	SLS	3.8578E-05	(2.78947%)	65.996	(131.56491%)	6.5304E-02	42
			SCE-UA		3.9377E-05	(0.77611%)	74.998	(163.15088%)	6.5034E-02	453
			Simplex	HMLE	3.8927E-05	(1.91004%)	36.620	(28.49123%)	1.9585E-03	66
			SCE-UA		3.8928E-05	(1.90752%)	36.666	(28.65263%)	1.9385E-03	490
	Very Wet	10	Simplex	SLS	3.6902E-05	(7.01273%)	74.337	(160.83158%)	5.0894E-01	66
			SCE-UA		3.6819E-05	(7.22187%)	74.991	(163.12632%)	5.0852E-01	429
			Simplex	HMLE	3.7304E-05	(5.99975%)	64.646	(126.82807%)	1.6856E-02	46
			SCE-UA		3.6824E-05	(7.20927%)	74.998	(163.15088%)	1.6655E-02	452
		15	Simplex	SLS	4.0026E-05	(0.85927%)	17.046	(40.18947%)	1.6888E+00	43
			SCE-UA		4.0322E-05	(1.60514%)	10.002	(64.90526%)	1.6736E+00	396
			Simplex	HMLE	4.1101E-05	(3.56810%)	13.475	(52.71930%)	4.9625E-02	47
			SCE-UA		4.1236E-05	(3.90828%)	10.001	(64.90877%)	4.9437E-01	477

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A28. Results of K_i-Kf ($\tau_c = 0.0$) parameter optimization problem with error-free data, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
[a] ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	[b] Kf		[c] Ki*		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	1.7190E-04	(0.01164%)	28.451	(0.17193%)	4.9920E-08	88
			SCE-UA		1.7189E-04	(0.00756%)	28.457	(0.15088%)	4.9906E-08	755
			Simplex	HMLE	1.7189E-04	(0.00582%)	28.494	(0.02105%)	7.8055E-10	86
			SCE-UA		1.7189E-04	(0.00582%)	28.485	(0.05263%)	7.7614E-10	530
		15	Simplex	SLS	1.7188E-04	(0.00000%)	28.520	(0.07018%)	5.7422E-08	102
			SCE-UA		1.7188E-04	(0.00000%)	28.501	(0.00351%)	5.7284E-08	623
			Simplex	HMLE	1.7188E-04	(0.00000%)	28.503	(0.01053%)	9.1509E-10	115
			SCE-UA		1.7188E-04	(0.00000%)	28.500	(0.00000%)	9.1660E-10	536
	Wet	10	Simplex	SLS	1.7187E-04	(0.00582%)	28.516	(0.05614%)	3.0779E-08	83
			SCE-UA		1.7187E-04	(0.00582%)	28.510	(0.03509%)	3.0769E-08	530
			Simplex	HMLE	1.7189E-04	(0.00582%)	28.462	(0.13333%)	7.5819E-10	101
			SCE-UA		1.7192E-04	(0.02327%)	28.445	(0.19474%)	4.3590E-13	631
		15	Simplex	SLS	1.7189E-04	(0.00582%)	28.444	(0.19649%)	2.6375E-08	93
			SCE-UA		1.7189E-04	(0.00582%)	28.447	(0.18596%)	2.6302E-08	664
			Simplex	HMLE	1.7188E-04	(0.00000%)	28.513	(0.04561%)	8.2139E-10	109
			SCE-UA		1.7188E-04	(0.00000%)	28.449	(0.17895%)	8.2920E-10	579
	Very Wet	10	Simplex	SLS	1.7188E-04	(0.00000%)	28.499	(0.00351%)	2.6539E-08	93
			SCE-UA		1.7188E-04	(0.00000%)	28.502	(0.00702%)	2.6417E-08	23
			Simplex	HMLE	1.7188E-04	(0.00000%)	28.497	(0.01053%)	8.8433E-10	95
			SCE-UA		1.7188E-04	(0.00000%)	28.504	(0.01404%)	8.8102E-10	683
		15	Simplex	SLS	1.7188E-04	(0.00000%)	28.484	(0.05614%)	2.7889E-08	117
			SCE-UA		1.7188E-04	(0.00000%)	28.484	(0.05614%)	2.7925E-08	628
			Simplex	HMLE	1.7188E-04	(0.00000%)	28.489	(0.03860%)	8.6064E-10	113
			SCE-UA		1.7188E-04	(0.00000%)	28.488	(0.04211%)	8.6085E-10	763

