

IMPACT OF PARAMETER PROBABILITY DISTRIBUTION ON
MODEL OUTPUT UNCERTAINTY USING THE AGNPS MODEL

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Chapter	Page
REFERENCES	59
APPENDIXES	64
APPENDIX A-- COMP. TABLE OF CONTENTS UPDATES AGNPS INPUT DATA	65

Chapter	page
I. INTRODUCTION 1
Statement of the problem 2
II. REVIEW OF LITERATURE 4
Model validation 4
Uncertainty analysis 6
Sensitivity analysis 7
Methods of estimating uncertainty 10
III. OBJECTIVE 14
IV. DESCRIPTIONS OF THE MODEL AND THE DATASET. 16
Description of the model 16
Algorithm of the AGNPS model 17
Data descriptions 20
V. SENSITIVITY ANALYSIS AND SIMULATION PROCEDURE 23
Sensitivity Analysis 23
Simulation Procedure 26
Normal Distribution 27
Lognormal Distribution 28
Uniform Distribution 29
Triangular Distribution 29
VI. RESULTS, CONCLUSIONS AND RECOMMENDATIONS. 37
Results of the simulation runs 37
Analysis of the simulation results 43
Conclusions and Recommendations 47

LIST OF TABLES

Table		Page
5-1	AGNPS input parameters with their distributions and values of Cv 32
5-2	Input parameters and their distributions used in the first run. 33
5-3	Input parameters and their distributions used in the second run. 33
5-4	Input parameters and their distributions used in the third run. 34
5-5	Input parameters and their distributions used in the fourth run. 34
5-6	Input parameters and their distributions used in the fifth run. 35
5-7	Input parameters and their distributions used in the sixth run. 35
5-8	Input parameters and their distributions used in the seventh run. 36
6-1	Descriptive statistics of the first simulation run. 37
6-2	Descriptive statistics of the second simulation run. 38
6-3	Descriptive statistics of the third simulation run 38
6-4	Descriptive statistics of the fourth simulation run 39
6-5	Descriptive statistics of the fifth simulation run 39
6-6	Descriptive statistics of the sixth simulation run 40
6-7	Descriptive statistics of the seventh simulation run 40
6-8	t- values resulting from statistical test on means. 43
6-9	The lower and upper 90% CIs of the AGNPS model outputs for all simulation runs 45
6-10	Observed average values of the outputs of AGNPS. 46

LIST OF FIGURES

Figure		Page
6-1	Runoff probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs 49
6-2	Runoff probability distribution for the 1st, 4th and the 6th simulation runs 50
6-3	Sediment probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs 51
6-4	Sediment probability distribution for the 1st, 4th and the 6th simulation runs 52
6-5	Nitrogen in runoff probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs 53
6-6	Nitrogen in runoff probability distribution for the 1st, 4th and the 6th simulation runs 54
6-7	Nitrogen in sediment probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs 55
6-8	Nitrogen in sediment probability distribution for the 1st, 4th and the 6th simulation runs 56
6-9	Phosphorus in sediment probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs 57
6-10	Phosphorus in sediment probability distribution for the 1st, 4th and the 6th simulation runs 58

CHAPTER I

INTRODUCTION

"And we have made from water every living thing" (The Noble Qur'an, 21: 30).

Hydrology, which is the scientific study of the properties, distribution, and effects of water on the earth's surface, is a very important subject, as water is considered to be the main requirement for life on this earth. Water is essential for human use, crop production, industry and so on. Man has been always concerned about the quality and quantity of the water resources available. Hydrologists have been working to understand the systems of hydrologic events taking place in nature. Hydrologic/Water Quality models have been developed to represent natural hydrologic processes in a simple way and to help us understand hydrologic systems, to be used as analysis and design tools, and to be used for organizing and interpreting research (Barfield et al., 1989). Many studies on different aspects of the hydrologic cycle have been conducted. Some important natural hydrologic variables are rainfall excess (runoff) and sediment loads. Nutrients in runoff and sediment might be a source of water pollution. Therefore, models have been developed to analyze and provide estimates of runoff water quality.

Hydrologic/Water Quality (H/WQ) models are a collection of physical laws and empirical observations written in mathematical terms and combined in a way that produces a set of results (outputs) based on a set of known and/or assumed conditions (inputs) (Haan, 1989). Models may be physically based, conceptual, empirical or a combination of these. Regardless of how models are classified, they can be represented as

$$O = f(i, p, t) + e$$

where O represents the H/WQ responses, f represents a collection of functional relationships (composing the model), i represents model inputs, p represents the parameters of the model, t is time, and e represents errors in the estimation of O. Model parameters must be estimated from observed hydrologic data. There may be a number of data points to model using several model inputs and producing several model outputs. Model outputs may be runoff, sediment load, nitrate or phosphorus concentration, and/or other quantities of interest. The validity and applicability of a model depend on the characteristics of the data used to estimate the model parameters. The data used to estimate input parameters must be representative of the situation in which the model is going to be used.

Statement of the problem

Models require as inputs weather data like rain and temperature, and other parameters which must be estimated for the model to function. In hydrologic/water quality models, input parameters are generally represented by average values. However, there is a great deal of uncertainty as to the accuracy of the average values assigned to the parameters used.

Naturally if the parameters of a model are uncertain, the output produced by the model will be uncertain as well. Because of the randomness of hydrologic events, one would naturally think about dealing with the random variability of the various model parameters so that their uncertain behavior may be characterized through probability distributions (Ben Salem, 1986). These distributions express the modelers degree of belief that parameter values will be in certain intervals in parameter space. There are two primary means for quantifying this uncertainty. Monte Carlo Simulation and First Order Analysis. One of the problems encountered in Monte Carlo Simulation is the form of the input parameter distribution. In this study the focus will be on the effect of input parameter uncertainty on the uncertainty of model outputs.

In fact this study is a continuation of a study conducted by Prabhu (1995). In his study, Prabhu used the AGNPS (Agricultural NonPoint Source) model to illustrate a statistical model evaluation protocol. Prabhu used one set of probability distributions for the input parameters; however, he was not certain that the correct distributions had been selected. The uncertainty that results in model outputs is logically dependent on the amount and form of the uncertainty in the input parameters as reflected in the probability distributions of these parameters. In this study the same input parameters used by Prabhu will be employed. To assess the importance of the input parameter distributions, different combinations of input parameter distributions and variances will be used. The impact of changing the distributions and reduction of variances of input parameters on the uncertainty of model outputs will be studied.

CHAPTER II

REVIEW OF LITERATURE

Literature reviewed in support of this study included works about model validation, the importance of uncertainty analysis to H/WQ models, sensitivity analysis, and methods of estimating the uncertainty in model predictions.

Model Validation

Model validation can be defined as the process of demonstrating that a model, within its domain of applicability, behaves with satisfactory accuracy consistent with the study objectives (Balci, 1987). However, such an 'ideal' validation is difficult to achieve for models simulating natural processes. In the case of H/WQ models, such a level of validation is impossible, because of the heterogeneous nature of the hydrologic media and the uncertainties associated with spatial and temporal variability (Hassanizadeh and Carrera, 1992).

The qualitative validity of a model depends on the modelers or users judgment and can help in terming the model as good, fair, poor or such. For some models, quantitative

validation may not be feasible. In such a case, an attempt should be made to quantify the uncertainties in the model predictions due to the error associated with each of the input parameters (Prabhu, 1995). The problem in model validation, according to Ditmars et al., (1987) is that as the number of model dimensions and variables increase, the number of possible combinations of predictions and data becomes very large. As for the output analysis, when scattergram regressions are used, obtaining a regression coefficient of one is clearly not sufficient to guarantee agreement between observed and predicted values. A number of researchers (Luis and McLaughlin, 1992; Martinec and Rango, 1989; Reckhow et al., 1990; Thomann, 1982; Loague and Green, 1991; Garrick et al., 1978; Chiew et al., 1993; Reckhow and Chapra, 1983) evaluated models on the basis of statistical tests. They used various models for illustration.

Luis and McLaughlin (1992) state that the errors which contribute towards differences in prediction from a model and the actual observations can be grouped into three distinct sources. They illustrate this by using a model which predicts the moisture movement through an unsaturated porous medium. The objective of the model is to predict the mean distribution of moisture content over time and space. The three error sources in this context are (i) measurement error or the difference between the measured and the true values of moisture content, (ii) spatial heterogeneity or the difference between the large scale trend to be predicted and the true small scale values of moisture content, and (iii) model error or the difference between the model's prediction and the actual large scale trend.

They further note the difference between model validation, which addresses the question of whether or not a model adequately represents observed phenomena, and accuracy

assessment, which pertains to the larger question of how well a model will perform under conditions that have not yet been observed. They observe that if the model's basic structure (set of governing equations) is correct, then the accuracy assessment reduces to an evaluation of the effects of parameter estimation errors.

Uncertainty Analysis

Uncertainty analysis applied to H/WQ models is the process by which one evaluates the impact of uncertainty in the model parameters and weather on the results produced by models. Uncertainty analysis for hydrologic and water quality modeling is very important when making management decisions concerning water resources, whether that decision deals with quantities of water or water quality (Haan, 1995a).

The importance of incorporating uncertainty analysis into H/WQ models has been emphasized by many authors (Beck, 1987; Reckhow, 1994; Haan et al., 1995; Hession et al., 1995; Kumar and Heatwole, 1995). Several researchers have compared the accuracy, applicability and computational demands of various sensitivity and uncertainty analysis techniques. Thomas (1982) discussed the use of Latin Hypercube sampling as a means of obtaining an output probability distribution function (pdf) and cumulative density function (cdf). Doctor (1989) summarized various sensitivity and uncertainty analysis procedures. Usually, parameter values used as input to models are only estimates since the actual values are not known with certainty. Rejeski (1993) referred to "modeling honesty" as the truthful representation of model limitations and uncertainties. Beven (1993) and Haan (1995a)

suggested that the inclusion of uncertainty analysis in modeling activities can be interpreted as intellectual honesty. Reckhow (1994) suggested that all scientific uncertainties must be estimated and included in modeling activities.

Determining the uncertainty to assign to input parameters is one of the major hurdles that must be addressed in overall evaluation of uncertainty associated with hydrologic and water quality modeling. When estimating input parameters for a model, we might get some guidance from the user manual of that model, from our own experience, or from the literature and see what kind of variability might be present. Our goal is to come up with the following quantities in order of priority: the expected value, the variance, and the distributional shape (Haan, 1995b).

Sensitivity Analysis

It is very clear that considerable work may be involved in gathering the data required to characterize the uncertainty in each input parameter and the parameters as a whole. Therefore, one should identify the parameters that are important to the process being modeled. Procedures to identify the parameters that have the greatest impact on model predictions include sensitivity analysis. The application of sensitivity analysis to hydrologic problems has been examined by several researchers. Most sensitivity studies were conducted using complex hydrologic models.

A number of methods have been employed by researchers for sensitivity analysis. The most commonly used method was proposed by Coleman and Decoursey (1976). When

sensitivity with respect to one parameter is being determined, the other parameters will be held constant at values determined to be the most appropriate for the watershed being studied. Majkowski et al. (1981) argue that sensitivity analysis and its extensions enable the modelers to examine the influence of input parameter errors on predictions made by the model. The acceptance level of output uncertainty depends on the system under consideration, the modeling objectives and the modeler's knowledge of the system.

Majkowski et al. (1981) extend the sensitivity analysis to parameter estimation by means of so called additive sensitivity analysis. They analyzed the uncertainties in outputs produced by the uncertainties in the input parameters and defined the deviance measure, D . Using linear theory, the variance of the distribution of the logarithm of D can be found. They contend that by comparing the magnitude of the components of the variance, the particular input errors which contribute to total variance can be found. This will lead to identifying parameters which require more accurate determinations of their values.

Tiscareno-Lopez et al. (1993) conducted stochastic sensitivity analysis on the WEPP model. They argue that for any assessment situations, model parameters are best represented by a frequency distribution (or range) of values. They performed multiple linear regression analysis using model inputs generated by the MCS method and model outputs. The uncertainty in model parameters was finally assessed from the regression coefficients of the linear equation.

Deer-Ascough and Nearing (1994) performed a sensitivity analysis on the WEPP model using parameters for three soil types and three different management practices. They used a deterministic sensitivity analysis. They contend that with this approach, the absolute

sensitivity coefficient, while still reflecting linear response, would provide a better examination of the nonlinearity of responses between series of input and output parameters.

