APPLICATION OF STOCHASTIC MODEL EVALUATION PROTOCOL ON EPIC AND AGNPS

By

SANDEEP PRABHU

Bachelor of Engineering

University of Mysore

Mysore, India

1991

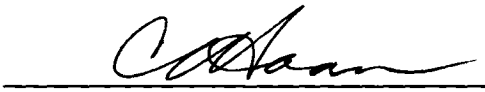
Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
May, 1995

APPLICATION OF STOCHASTIC MODEL

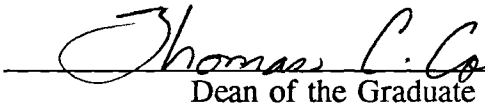
EVALUATION PROTOCOL ON

EPIC AND AGNPS

Thesis Approved:



Thesis Advisor



Dean of the Graduate College

ACKNOWLEDGEMENTS

I wish to express sincere appreciation to my advisor, Dr. C. T. Haan for his advice, kind guidance and especially for his wonderful patience throughout my graduate program. Many thanks go to Dr. D. Storm and Dr. M. Smolen for serving on my graduate committee. Their suggestions and support were very helpful for this study.

I need to express my sincere appreciations for Dr. George Sabbagh whose support was vital for this effort. I also acknowledge many thanks to Dr. Edwards, Assistant Professor, University of Arkansas for providing me with the data for this study. I appreciate the helpful suggestions by Mr. T. S. Ramanarayanan.

I would also like to express my sincere gratitude to Biosystems and Agricultural Engineering Department for providing me with financial resources and made my graduation a reality.

I would like to dedicate this book to my parents Vatsala and Vasudev, who have encouraged and supported me in every aspect of my life's endeavors.

Finally, my sincere gratitude for Balaji, Meyyappan and Jawahar who were very patient with me and who made my stay in Stillwater a wonderful experience. Many thanks to the Duck gang for fun.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figures Page

NOMENCLATURE

AGNPS	AGricultural Non Point Source
BD	Bulk Density
cdf	Cumulative Distribution Function
CI	Confidence Intervals
CN	Curve Number
C_v	Coefficient of Variation
EPIC	Erosion Productivity Impact Calculator
FC	Field Capacity
FOA	First Order Analysis
K-S	Kolmogorov Smirnov
l	Lower Limit
LN	Lognormal
MCS	Monte Carlo Simulation
N	Nitrogen
P	Phosphorus
pdf	Probability Distribution Function
S	Retention Parameter
u	Upper Limit

CHAPTER I

INTRODUCTION

Hydrologic/water quality models are developed to represent nature in its simplified form. Modeling is much more than reading data from tables and graphs and inputing them into a file in a computer. Models range in complexity from representing one or two processes with a few parameters to complex models which group the hydrologic processes into modules with many parameters. Models are used as an analysis and design tool and to improve our understanding of hydrologic systems (Barfield et al., 1989).

Any model consists of a number of parameters which are based on many physical processes and/or numbers representing the state of nature. There are many uncertainties involved in modeling. Vicens et al. (1975) classifies hydrologic uncertainty into three categories: inherent variability in natural processes which the modelers are trying to represent, uncertainty involved in physical representation of the processes in the model itself and uncertainty due to parameters that reflects incomplete models, incomplete information and inadequate estimation techniques. It is this later source of uncertainty that is addressed in this work.

Given so much uncertainty associated with a modeling effort, an evaluation of the model to determine how well it predicts the output is of immense interest to model users. A rigorous validation of models is called for. Validation refers to the process of determining the ability of the model to estimate the quantities the model was designed to estimate. Likewise verification refers to a process of demonstrating that the model algorithms perform as they were intended to perform. Calibration is a procedure whereby model parameters are varied, manually or otherwise, to produce parameter estimates that meet some criteria regarding the error in the predictions being made by the model (Haan et al., 1993).

When a model is being developed it will be tested in a research setting. DeCoursey (1988) notes that from a series of papers at an International Symposium, "..Only one paper shows performance of the model against real data". The causes for this lack of model evaluation is analyzed by an ASCE task committee (1993). It notes that "... Such work (validating and/or field testing) is not as interesting as trying new concepts and models. Finally good testing is a lot of work... will probably not reinforce previous claims ".

To be fair to the model developers, the actual processes occurring in the field are more complex and variable than currently represented in the most sophisticated models. Algorithms are included in a model that are designed to represent processes that are not included in the model or are partially represented in the model. The estimation of even physically based parameters from data measured to represent these physical processes may not yield the best estimates for the parameters (Haan et al., 1993).

Summing up, the fruitful transfer of models to the end user requires some kind of assessment of the model. Many researchers have evaluated models based on some statistical tests. These evaluations suffer from a number of limitations. Morever the scientific community has not come to any unanimous conclusions about the validity of these tests.

CHAPTER II

REVIEW OF LITERATURE

Literature reviewed in support of this study included works which addressed model evaluation, model validation and model calibration. While the literature concerned with the model evaluation effort is given more attention and reviewed in detail, it was felt the review of literature on calibration, validation and verification is important as they constitute a major part of model evaluation effort. Literature pertaining to sensitivity analysis and Monte Carlo Analysis are reviewed in later chapters.

The last task in model development is the validation of the model. This is usually done by comparing the model simulated values with observed values. Generally the validation is done for individual sites. The comparisons are summarized in tables and/or graphs. Some peer groups have tried to establish some standards in model testing.