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A29. Results of K_i-K_f (τ_c = 0.0) parameter optimization problem with error-free data, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	b Kf		c Ki*		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	3.7366E-03	(0.00268%)	28.445	(0.19298%)	5.0414E-06	108
			SCE-UA		3.7366E-03	(0.00268%)	28.460	(0.14035%)	5.0528E-08	595
			Simplex	HMLE	3.7366E-03	(0.00268%)	28.432	(0.23860%)	7.9930E-10	118
			SCE-UA		3.7367E-03	(0.00535%)	28.395	(0.36842%)	7.9921E-10	550
		15	Simplex	SLS	3.7365E-03	(0.00000%)	28.464	(0.12632%)	6.2739E-08	104
			SCE-UA		3.7365E-03	(0.00000%)	28.531	(0.10877%)	6.2779E-08	730
			Simplex	HMLE	3.7365E-03	(0.00000%)	28.527	(0.09474%)	1.0131E-09	93
			SCE-UA		3.7365E-03	(0.00000%)	28.480	(0.07018%)	1.0127E-09	579
	Wet	10	Simplex	SLS	3.7365E-03	(0.00000%)	28.487	(0.04561%)	1.8605E-08	100
			SCE-UA		3.7365E-03	(0.00000%)	28.486	(0.04912%)	1.8633E-08	708
			Simplex	HMLE	3.7366E-03	(0.00268%)	28.441	(0.20702%)	5.8503E-10	123
			SCE-UA		3.7366E-03	(0.00268%)	28.439	(0.21404%)	5.7750E-10	638
		15	Simplex	SLS	3.7364E-03	(0.00268%)	28.590	(0.31579%)	2.2040E-08	115
			SCE-UA		3.7364E-03	(0.00268%)	28.600	(0.35088%)	2.2033E-08	879
			Simplex	HMLE	3.7364E-03	(0.00268%)	28.630	(0.45614%)	6.5821E-10	94
			SCE-UA		3.7366E-03	(0.00268%)	28.439	(0.21404%)	5.7750E-10	638
	Very Wet	10	Simplex	SLS	3.7365E-03	(0.00000%)	28.502	(0.00702%)	2.5993E-08	103
			SCE-UA		3.7365E-03	(0.00000%)	28.500	(0.00000%)	2.5903E-08	629
			Simplex	HMLE	3.7365E-03	(0.00000%)	28.502	(0.00702%)	8.6620E-10	98
			SCE-UA		3.7365E-03	(0.00000%)	28.501	(0.00351%)	8.6934E-10	563
		15	Simplex	SLS	3.7365E-03	(0.00000%)	28.499	(0.00351%)	1.7698E-08	97
			SCE-UA		3.7365E-03	(0.00000%)	28.531	(0.10877%)	6.2779E-08	730
			Simplex	HMLE	3.7365E-03	(0.00000%)	28.498	(0.00702%)	5.9013E-10	87
			SCE-UA		3.7365E-03	(0.00000%)	28.498	(0.00702%)	5.8427E-10	731