Nofziger et al. (1993) evaluated a number of unsaturated vadoze zone models for important parameters using sensitivity and uncertainty analysis. They defined the sensitivity coefficient S , as

$$S = \frac{\partial O}{\partial I}$$

where O represents the output of interest and I represents the input parameter. S gives the absolute change in O for a unit change in I . Obviously for most hydrologic and water quality models, numerical procedures must be used since analytic partial derivatives can not be obtained. Thus, one has to approximate the above derivatives by the difference equation

$$S = \frac{\Delta O}{\Delta I}$$

The value of S calculated from these equations has units associated with it. This makes it difficult to compare sensitivities for different input parameters. This can be overcome by using the relative sensitivity, S_r , given by

$$S_r = \frac{\Delta O}{\Delta I} * \frac{I}{O}$$

where S_r represents the % change in O for a one % change in I . The relative sensitivity

coefficients are preferred since they are dimensionless and can be compared across parameters directly. Parameters can be ranked on the basis of their relative sensitivity coefficients and only the most sensitive ones retained for further analysis. Here the sensitivity coefficients reflect the change in output function due to a single input parameter. Uncertainty analysis may be used to incorporate simultaneous changes in more than one parameter and variability of the parameters (Nofziger et al., 1993).

Methods of Estimating Uncertainty

Uncertainty analysis methods appropriate for use with spatially correlated input variables included first and second order approximations, MCS, and “deterministic” uncertainty analysis. There are two main categories of methods for estimating the uncertainty in model predictions: Monte Carlo methods and first-order variance propagation (Beck, 1987; Summers et al., 1993; Zhang et al., 1993). A number of works address the formulation of first order analysis procedures and the potential for errors in their use. Dettinger and Wilson (1981) formulated the FOA approximation of the covariance matrix and the second order approximation of the mean of a vector of time and space dependent model outputs. They noted that the first and second order analysis procedure could be applied to nonlinear systems with reasonably small coefficients of variation and cited the 0.2 limit for the coefficient of variation proposed in Benjamin and Cornell (1970).

Numerous studies have been completed in which the results of a FOA have been compared with the results of a MCS. Song and Brown (1990) used the Streeter-Phelps

equation as an example and compared the results of MCS and FOA to estimate model output variance when correlations between the model parameters were included or ignored in the analysis. Huang (1986) looked at the uncertainty in the design of an open channel to carry the flow through a sluice gate. He used triangular distributions for uncertain parameters, such as gate coefficient, Manning's n , gate submergence coefficient, and various geometry parameters, which were assumed to be independent. The FOA mean and variance of the load (flow) and resistance (channel capacity) were calculated. The FOA of overall reliability (probability of not failing) was computed as 0.987 for load and resistance normally distributed and as 0.991 for load and resistance lognormally distributed. The result of a MCS was 0.997. The author did not speculate as to the cause of the difference. The need to make distributional assumptions was cited as a problem with both procedures.

It was found that the FOA techniques have a number of theoretical shortcomings that reduce their utility (Summers et al., 1993). For example, FOA is restricted by assumptions of linearity and the magnitudes of input parameter variance (Gardner and O'Neill, 1983; Summers et al., 1993). First order approximation deteriorates if the coefficient of variation of the model parameters is greater than 10-20 % (Zhang et al., 1993). Therefore, given the limitations of the FOA, Monte Carlo Simulation procedures are the preferred methods of propagating uncertainty in complex, watershed-level models (Haan, 1989; Summers et al., 1993; Taskinen et al., 1994; Haan and Zhang, 1995; Kumar and Heatwole, 1995; Prabhu, 1995).

The Monte Carlo Simulation method is a stochastic method. In this method many pseudo random observations have to be generated from an assumed parent probability

density function (PDF). The Monte Carlo method is probably the most powerful and commonly used technique for uncertainty analysis of a complex system (Carsel et al., 1988a,b). The technique requires knowledge of the statistical distribution (PDF) of each independent variable together with its mean, variance, and correlation with other independent variables. The subsequent simulations are based on the unbiased selection of values of the independent variables from their respective statistical distributions. The process ends when enough output has been obtained to yield a clear statistical description of the dependent variable.

Booth (1989) generalized the Monte Carlo method into four steps. (i) Specification of a parametric statistical model (PDF) for the joint distribution of the input vector, x , for a random y chosen within the given classification. The PDF may come from the analysis of real observations of the input vector, X , or from similar studies conducted in the past. (ii) Estimation of the parameters of the specified PDF using either observed input vectors, X_1, X_2, \dots, X_n , at a sample of n sites within the given classification or the resulting parameters estimated in similar studies. (iii) Generate many pseudo input vectors from the PDF in (i) with parameters in (ii). (vi) Run the model for each pseudo input vector to obtain a probability distribution for the output variability.

The Monte Carlo method has been widely employed in many disciplines in addition to hydrology. Shaffer (1988) used the Monte Carlo method to estimate the confidence bands for a soil-crop simulation model. Carsel et al., (1988a,b) used a similar procedure to generate PRZM model parameters for both the unsaturated and saturated zones in making regional assessments of pesticide residue loading to ground water. The Monte Carlo technique can

also be used to study the sensitivity of model prediction corresponding to the uncertainties of a particular model parameter. Alcamo and Bartnicki (1987) used the method to determine the sensitivity of a sulfur-air transport model to its parameters under a prescribed 20% coefficient of variation. Borah and Haan (1989) studied the uncertainties associated with parameter estimation by introducing prescribed errors into each value of the precipitation and synthetic runoff records of the USGS Precipitation Runoff Modeling System.

CHAPTER III

OBJECTIVE

As has been established, often considerable uncertainty exists in the values assigned to the input parameters of a H/WQ model. Obviously the values assigned to the input parameters have an impact on the results generated by the model.

The process by which one evaluates the impact of uncertain knowledge of model parameters and weather data on the results produced by models is known as uncertainty analysis. Uncertainty is often thought of in qualitative terms. When it comes to modeling and decision making, one must be able to quantify uncertainty. This quantification is generally done through the use of probabilistic statements and probability distributions.

One difficulty in uncertainty analysis is the determination of the correct probability distribution to describe model input parameters. In his study using the AGNPS model, Prabhu (1995) used one set of distributions to describe the input parameters. This set of distributions was chosen based on a study of the literature and a rational analysis of the problem. Uncertainty exists as to the proper pdf to use. Therefore, in this study distributions for the AGNPS input parameters will be changed to determine the impact of this change on the output pdfs from the model. Also the variances of the input parameters will be reduced

and the impact of this reduction on the model results will be observed. The AGNPS model will be used.

The objective of this study is to investigate the impact of model input parameter probability distributions on model output uncertainty predicted by Monte Carlo Simulation.

CHAPTER IV

DESCRIPTIONS OF THE MODEL AND THE DATASET

Description of the Model

The 92-500, Section 208 Federal Law, requiring all states to evaluate upland erosion and determine its effect on water quality, the need for a uniform method for evaluating agricultural watersheds in Minnesota, and the importance of runoff from agricultural lands as a nonpoint source of pollution, lead to the development of AGNPS (Young et al., 1987).

The AGNPS (AGricultural Nonpoint Source) model was developed by the Agricultural Research Service (ARS) in cooperation with the Minnesota Pollution Control Agency (MPCA) and the Soil Conservation Service (SCS). The model was developed to analyze and provide estimates of runoff water quality from agricultural watersheds ranging in size from a few hectares to upwards of 20,000 ha (Young et al., 1989). AGNPS is a distributed parameter, single event based model, and works on a cell basis. These cells are uniform square areas subdividing the watershed. Data required for each cell include land use, soil, vegetation type and maturity, cultural practice, fertilizer application, SCS curve number, slope, and other aspects (Summer et al., 1990).

The model simulates runoff, sediment, and nutrient transport from agricultural watersheds. The nutrients considered include nitrogen (N) and phosphorus (P), both essential plant nutrients and major contributors to surface water pollution. The basic components of the model are hydrology, erosion, sediment transport, and transport of nitrogen, phosphorus, and chemical oxygen demand. Accuracy of the results can be increased by reducing the cell size, but this increases the time and labor required to run the model. Conversely, enlarging the cell size reduces time and labor, but the savings must be balanced against the loss of accuracy resulting from treating larger areas as homogeneous units (Young et al., 1989).

Algorithm of the AGNPS model.

Hydrology

Runoff volume and peak flow rate are calculated in the hydrology part of the model. Runoff volume estimates are based on the SCS curve number method. The basic equation is

$$Q = \frac{(P - 0.2S)^2}{P + 0.8S} \quad P \geq 0.2S$$

where Q is the runoff volume, P is the rainfall, and S is the retention parameter, all expressed in the same dimensions of length. Runoff will not occur until the precipitation is greater than

0.2S. The retention parameter is defined in terms of a curve number (CN), as

$$S = \frac{1000}{CN} - 10$$

The curve number depends upon land use, soil type, and hydrologic soil conditions. Peak runoff rate for each cell is estimated using the following empirical relationship proposed by Smith and Williams (1980).

$$Q_p = 3.79A^{0.7}CS^{0.16}(RO/25.4)^{(0.903A^{0.017})}LW^{-0.19}$$

where Q_p is the peak flowrate in $m^3 s^{-1}$; A is the drainage area in km^2 ; CS is the channel slope in m/km ; RO is the runoff volume in mm; and LW is the watershed length-width ratio, calculated by L^2/A , where L is the watershed length.

Erosion and sediment transport

A modified form of the Universal Soil Loss Equation (USLE) is used to estimate upland erosion for single storms as

$$SL = (EI) KLSCP (SSF)$$

where SL is the soil loss, EI is the product of the storm total kinetic energy and maximum 30-minute intensity, K is the soil erodibility factor, which is a measure of a soil's resistance to the erosive powers of rainfall energy and runoff. Experimentally, soil erodibility is the soil

loss per unit rainfall index on a standard erosion plot, LS is the topographic factor, C is the cover and management factor, which accounts for above-ground effects, surface effects, and below-surface effects, P is the supporting practice factor, which is used to evaluate the effects of contour tillage, strip cropping, terracing, subsurface drainage, and dryland farm surface roughening, and SSF is a factor to adjust for slope shape within the cell.

After runoff and upland erosion are calculated, detached sediment is routed from cell to cell through the watershed to the outlet. The basic routing equation is derived from the steady-state continuity equation.

Chemical transport.

Transport of N, P and chemical oxygen demand (COD) throughout the watershed are estimated in the chemical transport part of the model. Chemical transport calculations are divided into soluble and sediment absorbed phases. Nutrient yield in the sediment absorbed phase is calculated using total sediment yield from a cell, as

$$Nut_{sed} = (Nut_f) Q_s(x) E_R$$

where Nut_{sed} is N or P transported by sediment; Nut_f is N or P content in the field soil; and E_R is the enrichment ratio

$$E_R = 7.4 Q_s(x)^{-0.2} T_f$$

where $Q_s(x)$ is sediment yield and T_f is a correction factor for soil texture. Soluble nutrient estimates consider the effects of nutrient levels in rainfall, fertilization, and leaching.

Soluble nutrients contained in runoff are estimated by

$$Nut_{sol} = C_{nut} Nut_{ext} Q$$

where Nut_{sol} is the concentration of soluble N or P in the runoff, C_{nut} is the mean concentration of soluble N or P at the soil surface during runoff, Nut_{ext} is an extraction coefficient of N and P for movement into runoff and Q is the total runoff.

Data Descriptions

Since the same site of study used by Prabhu will be used in this study, the majority of the following information was taken from Prabhu (1995). The data used in this study are from a research field in northwestern Arkansas (lat. 36° N long. 94° W). These data were provided by researchers at the University of Arkansas and are explained in detail in Edwards et al. (1993). The data were collected from the field WA.

The area of the field is 3.61 acres, and it was considered as a single cell. The crop cover for this field is predominantly tall fescue. The field has predominantly a Linker Loam soil. The Linker series consist of well-drained, moderately permeable soils. The runoff is medium and the erosion hazard is severe with these soils. The slopes are usually 3 to 8 percent and have five layers of soil (Soil Survey, Washington County, Arkansas).

Since AGNPS is an event based model, a precipitation event of 3.74 inches on July 30, 1992 is used in this study. That rainfall event had a preceding event of 0.39 inches on July 28, 1992. It was assumed that antecedent condition would require that CN value to be

changed. So the average value of CN(I) and CN(II) conditions was used. The CN(II) value is 79 taken from Edwards et al. (1993), and CN(I) was calculated using the following equation from Haan et al. (1994).

$$CN(I) = \frac{4.2CN(II)}{10 - 0.058CN(II)}$$

So

$$CN(I) = \frac{4.2 * 79}{10 - 0.058 * 79} = 61.74$$

The average value of these two conditions (79 and 61.74) is about 70 and that value is used as CN. The event is assumed to be of 24 hour duration. For peak flow calculations, AGNPS option is chosen. For the hydrograph shape factor, which allows the user to choose the method for calculating the triangular hydrograph, the K coefficient method is chosen and the default value of 484 is chosen for K coefficient.