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A30. Results of K_i-K_f ($\tau_c = 0.0$) parameter optimization problem with error-free data, Equation 3.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0	Dry	10	Simplex	SLS	3.9687E-05	(0.00504%)	28.376	(0.43509%)	4.7344E-08	150
			SCE-UA		3.9687E-05	(0.00504%)	28.376	(0.43509%)	4.7416E-08	655
			Simplex	HMLE	3.9687E-05	(0.00504%)	28.342	(0.55439%)	7.4618E-10	161
			SCE-UA		3.9687E-05	(0.00504%)	28.354	(0.51228%)	7.4826E-10	529
		15	Simplex	SLS	3.9681E-05	(0.01008%)	28.929	(1.50526%)	6.8755E-08	109
			SCE-UA		3.9682E-05	(0.00756%)	28.364	(0.47719%)	6.8649E-08	694
			Simplex	HMLE	3.9675E-05	(0.02520%)	29.604	(3.87368%)	9.4408E-08	160
			SCE-UA		3.9687E-05	(0.00504%)	28.354	(0.51228%)	7.4826E-10	529
	Wet	10	Simplex	SLS	3.9686E-05	(0.00252%)	28.435	(0.22807%)	3.1767E-08	127
			SCE-UA		3.9686E-05	(0.00252%)	28.451	(0.17193%)	3.1775E-08	794
			Simplex	HMLE	3.9686E-05	(0.00252%)	28.416	(0.29474%)	7.4219E-10	130
			SCE-UA		3.9686E-05	(0.00252%)	28.415	(0.29825%)	7.6982E-10	644
		15	Simplex	SLS	3.9681E-05	(0.01008%)	28.474	(0.09123%)	2.4021E-08	141
			SCE-UA		3.9681E-05	(0.01008%)	28.519	(0.06667%)	2.3916E-08	649
			Simplex	HMLE	3.9686E-05	(0.00252%)	28.436	(0.22456%)	7.5292E-10	117
			SCE-UA		3.9681E-05	(0.01008%)	28.515	(0.05263%)	7.5117E-10	616
	Very Wet	10	Simplex	SLS	3.9681E-05	(0.01008%)	28.504	(0.01404%)	2.2677E-08	125
			SCE-UA		3.9681E-05	(0.01008%)	28.503	(0.01053%)	2.2710E-08	836
			Simplex	HMLE	3.9681E-05	(0.01008%)	28.505	(0.01754%)	7.5292E-10	144
			SCE-UA		3.9681E-05	(0.01008%)	28.502	(0.00702%)	7.5117E-10	531
		15	Simplex	SLS	3.9681E-05	(0.01008%)	28.489	(0.03860%)	2.4975E-08	127
			SCE-UA		3.9681E-05	(0.01008%)	28.487	(0.04561%)	2.4995E-08	572
			Simplex	HMLE	3.9681E-05	(0.01008%)	28.487	(0.04561%)	8.3130E-10	114
			SCE-UA		3.9681E-05	(0.01008%)	28.490	(0.03509%)	8.3181E-10	626

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A31. Results of K_i-K_f (τ_c = 0.0) parameter optimization problem for ρ = 0.25, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	1.7490E-04	(1.75704%)	10.859	(61.89825%)	6.0561E-03	46
			SCE-UA		1.7503E-04	(1.83267%)	10.003	(64.90175%)	6.0492E-03	442
			Simplex	HMLE	1.7463E-04	(1.59995%)	10.182	(64.27368%)	9.0575E-05	57
			SCE-UA		1.7467E-04	(1.62323%)	10.002	(64.90526%)	9.0664E-05	446
		15	Simplex	SLS	1.6957E-04	(1.34396%)	70.160	(146.17544%)	1.0677E-01	39
			SCE-UA		1.6907E-04	(1.63486%)	74.959	(163.01404%)	1.0673E-01	510
			Simplex	HMLE	1.6972E-04	(1.25669%)	67.650	(137.36842%)	1.6887E-03	35
			SCE-UA		1.6892E-04	(1.72213%)	74.993	(163.13333%)	1.6876E-03	510
	Wet	10	Simplex	SLS	1.7396E-04	(1.21015%)	10.324	(63.77544%)	7.0902E-03	55
			SCE-UA		1.7368E-04	(1.04724%)	10.001	(64.90877%)	7.0679E-03	475
			Simplex	HMLE	1.7374E-04	(1.08215%)	10.446	(63.34737%)	2.1399E-04	54
			SCE-UA		1.7401E-04	(1.23924%)	10.001	(64.90877%)	2.1378E-04	481
		15	Simplex	SLS	1.7028E-04	(0.93088%)	44.803	(57.20351%)	4.5031E-02	30
			SCE-UA		1.7370E-04	(1.05888%)	10.018	(64.84912%)	4.4585E-02	472
			Simplex	HMLE	1.7018E-04	(0.98906%)	47.898	(68.06316%)	1.4369E-03	33
			SCE-UA		1.6755E-04	(2.51920%)	74.607	(161.77895%)	1.4358E-09	544
	Very Wet	10	Simplex	SLS	1.6168E-04	(5.93437%)	65.024	(128.15439%)	4.6901E-01	35
			SCE-UA		1.5935E-04	(7.28997%)	74.993	(163.13333%)	4.6708E-01	432
			Simplex	HMLE	1.6303E-04	(5.14894%)	62.333	(118.71228%)	1.5502E-02	38
			SCE-UA		1.5934E-04	(7.29579%)	74.995	(163.14035%)	1.5398E-02	469
		15	Simplex	SLS	1.7369E-04	(1.05306%)	10.000	(64.91228%)	2.7874E+00	104
			SCE-UA		1.7359E-04	(0.99488%)	10.018	(64.84912%)	2.7873E+00	437
			Simplex	HMLE	1.7371E-04	(1.06470%)	10.001	(64.90877%)	9.2654E-02	100
			SCE-UA		1.7374E-04	(1.08040%)	10.001	(64.90877%)	9.2654E-02	422

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A32. Results of K_i-K_f ($\tau_c = 0.0$) parameter optimization problem for $\rho = 0.25$, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.25	Dry	10	Simplex	SLS	3.7589E-03	(0.59949%)	51.326	(80.09123%)	2.2805E-01	30
			SCE-UA		4.9798E-03	(33.27445%)	74.945	(162.96491%)	2.2773E-01	515
			Simplex	HMLE	3.7589E-03	(0.59949%)	51.326	(80.09123%)	3.6199E-03	31
			SCE-UA		4.9801E-03	(33.28248%)	74.808	(162.48421%)	3.6142E-03	578
		15	Simplex	SLS	3.7039E-03	(0.87247%)	52.403	(83.87018%)	4.7400E-01	33
			SCE-UA		3.6855E-03	(1.36491%)	74.963	(163.02807%)	4.7361E-01	479
			Simplex	HMLE	3.6976E-03	(1.04108%)	56.202	(97.20000%)	7.4675E-03	33
			SCE-UA		3.6833E-03	(1.42379%)	74.777	(162.37544%)	7.4659E-03	502
	Wet	10	Simplex	SLS	3.6539E-03	(2.21062%)	74.794	(162.43509%)	8.1763E-02	59
			SCE-UA		3.6504E-03	(2.30430%)	74.995	(163.14035%)	8.1708E-02	527
			Simplex	HMLE	3.6875E-03	(1.31139%)	50.493	(77.16842%)	2.6591E-03	37
			SCE-UA		3.6507E-03	(2.29734%)	74.930	(162.91228%)	2.6219E-03	440
		15	Simplex	SLS	3.7186E-03	(0.47906%)	72.503	(154.39649%)	3.0739E-01	56
			SCE-UA		3.7150E-03	(0.57540%)	74.995	(163.14035%)	3.0703E-01	470
			Simplex	HMLE	3.7219E-03	(0.39074%)	71.661	(151.44211%)	9.5810E-03	54
			SCE-UA		3.7165E-03	(0.53526%)	75.000	(163.15789%)	9.5714E-03	451
	Very Wet	10	Simplex	SLS	3.7095E-03	(0.72260%)	46.694	(63.83860%)	9.4521E-01	32
			SCE-UA		3.6775E-03	(1.57902%)	56.493	(98.22105%)	9.4404E-01	485
			Simplex	HMLE	3.6739E-03	(1.67536%)	50.995	(78.92982%)	3.1328E-02	31
			SCE-UA		3.6544E-03	(2.19724%)	63.494	(122.78596%)	3.1262E-02	585
		15	Simplex	SLS	3.6292E-03	(2.87167%)	10.000	(64.91228%)	2.1079E+00	121
			SCE-UA		3.6288E-03	(2.88238%)	10.002	(64.90526%)	2.1079E+00	427
			Simplex	HMLE	3.6488E-03	(2.34712%)	10.001	(64.90877%)	6.0593E-02	107
			SCE-UA		3.6418E-03	(2.53446%)	10.006	(64.89123%)	6.0594E-02	397