The shape of the slope is assumed to be uniform, which takes the value of 1. For the soil parameters, the K-factor is estimated from the soil erodibility nomograph of Agriculture Handbook number 537, "Predicting Rainfall Erosion Losses" (Wischmeier and Smith, 1978). The percentage of silt is 35.6. The percentage of the very fine sand is assumed to be negligible. The percentage of sand is 56.3. The percentage of organic matter is assumed to be 2 as the soil is brown in color (Soil Survey, Washington County, AR). The soil structure has a medium granular structure and has moderate permeability (Soil Survey, Washington

County, AR). With these conditions the K value is derived from the soil erodibility monograph as 0.24.

From Table 10 (Agriculture Handbook 537, Wischmeier and Smith, 1978) for "tall weeds or short bushes" category and a percent cover of 50% and ground cover of 80%, the C value is assumed to be 0.012 for grass. The P value is assumed to be 0.9 (Prabhu, 1995).

For the surface condition constant, good pasture is assumed with a value of 0.22. For the chemical oxygen demand (COD) factor, the pasture value of 60 is used as input. The soil texture number for 56% of sand and 35% of silt is 3. For this soil texture a number of default values regarding the soil Nitrogen, the soil P, Nitrogen (N) and the Phosphorus (P) coefficients were accessed. The value of the soil N is 0.001 lb N/lb soil. The N extraction coefficient for runoff is 0.05, the N extraction coefficient for leaching 0.25. The soil P is 0.0005 lb P/lb soil, P extraction coefficient for runoff is 0.025, and the P extraction coefficient for leaching is 0.25. The channel type is taken as the one without a definitive channel. Prabhu (1995) can be consulted for more detail on these parameter values.

CHAPTER V

Sensitivity Analysis and Simulation Procedure

Sensitivity Analysis

It is very difficult to collect the data required to characterize the uncertainty in the input parameters of a model. One would not want to go to all this work unless the parameter was important to the process being modeled. If a parameter has little or no effect on the output of a model, one would not want to spend a lot of time estimating that parameter or worrying about uncertainty in that parameter.

In order to identify the important parameters of a model, sensitivity analysis may be used to determine the sensitivity of model outputs to changes in values for model inputs. There are two types of sensitivity coefficients. One is called an absolute sensitivity coefficient or the sensitivity coefficient and the other a relative sensitivity coefficient. The coefficients are defined as

$$S = \frac{\partial O}{\partial P}$$

$$S_r = \frac{\partial O}{\partial P} \frac{P}{O}$$

where O and P represent particular model outputs and parameters (inputs) respectively. S gives the absolute change in O for a unit change in P while S_r gives the % change in O for a 1% change in P (Haan, 1995 b). When the sensitivity with respect to one parameter is being determined, the other parameters are held constant at values determined to be the most appropriate for the watershed under study. In this study the results of the sensitivity analysis on AGNPS performed by Prabhu (1995) will be used. Prabhu conducted the sensitivity analysis of AGNPS using 28 parameters. The analysis indicated the curve number (CN), slope, the P-factor (erosion control practice factor), the K-factor (soil erodibility factor), the C-factor (cover and management factor), soil nitrogen, nitrogen extraction coefficient for runoff, and nitrogen extraction coefficient for leaching are the most sensitive parameters.

Parameter uncertainty can be quantified using variances and/or probability distributions on the model parameters. For the Monte Carlo Simulation technique, the probability distribution of the parameters must be specified.

The selection of the most appropriate pdf to use for a particular parameter remains a challenge. The form of the probability distribution function often arises from the fundamental properties of the quantities we are attempting to represent. Often, distributions are selected on an empirical basis, because they provide a reasonable representation of the observed data (Morgan and Henrion, 1992). In his study Prabhu used the data published in the literature to determine the appropriate pdfs for the various parameters. He used the Kolmogorov-Smirnov test to evaluate the probability distributions that were selected. Based on the results of the test, Prabhu indicated the distributions and coefficient of variations (Cv), given in table 5-1, for the various parameters used in his study.

After determining the input parameters and their probability distributions, the probability distributions for the model outputs were determined by Prabhu (1995) using Monte Carlo Simulation (MCS). The Monte Carlo analysis is useful in characterizing the uncertainties due to the parameters. MCS can be performed by sampling the multivariate input distribution and performing a model simulation with the sampled parameter values to produce estimates of model output.

The output results of the simulation runs conducted by Prabhu were tested for goodness of fit for various distributions. The Chi-square goodness of fit test was used. Based on the results of these tests, Prabhu found the following distributions for the model outputs: for runoff it is normal; for sediment, nitrogen in runoff, nitrogen in sediment, and for phosphorus in sediment it is lognormal.

Once pdfs are determined, confidence intervals (CIs) can be placed on the model predictions. The width of these CIs depend on the level of significance and the applicable pdf. If the purpose of the study is to evaluate the model, predictions are compared with measured watershed responses. If the measured data fall within the CIs, the model may be considered to have performed satisfactorily from a statistical point of view. If the CIs are so wide they will be of little use to judge the model predictions, even though the predictions are within the CIs, the model may not be acceptable. This means that a statistically acceptable solution might be unacceptable in application (Haan et al., 1993).

There is also uncertainty associated with the measured responses of a watershed. This uncertainty can also be quantified in the form of a pdf. If the pdfs of the model response and the watershed measured values are plotted together, the degree of overlap of the pdfs

indicates the predictive ability of the model. If some criteria of model acceptability is given, then it is possible to determine the probability that the model will fulfill that criteria (Haan et al., 1993).

Simulation Procedure

The Monte Carlo Simulation method is a stochastic method, which requires the generation of a number of random observations from the assumed parent multivariate probability density function. The random observations used in this study were generated using the random number generation function from Microsoft Excel. The parameters were assumed to be independent. For all parameters which have a normal or lognormal distribution, random observations were generated from a normal distribution and then transformed to the corresponding distribution if necessary. For parameters which have a uniform or triangular distribution, random observations were generated from uniform distribution on the interval 0 to 1 and then transformed to the appropriate distribution. Different seeds were used when generating these random numbers.

In Monte Carlo Simulation the number of simulation runs is very important. To determine the required number of runs, Prabhu (1995) conducted simulations that involved treating only the curve number as a random variable. The curve number was selected, because it is the most significant parameter affecting runoff as defined by the sensitivity analysis. The means of these runs were determined. The analysis was confined to a single event of 3.74 inches of precipitation on July 30, 1992. The results based on runoff were

obtained. Based on these results, it was found that the mean stabilized with about 1500 simulations. Therefore, it was decided that 1500 simulations were adequate to define the output distributions. The next step was to take the parameters given in table 5-1, make the required changes and perform 1500 simulation runs. There were two major types of changes, the first was changing the distribution of the input parameters (simulation runs number 1, 2, 3, 5 and 7). The second change was represented by a reduction of the variances of the parameters. The variance was reduced by reducing the Cv's of the parameters used in the first run by 0.5 in run number 4 and by 0.25 in run number 6. The computer program used in this study to produce the AGNPS input data files is given in Appendix A. A total of seven different combinations of distributions and variances of input parameters were investigated.

The types of the probability distribution functions used in this study are considered to be of the most common and useful distributions. These distributions with some of their properties are discussed below.

Normal Distribution

The normal, or Gaussian, distribution arises in many applications, in part because of the central limit theorem, which states the general result that if X is made up of the sum of the many small effects, then X might be expected to be normally distributed. Similarly if X is equal to the product of many small effects, then $\ln X$ can be expected to be normally distributed (Haan, 1977). The normal distribution is also commonly chosen because it is

well studied and frequently used in classical statistics. The normal distribution is commonly employed to represent uncertainty resulting from unbiased measurement errors. The normally distributed random variable takes on values over the entire range of real numbers. Evaluation of the CDF requires numerical approximation of the integral of the PDF, but solutions are commonly found in statistical tables and available computer subroutines. The parameters of the distribution are directly related to the first and second moments, and the skewness coefficient is zero due to the symmetry of the distribution. The parameters of the distribution are estimated from the sample mean and standard deviation.

Lognormal Distribution

The lognormal distribution results when the logarithm of the random variable is described by a normal distribution. That is, if X is lognormally distributed, then $Y = \ln X$ is normally distributed. The properties of the lognormal distribution follow directly, and probability computations are made on the normal variable Y , with subsequent transformation to the corresponding value of $X = \exp Y$. The lognormal distribution is often found to provide a good representation for physical quantities that are constrained to being non-negative, and are positively skewed. The lognormal distribution is particularly appropriate for representing large uncertainties that are expressed on a multiplicative or order-of-magnitude basis. The parameters of the distribution are equivalent to the mean and standard deviation of $Y = \ln X$.

Uniform Distribution

The uniform distribution provides one of the simplest means of representing the uncertainty in model input. Its use is appropriate when we are able and willing to identify a range of possible values, but unable to decide which values within this range are more likely to occur than others. Parameters may be estimated from observed data using the method of moments, but are often determined using physical or subjective reasoning to determine minimum and maximum possible values for the random variable.

The values of the minimum, maximum and the mode of uniformly distributed parameters are given by

$$\hat{\alpha} = \bar{x} - \sqrt{3}S$$

$$\hat{\beta} = \bar{x} + \sqrt{3}S$$

$$C = \frac{\hat{\alpha} + \hat{\beta}}{2}$$

where \bar{x} is the mean, S is the standard deviation, $\hat{\alpha}$ is the minimum, $\hat{\beta}$ is the maximum and C is the mode.

Triangular Distribution

The triangular distribution is claimed to represent a least-biased assumption when the true distribution is unknown. For certain model input parameters, values toward the middle

of the range of possible values are considered more likely to occur than values near either extreme. When this is the case, the triangular distribution provides a convenient means of representing uncertainty. When uncertainties are large and asymmetric, both the uniform and triangular distributions can be modified to yield loguniform or logtriangular distributions, in which $Y = \ln X$ is assumed to have the indicated distribution. Computations and parameter estimation are based on Y , with subsequent transformation to the desired random variable by $X = \exp(Y)$.

For a triangular distribution the mean and variance are given by

$$\mu = \frac{1}{3}(\hat{\alpha} + \hat{\beta} + C)$$

$$\sigma^2 = \frac{1}{18}(\hat{\alpha}^2 + \hat{\beta}^2 + C^2 - \hat{\alpha}\hat{\beta} - \hat{\alpha}C - \hat{\beta}C)$$

where μ is the mean, σ is the standard deviation, $\hat{\alpha}$ is the minimum, $\hat{\beta}$ is the maximum and C is the mode.

For a symmetric triangular distribution the minimum, maximum and the mode of the parameter are given by

$$\hat{\alpha} = \bar{x} - \sqrt{6}S$$

$$\hat{\beta} = \bar{x} + \sqrt{6}S$$

$$C = \frac{\hat{\alpha} + \hat{\beta}}{2}$$

where \bar{x} is the mean, S is the standard deviation, $\hat{\alpha}$ is the minimum, $\hat{\beta}$ is the maximum and C is the mode.

For a non-symmetric triangular distribution with C given, and minimum ($\hat{\alpha}$) assumed to be 0, the maximum ($\hat{\beta}$) is calculated from

$$\hat{\beta} = 3\mu - C$$

where $\hat{\beta}$ is the maximum, μ is the mean and C is the mode.

The first simulation run can be considered the base run. The pdfs were the ones used by Prabhu (1995) and are shown in table 5-1. The second run used a uniform distribution for all parameters except the S -value. The third run was similar to the second except the S -value was also considered to be uniform. The fifth simulation run was similar to the first except the normal distribution was substituted for the lognormal and the uniform for the triangular. The seventh run used the triangular distribution for all parameters. The same means and variances were used for the parameters in runs 1, 2, 3, 5 and 7.

Runs four and six were similar to run number one except the C_v on the parameters was reduced by 0.5 for run four and another 0.5 (a total of 0.25) for run six.

Thus runs 1, 2, 3, 5, and 7 used the same means and variances, but different distributions. While runs 1, 4, and 6 used the same distributions, but different variances.

Tables 5-2 through 5-8 summarize the distributions, their means and variances.

Table 5-1. AGNPS input parameters with their distributions and values of Cv.

(Taken from Prabhu, 1995).