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A33. Results of K_i-K_f ($\tau_c = 0.0$) parameter optimization problem for $\rho = 0.25$, Equation 3.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Fn.	No. Iterations
0.25	Dry	10	Simplex	SLS	3.9143E-05	(1.36576%)	67.149	(135.61053%)	2.6258E-01	42
			SCE-UA		3.8994E-05	(1.74121%)	74.983	(163.09825%)	2.6244E-01	472
			Simplex	HMLE	3.9069E-05	(1.55222%)	67.759	(137.75088%)	4.1093E-03	44
			SCE-UA		3.8944E-05	(1.86720%)	74.969	(163.04912%)	4.1400E-03	493
		15	Simplex	SLS	4.0553E-05	(2.18722%)	16.388	(42.49825%)	7.1027E-01	48
			SCE-UA		4.0660E-05	(2.45685%)	10.016	(64.85614%)	7.0945E-01	481
			Simplex	HMLE	4.0668E-05	(2.47701%)	16.830	(40.94737%)	1.1229E-02	50
			SCE-UA		4.0718E-05	(2.60300%)	10.090	(64.59649%)	1.1226E-02	507
	Wet	10	Simplex	SLS	3.9970E-05	(0.71816%)	60.888	(113.64211%)	1.5650E-01	37
			SCE-UA		3.9668E-05	(0.04284%)	74.993	(163.13333%)	1.5484E-01	451
			Simplex	HMLE	3.9900E-05	(0.54177%)	59.797	(109.81404%)	4.8211E-03	41
			SCE-UA		3.9709E-05	(0.06048%)	74.976	(163.07368%)	4.8027E-03	529
		15	Simplex	SLS	2.5000E-05	(37.00391%)	14.950	(47.54386%)	1.4230E-01	85
			SCE-UA		2.5001E-05	(37.00139%)	10.028	(64.81404%)	1.3862E-01	391
			Simplex	HMLE	2.5000E-05	(37.00391%)	14.950	(47.54386%)	4.1192E-03	85
			SCE-UA		2.5001E-05	(37.00139%)	10.016	(64.85614%)	3.9974E-03	397
	Very Wet	10	Simplex	SLS	4.0859E-05	(2.95830%)	15.003	(47.35789%)	1.2074E+00	46
			SCE-UA		4.0524E-05	(2.11415%)	30.092	(5.58596%)	1.2047E+00	492
			Simplex	HMLE	4.1708E-05	(5.09739%)	15.384	(46.02105%)	3.9658E-02	55
			SCE-UA		4.1024E-05	(3.37407%)	17.038	(40.21754%)	3.9657E-02	591
		15	Simplex	SLS	3.8554E-05	(2.84994%)	55.969	(96.38246%)	1.8356E+00	112
			SCE-UA		3.8555E-05	(2.84742%)	55.976	(96.40702%)	1.8356E+00	554
			Simplex	HMLE	3.8580E-05	(2.78443%)	55.021	(93.05614%)	6.0839E-02	130
			SCE-UA		3.8688E-05	(2.51228%)	48.339	(69.61053%)	6.0588E-02	572

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A34. Results of K_i-K_f (τ_c = 0.0) parameter optimization problem for ρ = 0.50, Equation 1.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	1.7670E-04	(2.80428%)	10.304	(63.84561%)	7.9130E-03	50
			SCE-UA		1.7649E-04	(2.68210%)	10.003	(64.90175%)	7.9040E-03	486
			Simplex	HMLE	1.7593E-04	(2.35630%)	10.036	(64.78596%)	1.1467E-04	49
			SCE-UA		1.7588E-04	(2.32721%)	10.003	(64.90175%)	1.1466E-04	432
		15	Simplex	SLS	1.6817E-04	(2.15848%)	59.888	(110.13333%)	1.3561E-01	38
			SCE-UA		1.6681E-04	(2.94973%)	74.985	(163.10526%)	1.3531E-01	491
			Simplex	HMLE	1.6842E-04	(2.01303%)	58.556	(105 45965%)	2.1862E-03	99
			SCE-UA		1.6681E-04	(2.94973%)	74.998	(163.15088%)	2 1825E-03	497
	Wet	10	Simplex	SLS	1.7653E-04	(2.70538%)	17.081	(40.06667%)	7.9657E-03	39
			SCE-UA		1.7790E-04	(3.50244%)	12.911	(54.69825%)	7.7596E-03	568
			Simplex	HMLE	1.7653E-04	(2.70538%)	14.223	(50.09474%)	1.8704E-04	48
			SCE-UA		1.8702E-04	(8.80847%)	14.162	(50.30877%)	1.8702E-04	561
		15	Simplex	SLS	1.6813E-04	(2.18175%)	72.494	(154.36491%)	6.9699E-02	39
			SCE-UA		1.6776E-04	(2.39702%)	74.991	(163.12632%)	6.9643E-02	487
			Simplex	HMLE	1.6815E-04	(2.17012%)	65.149	(128.59298%)	2.0395E-03	53
			SCE-UA		1.6810E-04	(2.19921%)	67.166	(135.67018%)	2.0387E-03	527
	Very Wet	10	Simplex	SLS	1.5523E-04	(9.68699%)	66.690	(134.00000%)	3.2048E-01	34
			SCE-UA		1.5957E-04	(7.16197%)	49.592	(74.00702%)	3.2012E-01	469
			Simplex	HMLE	1.5379E-04	(10.52478%)	67.515	(136.89474%)	9.6950E-03	37
			SCE-UA		1.5198E-04	(11.57785%)	74.985	(163.10526%)	9.6756E-03	487
		15	Simplex	SLS	1.7568E-04	(2.21084%)	36.834	(29.24211%)	1.2889E+00	123
			SCE-UA		1.7566E-04	(2.19921%)	37.044	(29.97895%)	1.2889E+00	498
			Simplex	HMLE	1.7568E-04	(2.21084%)	36.834	(29.24211%)	4.2962E-02	123
			SCE-UA		1.7583E-04	(2.29811%)	35.497	(24.55088%)	4.2958E-02	525

a Correlation coefficient of sediment concentration; for ρ = 0, no random error

b True value of 1.7188E-04 and starting value of 2.25E-04

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A35. Results of K_i-Kf ($\tau_c = 0.0$) parameter optimization problem for $\rho = 0.50$, Equation 2.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	3.7300E-03	(0.17396%)	49.968	(75.32632%)	2.1134E-01	32
			SCE-UA		3.6936E-03	(1.14813%)	74.986	(163.10877%)	2.1117E-01	457
			Simplex	HMLE	3.7300E-03	(0.17396%)	49.968	(75.32632%)	3.2693E-03	32
			SCE-UA		3.7030E-03	(0.89656%)	70.375	(146.92982%)	3.2691E-03	361
		15	Simplex	SLS	3.6745E-03	(1.65931%)	23.108	(18.91930%)	5.4142E-01	38
			SCE-UA		3.6880E-03	(1.29801%)	10.005	(64.89474%)	5.4098E-01	434
			Simplex	HMLE	3.6753E-03	(1.63790%)	22.838	(19.86667%)	8.1919E-03	39
			SCE-UA		3.6851E-03	(1.37562%)	10.063	(64.69123%)	8.1659E-03	555
	Wet	10	Simplex	SLS	3.7929E-03	(1.50943%)	27.955	(1.91228%)	1.0876E-01	33
			SCE-UA		3.8099E-03	(1.96441%)	10.013	(64.86667%)	1.0804E-01	518
			Simplex	HMLE	3.7854E-03	(1.30871%)	25.333	(11.11228%)	3.4619E-03	38
			SCE-UA		3.8069E-03	(1.88412%)	10.000	(64.91228%)	3.4311E-03	504
		15	Simplex	SLS	3.6738E-03	(1.67804%)	23.378	(17.97193%)	1.5185E-01	40
			SCE-UA		3.6849E-03	(1.38097%)	10.023	(64.83158%)	1.5151E-01	511
			Simplex	HMLE	3.6731E-03	(1.69678%)	23.647	(17.02807%)	4.8853E-03	35
			SCE-UA		3.6843E-03	(1.39703%)	10.015	(64.85965%)	4.8650E-03	465
	Very Wet	10	Simplex	SLS	3.9669E-03	(6.16620%)	10.121	(64.48772%)	1.0311E+00	67
			SCE-UA		3.9574E-03	(5.91195%)	10.003	(64.90175%)	1.0298E+00	441
			Simplex	HMLE	3.9484E-03	(5.67108%)	10.459	(63.30175%)	3.4258E-02	55
			SCE-UA		3.9548E-03	(5.84237%)	10.004	(64.89825%)	3.4128E-02	463
		15	Simplex	SLS	3.7501E-03	(0.36398%)	10.000	(64.91228%)	9.3284E-01	114
			SCE-UA		3.7500E-03	(0.36130%)	10.005	(64.89474%)	9.3285E-01	397
			Simplex	HMLE	3.7488E-03	(0.32919%)	10.000	(64.91228%)	3.0920E-02	95
			SCE-UA		3.7491E-03	(0.33721%)	10.003	(64.90175%)	3.0940E-02	443