PARAMETER	DISTRIBUTION	Cv
Retention parameter (S)	Lognormal	0.5
Slope	Lognormal	0.3
K - Factor	Triangular	0.14
C - Factor	Triangular	0.2
P - Factor	Triangular	0.05
Soil Nitrogen, lbs/ac	Lognormal	0.5
Nit. runoff coeff.	Lognormal	0.5
Nit. leaching coeff.	Lognormal	0.5

Table 5-2. Input parameters and their distributions used in the first run.

Parameter	Distribution	Mean	Cv	Min.	Max.	Mode
S -Value	Lognormal	2.66	0.50			
Slope	Lognormal	4.00	0.30			
K-Factor	Triangular	0.24	0.14	0.158	0.322	0.24
C-Factor	Triangular	0.012	0.20	0.006	0.018	0.012
P-Factor	Triangular	0.90	0.05	0.80	1.00	0.93
Soil N	Lognormal	0.001	0.50			
N RO Coeff.	Lognormal	0.05	0.50			
N Leach. Coeff.	Lognormal	0.25	0.50			

Table 5-3. Input parameters and their distributions used in the second run.

Parameter	Distribution	Mean	Cv	Min.	Max	Mode
S-Value	Lognormal	2.66	0.50			
Slope %	Uniform	4.00	0.30	1.92	6.08	4.00
K-Factor	Uniform	0.24	0.14	0.18	0.30	0.24
C-Factor	Uniform	0.012	0.20	0.008	0.016	0.012
P-Factor	Uniform	0.90	0.05	0.82	0.98	0.90
Soil N	Uniform	0.001	0.50	0.00013	0.0019	0.001
N RO Coeff.	Uniform	0.05	0.50	0.0067	0.093	0.05
N Lch. Coeff.	Uniform	0.25	0.50	0.0335	0.467	0.25

Table 5-4. Input parameters and their distributions used in the third run.

Parameter	Distribution	Mean	Cv	Min.	Max.	Mode
S-Value	Uniform	2.66	0.50	0.36	4.96	2.66
Slope %	Uniform	4.00	0.30	1.92	6.08	4.00
K-Factor	Uniform	0.24	0.14	0.18	0.30	0.24
C-Factor	Uniform	0.012	0.20	0.008	0.016	0.012
P-Factor	Uniform	0.90	0.05	0.82	0.98	0.90
Soil N	Uniform	0.001	0.50	0.00013	0.0019	0.001
N RO Coeff.	Uniform	0.05	0.50	0.0067	0.093	0.05
N Leach. Coeff.	Uniform	0.25	0.50	0.0335	0.467	0.25

Table 5-5. Input parameters and their distributions used in the fourth run.

Parameter	Distribution	Mean	Cv	Min.	Max.	Mode
S-Value	Lognormal	2.66	0.25			
Slope %	Lognormal	4.00	0.15			
K-Factor	Triangle	0.24	0.07	0.199	0.281	0.24
C-Factor	Triangle	0.012	0.10	0.0091	0.0149	0.012
P-Factor	Triangle	0.90	0.025	0.845	0.955	0.90
Soil N	Lognormal	0.001	0.25			
N Runoff Coeff.	Lognormal	0.05	0.25			
N Leach. Coeff.	Lognormal	0.25	0.25			

Table 5-6. Input parameters and their distributions used in the fifth run.

Parameter	Distribution	Mean	Cv	Min.	Max.	Mode
S-Value	Normal	2.66	0.50			
Slope	Normal	4.00	0.30			
K-Factor	Uniform	0.24	0.14	0.18	0.30	0.24
C-Factor	Uniform	0.012	0.20	0.008	0.016	0.012
P-Factor	Uniform	0.90	0.05	0.82	0.98	0.90
Soil N	Normal	0.001	0.50			
N RO Coeff.	Normal	0.05	0.50			
N Leach. Coeff.	Normal	0.25	0.50			

Table 5-7. Input parameters and their distributions used in the sixth run.

Parameter	Distribution	Mean	Cv	Min	Max	Mode
S-Value	Lognormal	2.66	0.125			
Slope	Lognormal	4.00	0.075			
K-Factor	Triangular	0.24	0.035	0.219	0.261	0.24
C-Factor	Triangular	0.012	0.05	0.011	0.0135	0.012
P-Factor	Triangular	0.90	0.0125	0.872	0.928	0.90
Soil N	Lognormal	0.001	0.125			
N RO Coeff.	Lognormal	0.05	0.125			
N Leach. Coeff.	Lognormal	0.25	0.125			

Table 5-8. Input parameters and their distributions used in the seventh run.

Parameter	Distribution	Mean	Cv	Min	Max	Mode
S-Value	Triangular	2.66	0.5	0	6.293	1.687
Slope	Triangular	4.00	0.3	1.061	6.939	4
K-Factor	Triangular	0.24	0.14	0.158	0.322	0.24
C-Factor	Triangular	0.012	0.2	0.00612	0.018	0.012
P-Factor	Triangular	0.90	0.05	0.79	1.01	0.90
Soil N	Triangular	0.001	0.5	0	0.0024	0.00064
N RO Coeff.	Triangular	0.05	0.5	0	0.118	0.0318
N Leach. Coeff.	Triangular	0.25	0.5	0	0.591	0.159

CHAPTER VI

RESULTS, CONCLUSIONS AND RECOMMENDATIONS

Results of the Simulation runs

If one assumes that the AGNPS model is valid, the uncertainty in model outputs is due to uncertainty in input parameters. A measure of parameter uncertainty is the coefficient of variation (Cv), which is a function of the mean and standard deviation. The output results of the 1500 simulation runs were obtained and analyzed. Statistical properties of the outputs for each simulation run are given in tables 6-1 through 6-7.

Table 6-1. Descriptive statistics of the first simulation run.

STATS	RUNOFF, inches	SED.,tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN	0.150	0.050	0.010	0.050	0.060
MAX	3.070	1.570	17.930	3.930	0.940
MEAN	1.827	0.283	2.200	0.463	0.230
VAR	0.280	0.034	4.986	0.131	0.014
STD DEV	0.529	0.184	2.232	0.362	0.117
Cv	0.290	0.650	1.013	0.781	0.510

Table 6-2. Descriptive statistics of the second simulation run.

STATS	RUNOFF, inches	SED., tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN	0.150	0.060	0.010	0.020	0.070
MAX	3.070	0.960	18.150	2.030	0.630
MEAN	1.827	0.291	2.460	0.483	0.236
VAR	0.280	0.030	8.867	0.126	0.013
STD DEV	0.529	0.173	2.980	0.354	0.112
Cv	0.290	0.595	1.211	0.733	0.475

Table 6-3. Descriptive statistics of the third simulation run.

STATS	RUNOFF, inches	SED., tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN	0.930	0.060	0.050	0.020	0.070
MAX	3.280	0.990	22.410	2.320	0.640
MEAN	1.849	0.291	2.930	0.483	0.236
VAR	0.441	0.030	14.187	0.125	0.013
STD DEV	0.664	0.173	3.767	0.353	0.112
Cv	0.359	0.595	1.286	0.731	0.475

Table 6-4. Descriptive statistics of the fourth simulation run.

STATS	RUNOFF, inches	SED., tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN	0.780	0.100	0.050	0.150	0.110
MAX	2.490	0.710	7.840	1.550	0.470
MEAN	1.748	0.257	1.383	0.436	0.215
VAR	0.084	0.008	0.892	0.029	0.003
STD DEV	0.290	0.090	0.945	0.170	0.058
Cv	0.166	0.350	0.683	0.391	0.270

Table 6-5. Descriptive statistics of the fifth simulation run.

STATS	RUNOFF, inches	SED., tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN.	0.55	0.03	-6.24	-0.14	0.04
MAX.	3.74	1.15	50.41	2.44	0.73
MEAN	1.843	0.285	3.225	0.468	0.232
VAR	0.426	0.029	30.632	0.124	0.012
STD DEV	0.652	0.171	5.535	0.352	0.111
Cv	0.354	0.601	1.716	0.753	0.477

Table 6-6. Descriptive statistics of the sixth simulation run.

STATS	RUNOFF, inches	SED., tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN.	1.22	0.150	0.190	0.240	0.140
MAX.	2.14	0.500	3.390	0.900	0.370
MEAN	1.725	0.255	1.135	0.435	0.217
VAR.	0.023	0.0025	0.186	0.008	0.001
STD DEV	0.15	0.050	0.431	0.090	0.034
Cv	0.087	0.198	0.380	0.208	0.159

Table 6-7. Descriptive statistics of the seventh simulation run.

STATS	RUNOFF, inches	SED., tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN.	0.680	0.050	0.040	0.000	0.060
MAX.	3.620	1.130	28.290	2.870	0.720
MEAN	1.844	0.287	2.752	0.478	0.234
VAR.	0.392	0.095	12.937	0.123	0.012
STD DEV	0.626	0.172	3.597	0.351	0.111
Cv	0.340	0.598	1.307	0.743	0.474

The following is a summary of all simulation runs regarding changes in means and variances for each output parameter.

Runoff

The results of the first, second, third, fifth and seventh runs, showed similar means. The fourth and sixth runs showed similar means, but lower than the values of the other runs.

The first and second runs showed similar variances. The third, fifth and seventh simulation runs resulted in similar variances, but higher than other runs.

The fourth and the sixth runs indicated different values of variances (lower than those of the other runs):

Sediment

The mean values of the sediment resulted from the first, second, third and fifth runs were similar. The mean of the fourth and sixth runs were similar. The mean of the seventh simulation run was the highest among mean values of other simulation runs.

The first, second, third, and fifth simulation runs resulted in similar values of variances. The fourth and sixth runs resulted in lower values of variances. The seventh run resulted in a different value of variance.

Nitrogen in runoff

The first and second runs resulted in similar values of the mean. The third and seventh runs resulted in similar values of the mean. The fourth and sixth runs indicated

similar values of mean. The fifth run resulted in a higher value of the mean.

The results showed that each simulation run had a different value of variance.

Nitrogen in sediment

Results of the first, second, third, fifth and seventh simulation runs showed similar values for the mean. The fourth and sixth runs showed similar values of the mean, but lower than the values of other runs.

The second, third, fifth and seventh runs resulted in similar values of variances. The first run had the highest value, the fourth run had the lowest value and sixth run resulted in a different variance.

Phosphorus in sediment

The first, second, third, fifth and seventh runs showed almost similar values of the mean of the phosphorus in sediment. The fourth and sixth runs resulted in similar values of mean as well.

The first, second, third, fifth and seventh runs resulted in similar values of variances. The fourth and sixth runs resulted in similar values of variances.

Probability plots of the outputs are given in figures 6-1 through 6-10. Recall that simulations 1, 2, 3, 5 and 7 used different parameter distributions with the same means and variances, while simulation runs 1, 4 and 6 used the same pdfs with different variances.

The plots showed that the first, second, third, fifth and the seventh simulation runs have similar results for all output parameters. The results of the fourth and the sixth runs

were different.

The results of the fifth simulation run showed negative values for the nitrogen in runoff (-6.24), and nitrogen in sediment (-0.14), which is not possible. The negative values of the outputs obtained in this run were because the normal distribution was used. The range on any random variable that is normally distributed is the entire real line ($-\infty$ to $+\infty$). In order for the normal distribution to result in positive values of the outputs, the mean of the random variable should be 3 to 4 times greater than its standard deviation (Haan, 1977).

Statistical tests were conducted to determine if the means for the various simulations were statistically significantly different than the mean of the first or the base run. The results of these tests are presented in table 6-8.

Table 6-8. t- values resulting from statistical test on means.

Simulation number	Output Parameters				
	RO	Sed.	N. in RO	N. in SED	P. in SED
2	0	-1.2	-2.71	-1.53	-1.41
3	-1	-1.2	-6.46	-1.53	-1.41
4	5.07	4.9	13.05	2.61	4.46
5	-0.74	-0.3	-6.65	-0.38	-0.48
6	7.17	5.67	18.13	2.91	4.11
7	-0.8	-0.43	-5.05	-1.15	-0.96

$t > 1.645$ is significant.

These statistical tests may not be physically meaningful since the degrees of freedom were so large (1499) that a very small physical difference of the tests statistically significantly different. When in practice the difference is of no practical consequence.

Bartlett's test for homogeneity of variances was also conducted for runs 1, 2, 3, 5 and 7 for all outputs. Again the results indicate statistically significant difference when in practice the differences may be of no physical significance.

Analysis of the simulation results

Confidence intervals (CIs) can be computed such that a given percent of the output distribution is included in within these CIs. The upper and lower 95% confidence intervals for the output parameters of the seven simulation runs are calculated from the spread sheets containing the output values and the plotting positions corresponding to these values for the different parameters, the lower 90% values were taken as the values of the outputs corresponding to the 0.05 plotting position, and the upper 90% values were taken as the values of the output parameters corresponding to the 0.95 plotting position. They are given in table 6-9.

Table 6-9. The lower and upper 90% CIs of the AGNPS model outputs for all simulation runs.

OUTPUT	First run		Second run		Third run		Fourth run	
	L 90%	U 90%	L 90%	U 90%	L 90%	U 90%	L 90%	U 90%
Runoff, (in)	0.88	2.67	0.88	2.67	0.99	3.07	1.28	2.23
Sed. (tons)	0.11	0.72	0.1	0.66	0.1	0.65	0.15	0.42
Runoff N., (lbs/ac)	0.11	6.68	0.12	8.76	0.09	11.02	0.29	3.27
Sed. N., (lbs/ac)	0.14	1.23	0.07	1.17	0.07	1.17	0.23	0.75
Sed. P., (lbs/ac)	0.12	0.5	0.1	0.47	0.1	0.46	0.14	0.33

Table 6-9. Continued.

OUTPUT	Fifth run		Sixth run		Seventh run	
	L 90%	U 90%	L 90%	U 90%	L 90%	U 90%
Runoff, (in)	0.99	3.17	1.47	1.98	0.93	2.97
Sed. (tons)	0.09	0.63	0.19	0.33	0.1	0.64
Runoff N., (lbs/ac)	0.08	14.63	0.53	1.94	0.1	10.45
Sed. N., (lbs/ac)	0.05	1.15	0.31	0.59	0.09	1.17
Sed. P., (lbs/ac)	0.1	0.45	0.17	0.27	0.1	0.46

The observed average values of AGNPS outputs are presented in table 6-10 for comparison with the simulated results. Since the purpose of this study was not to evaluate AGNPS, further discussion of the observed and calculated results will not be given.

Table 6-10. Observed average values of the outputs of AGNPS.

OUTPUTS	OBSERVED VALUES
Runoff, (inches)	1.13
Sed. , (tons)	0.192
Runoff N., (lbs/ac)	0.117
Sed. N., (lbs/ac)	0.899
Sed. P., (lbs/ac)	0.566

Conclusions and Recommendations

The purpose of this study was to investigate whether the type of the distribution of the input parameters, or the variance of these parameters have an effect on the uncertainty of the model outputs. The AGNPS model was used in this study. A total of seven different simulation runs were conducted. The first, second, third, fifth and seventh runs used the same mean and Cv values, but different pdfs. The first, fourth and sixth runs used the same pdfs, but different values of Cv's. The results showed that changing the distribution of the input parameters (runs 1, 2, 3, 5 and 7) lead to minor changes in the of Cv's for most of the output parameters.

The results of the fourth and the sixth runs showed a drastic decrease in the values of the Cv's compared to the value of the first run, because I reduced the values of the Cv's of the input parameters used in the first run. The decrease of the Cv value of the outputs was proportional to the decrease of the Cv value used in the inputs.

In the fifth simulation run the means of some input parameters like the soil nitrogen, nitrogen coefficient for runoff and nitrogen coefficient for leaching are not 3 times greater than the standard deviation of these parameters. In this situation negative values for some of the inputs were generated from the normal distribution which resulted in negative values of the outputs. The mean of a hydrologic variables should exceed 3 or 4 times the standard deviation for these variables to be normally distributed.

In general one concludes that changing the type of the distribution of the input parameters has little or no effect on output uncertainty. It was very clear that the variance

of the input parameter distribution, has a significant impact on the uncertainty of the model outputs.

It is recommended that more comprehensive studies are needed using different H/WQ models and different distributional assumptions, to validate these results. It is also recommended that future studies of this subject should concentrate on the values of the variances of the input parameters rather than the type of distribution for these parameters, as the variances have a great impact on the uncertainty of the model outputs.

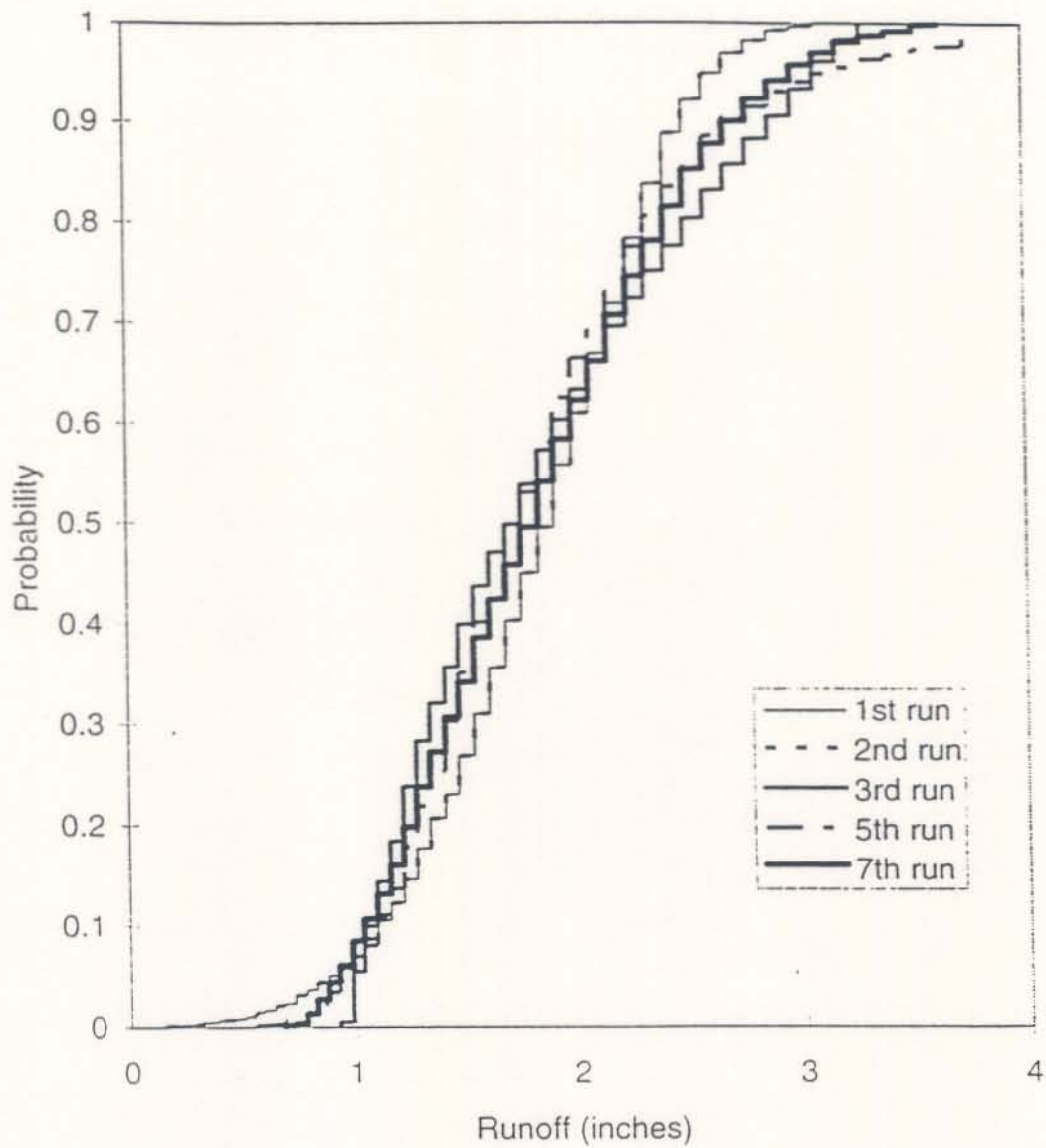


Figure 6-1. Runoff probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs.

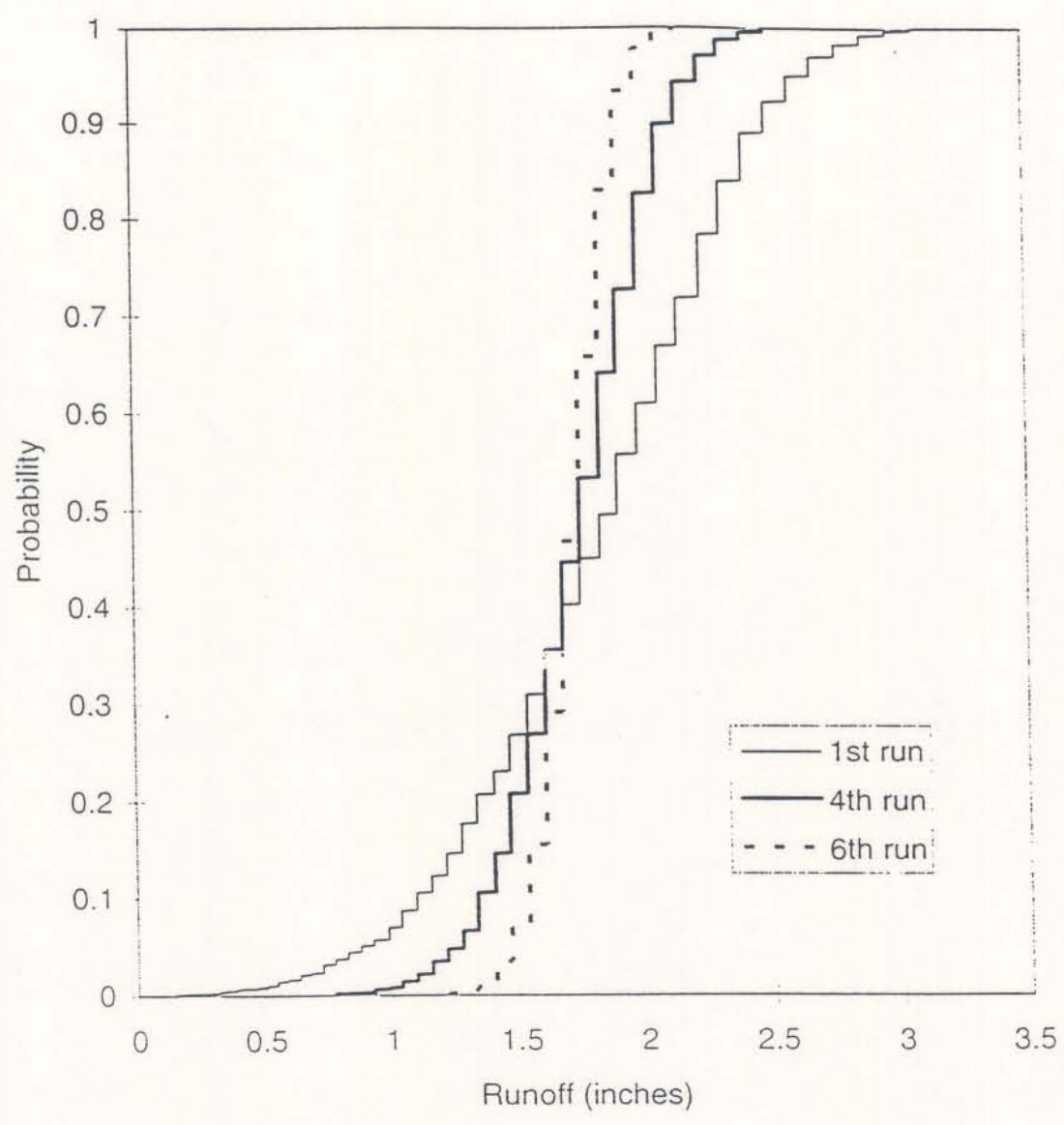


Figure 6-2. Runoff probability distribution for the 1st, 4th and the 6th simulation runs.