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.7365E-03 and starting value of 4.25E-03

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

Table A36. Results of K_i-Kf ($\tau_c = 0.0$) parameter optimization problem for $\rho = 0.50$, Equation 3.

					Parameter Estimates	(% of Error from True Values)				
a ρ	Antecedent Moisture	% Slope	Search Algorithm	Objective Function	*b* Kf		*c* Ki*		Value of Obj. Ftn.	No. Iterations
0.50	Dry	10	Simplex	SLS	3.8820E-05	(2.17966%)	65.802	(130.88421%)	2.5991E-01	44
			SCE-UA		3.8702E-05	(2.47701%)	74.931	(162.91579%)	2.5988E-01	486
			Simplex	HMLE	3.8776E-05	(2.29054%)	65.430	(129.57895%)	4.0110E-03	42
			SCE-UA		3.8650E-05	(2.60804%)	74.984	(163.10175%)	4.0096E-03	472
		15	Simplex	SLS	3.9513E-05	(0.43341%)	64.561	(126.52982%)	6.7175E-01	43
			SCE-UA		3.9431E-05	(0.64004%)	74.989	(163.11930%)	6.7143E-01	489
			Simplex	HMLE	3.9513E-05	(0.43341%)	64.561	(126.52982%)	1.0148E-02	43
			SCE-UA		3.9403E-05	(0.71060%)	74.983	(163.09825%)	1.0132E-02	419
	Wet	10	Simplex	SLS	3.9192E-05	(1.24228%)	74.750	(162.28070%)	7.0308E-02	65
			SCE-UA		3.9257E-05	(1.07849%)	74.996	(163.14386%)	7.0157E-02	424
			Simplex	HMLE	3.9488E-05	(0.49641%)	62.083	(117.83509%)	2.0821E-03	43
			SCE-UA		3.9281E-05	(1.01802%)	74.994	(163.13684%)	2.0739E-03	490
		15	Simplex	SLS	2.5000E-05	(37.00391%)	14.950	(47.54386%)	2.4882E-01	85
			SCE-UA		2.5000E-05	(37.00391%)	10.002	(64.90526%)	2.4377E-01	392
			Simplex	HMLE	2.5000E-05	(37.00391%)	14.950	(47.54386%)	7.2479E-03	80
			SCE-UA		2.5000E-05	(37.00391%)	10.011	(64.87368%)	7.1411E-03	420
	Very Wet	10	Simplex	SLS	3.7892E-05	(4.51808%)	59.086	(107.31930%)	4.2353E-01	46
			SCE-UA		3.7769E-05	(4.82802%)	63.494	(122.78596%)	4.2338E-01	512
			Simplex	HMLE	3.7934E-05	(4.41225%)	61.318	(115.15088%)	1.3682E-02	45
			SCE-UA		3.8243E-05	(3.63361%)	51.443	(80.50175%)	1.3642E-02	617
		15	Simplex	SLS	3.9018E-05	(1.68074%)	75.000	(163.15789%)	1.2892E+00	111
			SCE-UA		3.9013E-05	(1.69334%)	74.993	(163.13333%)	1.2893E+00	468
			Simplex	HMLE	3.8579E-05	(2.78695%)	75.000	(163.15789%)	4.2346E-02	125
			SCE-UA		3.8699E-05	(2.48457%)	74.999	(163.15439%)	4.2221E-02	484

a Correlation coefficient of sediment concentration; for $\rho = 0$, no random error

b True value of 3.9685E-05 and starting value of 9.00E-05

c True value of 28.5 and starting value of 42.5

* Values of Ki are multiplied by 10,000

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