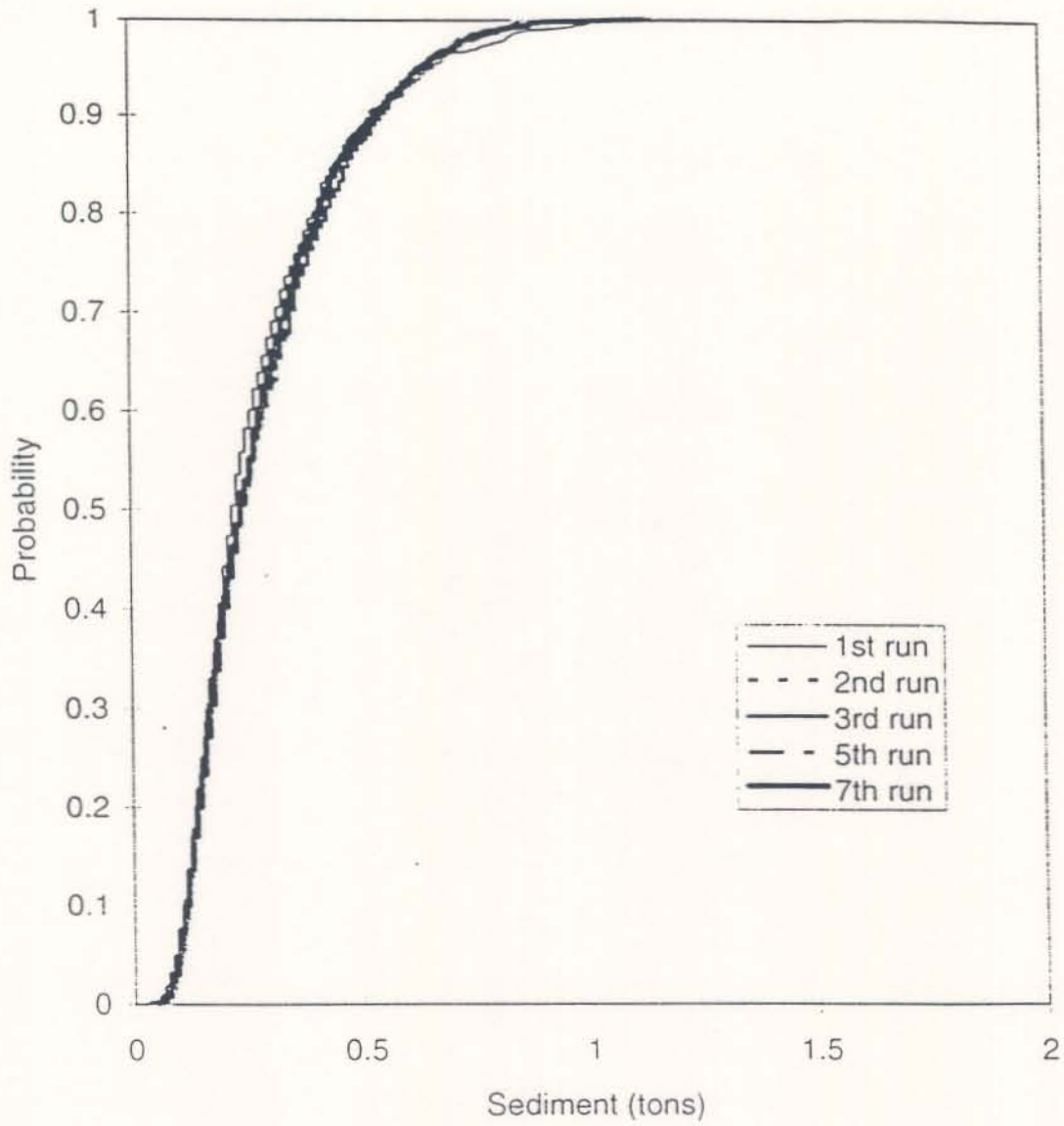


Figure 6-3. Sediment probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs.

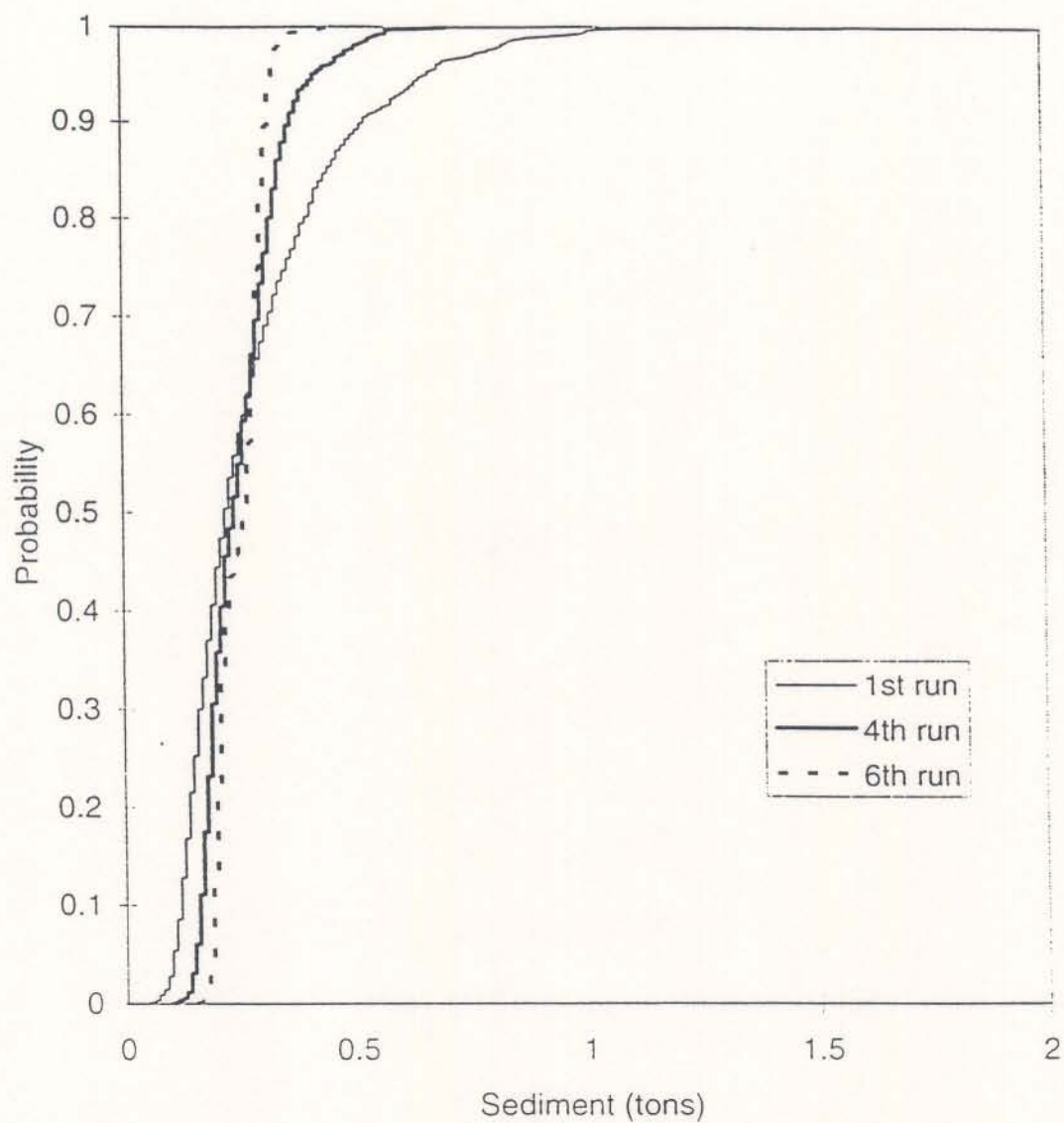


Figure 6-4. Sediment probability distribution for the 1st, 4th and the 6th simulation runs.

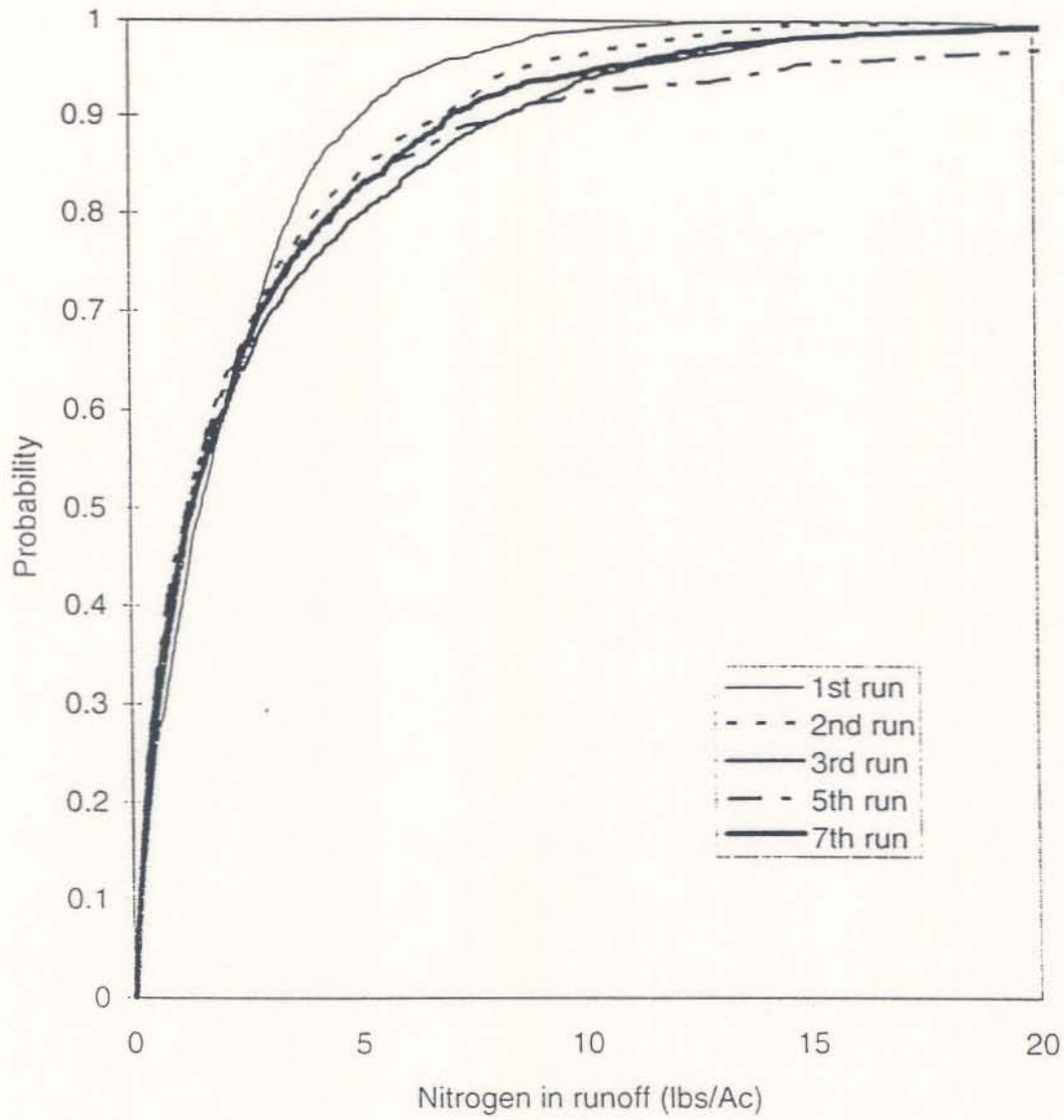


Figure 6-5. Nitrogen in runoff probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs.

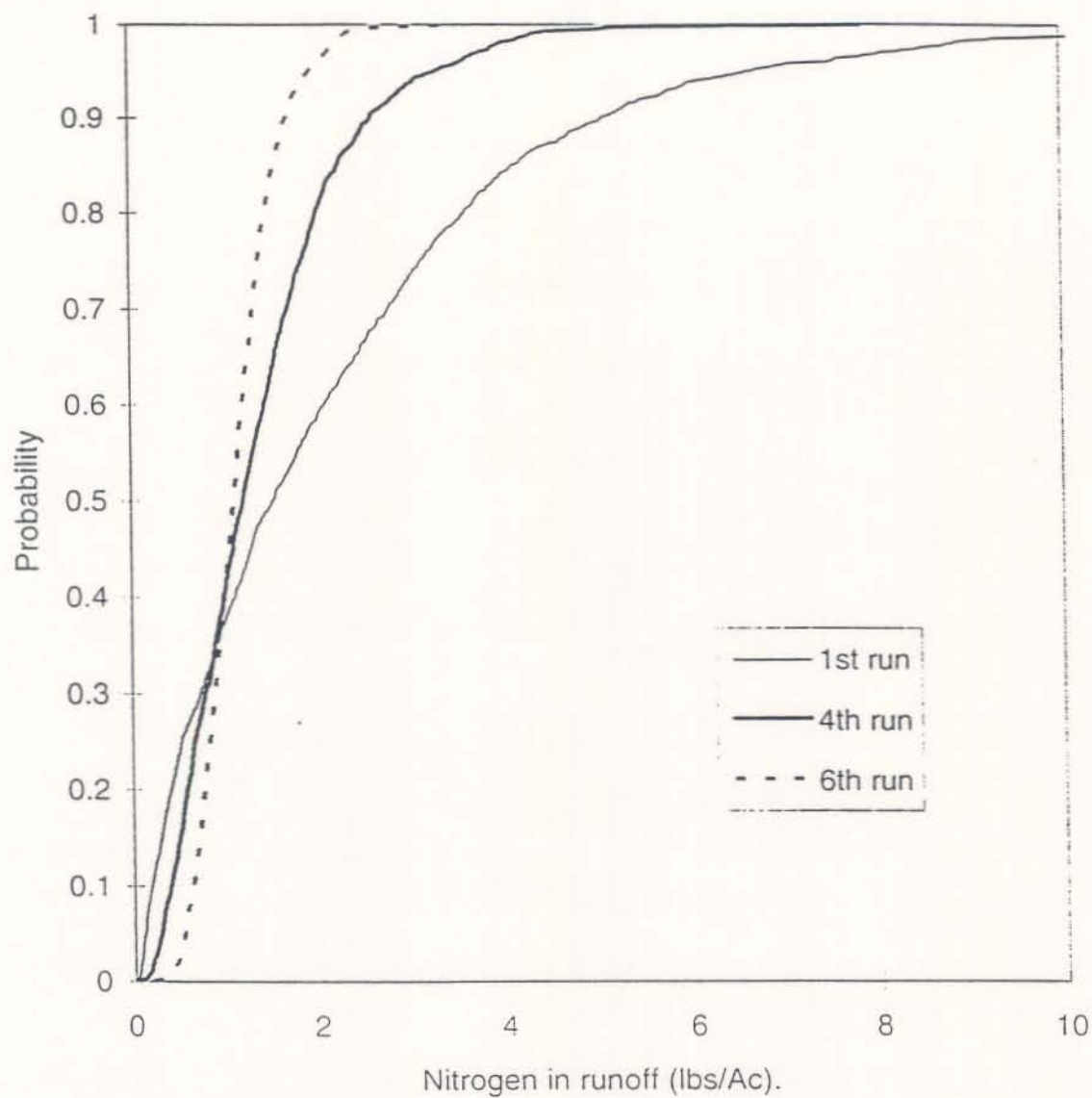


Figure 6-6. Nitrogen in runoff probability distribution for the 1st, 4th and the 6th simulation runs.

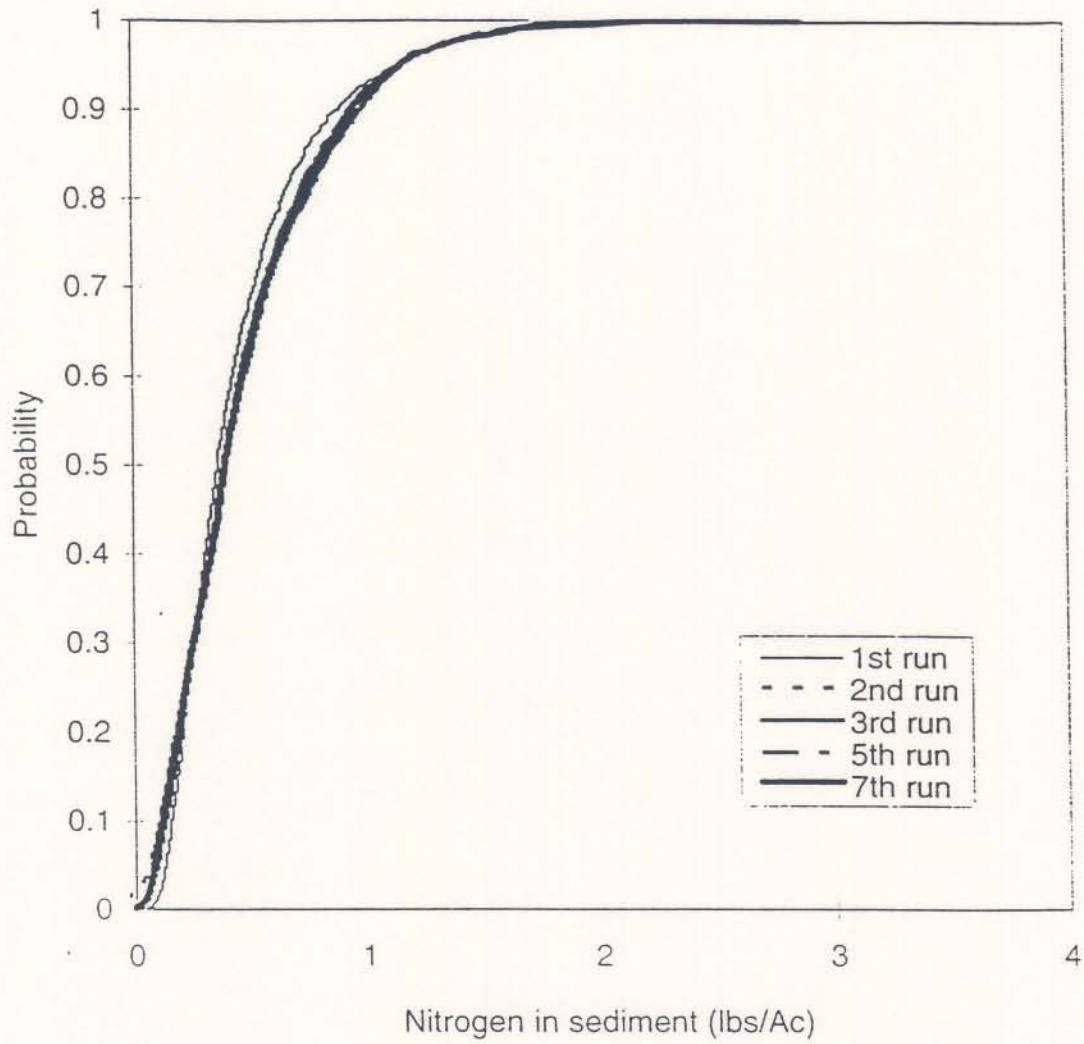


Figure 6-7. Nitrogen in sediment probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs.

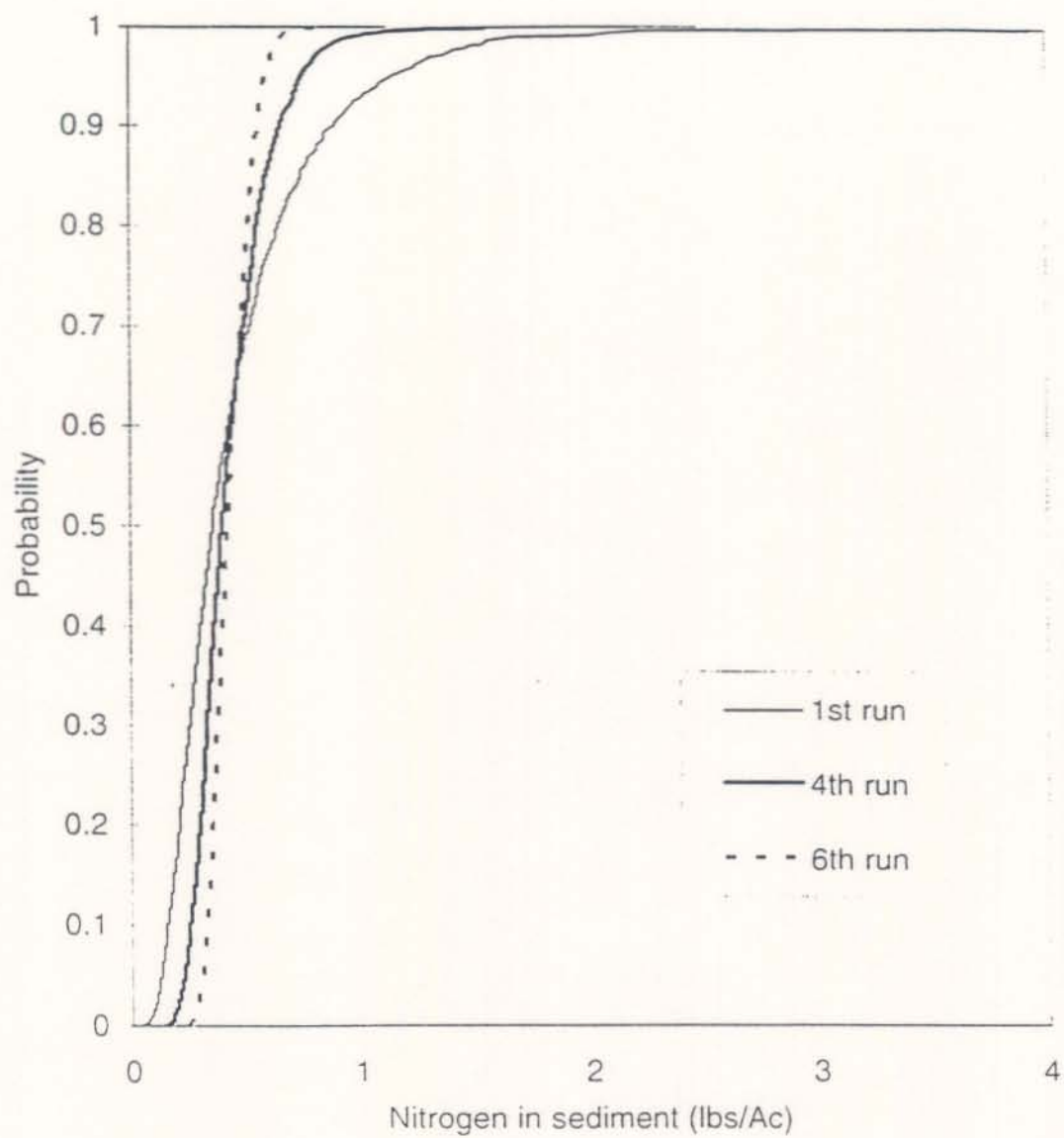


Figure 6-8. Nitrogen in sediment probability distribution for the 1st, 4th and the 6th simulation runs.

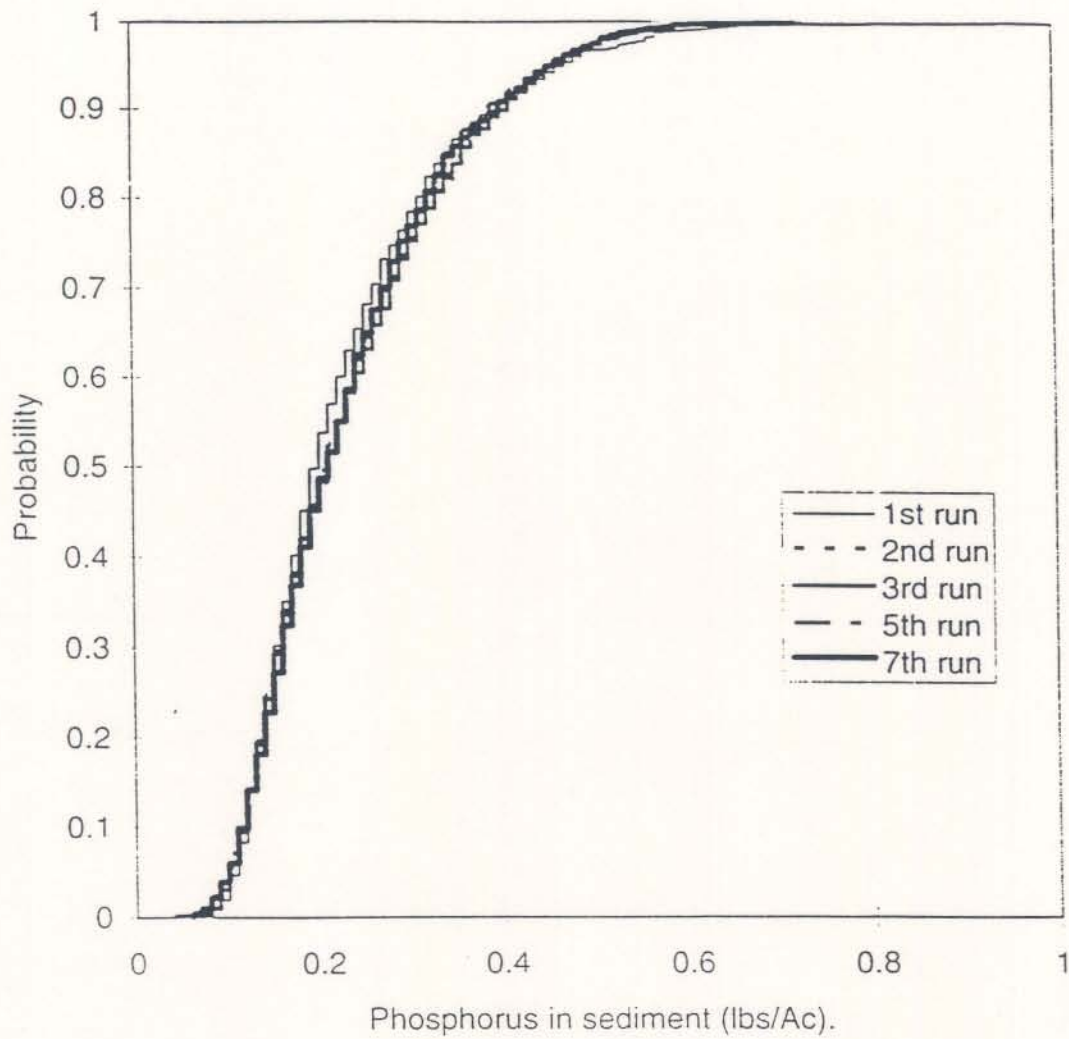


Figure 6-9. Phosphorus in sediment probability distribution for the 1st, 2nd, 3rd, 5th and the 7th simulation runs.

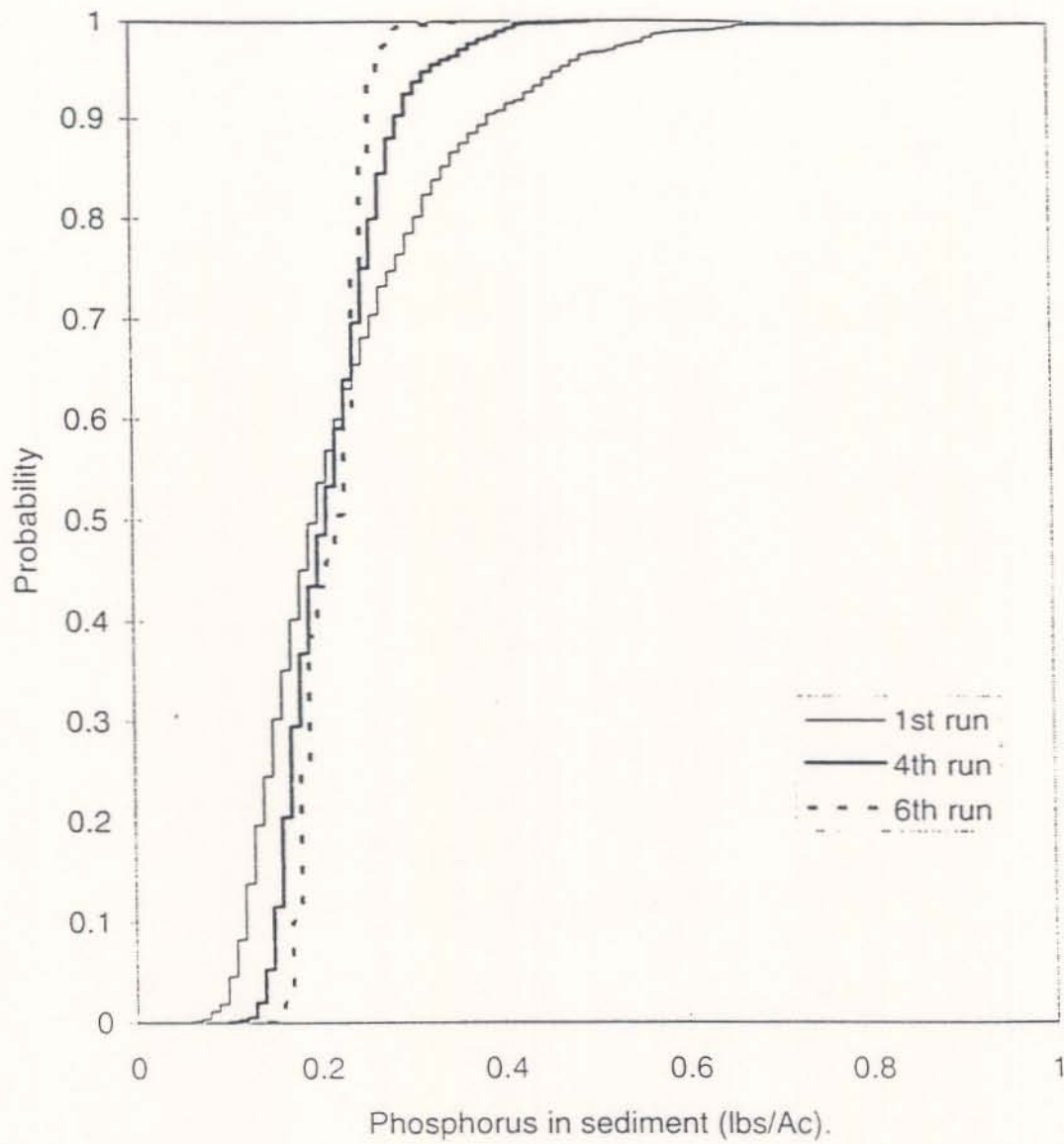


Figure 6-10. Phosphorus in sediment probability distribution for the 1st, 4th and the 6th simulation runs.

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A computer program that updates AGNPS input data files.

APPENDIX A

```

ccc agtst2.for      10/3/95
c
cc program to update AGNPS input data files
c
c ---- A "different" random number is used to update a parameter in a cell
c   if NSIMTYPE = 1
c ---- The "same" random number is used to update a parameter for all the
c   cells if NSIMTYPE = 2
c
c datagnps.fil: master input file
c agnpsin: the input file name that AGNPS reads
c countin: the file name where the counter value is saved
c randomin: the name of the file containing the random values sets
c valout: the file where the values extracted from distributions
c   are saved. This file will be generated to look at the
c   distributions of each parameter(if needed later in the analysis).
c parin: the file where the characteristics of parameter distributions
c   are saved
c ncell: # of cells in the watershed
c npar : # of parameters that will be updated
c idp: the I.D. # of the parameter
c idd: the I.D. # of the distribution
c avg: average value
c Cv : coefficient of variation
c xmin: minimum value
c xmax: maximum value
c xmode: mode value
c rval: random value
c actual: the value found from the distribution
c ncount: counter defining the line where to read the random # from
c
c -- nsimtype = defines if 1 or multiple random numbers are used
c     1 ==> complete independence between the cells
c     2 ==> complete correlation between the cells
c
dimension avg(20,8),Cv(20,8),xmin(20,8),xmax(20,8),
*      xmode(20,8),rval(20,8),actual(20,8)
integer idp(8),idd(8)
character agnpsin*30,countin*30,randomin(8)*30
character valout(8)*30,parin*30,tmpch(8)*80
open(1,file = 'agnpstst.fil', status = 'old')
read(1,*) agnpsin,countin,parin
open(6,file = agnpsin,status = 'old')

```

```

open(2,file = countin,status = 'old')
open(5,file = parin,status = 'old')
open(7,file = 'filtmp',status = 'unknown')
read(1,*) nsimtype
do 130 j = 1,8
  idp(j) = 0
  idd(j) = 0
do 130 i = 1,20
  avg(i,j) = 0
  Cv(i,j) = 0
  xmin(i,j) = 0
  xmax(i,j) = 0
  xmode(i,j) = 0
  actval(i,j) = 0
  rval(i,j) = 0
130 continue
read(5,*) ncell,npar
read(1,*,err=903) (randomin(k),k=1,npar)
read(1,*,err=902) (valout(k),k=1,npar)
C
read(5,*) (idp(k),idd(k),k=1,npar)
do 230 i = 1,ncell
do 230 j = 1,npar
  read(5,*) avg(i,j),Cv(i,j),xmin(i,j),xmax(i,j),xmode(i,j)
230 continue
read(6,310)tmpch(1)
write(7,311)tmpch(1)
read(6,310)tmpch(1)
write(7,311)tmpch(1)
read(6,310)tmpch(1)
write(7,311)tmpch(1)
read(6,310)tmpch(1)
write(7,311)tmpch(1)
read(6,310)tmpch(1)
write(7,311)tmpch(1)
read(6,310)tmpch(1)
write(7,311)tmpch(1)
read(6,310)tmpch(1)
write(7,311)tmpch(1)
310 format(A64)
311 format(t1,A64)
read(2,*)ncount
c
iun=10
do 334 mm=1,npar

```

```

426  continue
      endif
      write(iun,427) (actval(k,mm),k=1,ncell)
427  format(f7.3,19(',f7.3))
430  continue
c
c
  do 450 k=1,ncell
    read(6,*,err=901) i1,i2,i3,i4,i5,icn,slp,i8
c  write(*,701) i1,i2,i3,i4,i5,icn,slp,i8
    read(6,*,err=902) n1,p2,fk,fc,fp,p6,n7
    read(6,310) tmpch(3)
    read(6,703) tmpch(4),exsn,tmpch(5)
    read(6,*,err=903) exqn,t2,exfn,t4,k5
    do 440 mm=1,npar
      if(idp(mm).eq.1) icn=actval(k,mm)
      if(idp(mm).eq.2) slp=actval(k,mm)
      if(idp(mm).eq.3) fk=actval(k,mm)
      if(idp(mm).eq.4) fc=actval(k,mm)
      if(idp(mm).eq.5) fp=actval(k,mm)
      if(idp(mm).eq.6) exsn=actval(k,mm)
      if(idp(mm).eq.7) exqn=actval(k,mm)
      if(idp(mm).eq.8) exfn=actval(k,mm)
440  continue
      write(7,701) i1,i2,i3,i4,i5,icn,slp,i8
      write(7,702) n1,p2,fk,fc,fp,p6,n7
c  write(7,311) tmpch(2)
      write(7,311) tmpch(3)
      write(7,703) tmpch(4),exsn,tmpch(5)
      write(7,704) exqn,t2,exfn,t4,k5
c  write(7,311) tmpch(5)
      read(6,310) tmpch(3)
      write(7,311) tmpch(3)
      read(6,310) tmpch(3)
      write(7,311) tmpch(3)
      read(6,310) tmpch(3)
      write(7,311) tmpch(3)
      read(6,310) tmpch(3)
      write(7,311) tmpch(3)
701  format(6i8,f8.1,i8)
702  format(t9,i8,f8.3,f8.2,f8.4,2f8.2,i8)
703  format(a8,f8.4,a24)
704  format(t9,4f8.3,i8)

```



```

450 continue
    write(7,*)
    rewind (6)
    rewind (7)
    do 500 i = 1,10000
        read(7,310,end=510)tmpch(1)
        write(6,310)tmpch(1)
500 continue
510 continue
    go to 904
901 write(*,*) 'error 901 ',k
902 write(*,*) 'error 902 ',k
903 write(*,*) 'error 903 ',k
904  continue
    stop
    end
    Subroutine cn2out(nd,np,xav,xCv,xmn,xmx,xmd,rand,iCN)
c  write(*,*) 'in cn2out nd=',nd
    if(nd.eq.1) call lognorm (xav,xCv,sval,rand)
    if(nd.eq.2) call triangle (xmn,xmd,xmx,sval,rand)
    if(nd.eq.3) call normal (xav,xCv,sval,rand)
    if(nd.eq.4) call uniform(xmn,xmx,rand,sval)
    if(sval.lt.0) sval=0
    icn = 1000.0/(sval+10.0)
    return
    end
c
c  Subroutine lognorm(avval, coefvar, logval,ranval)
    Real avval,stddev,rnn,rnor,logval,coefvar
    ybar = 0.5*log((avval**2)/((coefvar**2)+1))
    stddev = sqrt(alog((coefvar**2)+1))
    tranval=ranval
    rnn = tranval
    rnor = ybar + rnn * stddev
c
C  The random value rnor would be converted to the
c  lognormal distribution by using exp function
c
    logval = exp(rnor)
    end
c
c  Subroutine normal(avval, coefvar, actual,ranval)
    Real avval,stddev,rnn,rnor,actual,coefvar

```

```

ybar = avval
stddev = coefvar*ybar
tranval=ranval
rnn = tranval
rnor = ybar + rnn * stddev
c
C The random value rnor would be converted to the
c lognormal distribution by using exp function
c
  actval = rnor
  end
c
  Subroutine triangle(a1, a2, a3, val,ranval)
C*** estimate paramter values from a triangular distribution
  Real a1, a2, a3, val,ranval
  tmp=a3-a1
  if(tmp.eq.0) tmp=-1
  area1=(a2-a1)/(a3-a1)
  If (ranval.le.area1) then
    val = a1 + sqrt((a3-a1)*(a2-a1)*ranval)
  else
    val = a3 - sqrt((a3-a2)*(a3-a1)*(1-ranval))
  endif
  end
c
  subroutine uniform(xmn,xmx,rand,sval)
c write(*,*) xmn,xmx,rand
  sval=xmn+(xmx-xmn)*rand
  end
c

```