An ASCE task committee (1993) discussed criteria for evaluation of watershed management models. Their recommendations for accomplishing this task were concerned with functions of the differences between observed and predicted data. They used mainly hydrograph models for illustration purposes. They reviewed some of the statistical tests used by some researchers (Martinec and Rango, 1989; Green and Stephenson, 1986). Even though they recommended some simple statistical tests, there were no criteria to

identify acceptable models from unacceptable models. They also did not address the problem of separating model evaluation from parameter estimation. Since there is no agreement at this stage in the research community concerning model evaluation, the statistical evaluations suggested by the committee may not be adaptable for standardization in scientific journals.

Shaeffer (1980) has presented a good treatise on the model evaluation methodology. This approach consists of six major tasks. Model examination, data evaluation, sensitivity analysis, validation studies and code comparison studies. He recommends validation should be part of model development. Validation types can be defined as statistical, deviative and qualitative. If the output is statistical in nature, the accuracy and precision of the predicted and measured quantities should match. Deviation validation can be applied in cases where the output can not be termed statistical, as the data are insufficient. A deviation coefficient, which measures deviation of the predicted values from the measured values can be employed. Qualitative validity depends on the modelers or users judgement and can help in terming the model as good, fair, poor or such. For some models, 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.

James and Burges (1982) also discuss model development in detail, focussing on model calibration and testing. They recommend steps to be carried out in model building, development, calibration, parameter estimation, evaluation etc.. They recognize the importance of sensitivity analysis in model evaluation. When a model is calibrated, the

model results should match the recorded data, and the estimates of parameter values should be consistent with the watershed characteristics. They recommend that model calibration be done in subsets of parameters because some parameters have greater effect on certain outputs than on others.

One method of calibration is a systematic search pattern, changing parameters one at a time to check for errors, until all the parameters are tested. Another method incorporates sensitivity analysis and judgement of the modeler and parameters are adjusted depending on the error in predictions. The disadvantage with these methods, according to the authors, is that the parameter estimation process varies with the local hydrologic conditions and are difficult to program and are very sensitive to data errors.

The authors also recommend that model developers incorporate means for computing both a) the error associated with the estimated values of the parameters (for assessment of the calibration) and b) the error associated with the quantities estimated by the model. They recognize that the scattergram plot can be an aid in some model calibration. For example, in modeling runoff, the plots will show whether low and high flows are modeled correctly. Logarithmic plots of flows tend to show poor model performance at low flows. These procedures can be expanded to model testing too.

Papers by Clarke (1973) , Loehle (1983) and Ditmars et al. (1987) explain the semantics involved in the model development and testing. Clarke (1973) classifies models broadly into different types like stochastic and deterministic which are further subdivided into stochastic-conceptual, stochastic-empirical, deterministic-conceptual, deterministic-empirical. The feature, according to Clarke, that all the models appear to

have in common is that the observed values deviate from the fitted values by a residual amount (ε_i). The respects in which they differ are in the assumptions made about fitted values and the assumptions made about ε_i. According to Loehle (1983), there are two kinds of models: theoretical (which corroborates the law of nature) and predictive models (which are calculation tools to predict certain aspects of real world). While evaluating the theoretical models, sometimes it might be that the theory fails to 'fit' the data. But then the data itself might be wrong or the experiment might have been done incorrectly.

In case of predictive models, there can also be two distinctions. Application models are based on well established laws and theories in which laws are applied to solve a problem and calculation tools which are methods for obtaining answers which may not be based on any laws at all.

The author claims that with some of the calculation tools it is possible to modify the structure and form of the applicable equations progressively till the error is negligible. In case of application models, the things subject to adjustment are the boundary conditions and input parameters, while taking into account the inherent noise, which may not be always detectable. The type of test applied for model evaluation should consider these factors.

Ditmars et al. (1987), divide model users into three separate groups. They are modelers, general model users and decision makers. Model users are more output oriented, i.e using models to solve problems. Modelers, who design the model, need to evaluate whether the basic simulated process matches the real world behavior. Decision makers are more concerned with the reliability of model results and their cost

effectiveness. The authors also point out the difference between verification and validation and also evaluation. They divide model development into six elements : (1) Identification of the problem, (2) Relationship of the model to the problem, (3) Solution scheme examination, (4) Model response studies, (5) Model calibration, and (6) Model validation.

The authors emphasize the need for critical evaluation of the code which constitutes the model and also the ultimate model outputs vis-a-vis the model users. They point out the need to take into account the physical processes involved, the dimensional aspects (for example, the growth of phytoplankton and nutrient distribution in a lake eutrophication model necessitates the use of two or three dimensions), the time and space scale involved, and the boundary conditions.

The problem in model validation according to the authors, 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.

These papers lack analysis of statistical tests that can be used for model evaluation. They do not explore the area of parametric uncertainty nor the uncertainty in measured data itself.

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 use 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 in 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 small scale 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 differences 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 accuracy assessment reduces to an evaluation of the effects of parameter estimation errors.

Model validation proceeds in such a way as to first estimate the effects of measurement error and spacial heterogeneity and then assumes that discrepancies between measurements and predictions which can not be explained by these factors must be due to the model error. The null hypothesis to test the model is that model error is negligible.

The authors use some statistical tests to test this hypothesis.

(i) Mean Residual Test - A sample mean computed from many measurement residuals should be close to zero if hypothesis H_0 is true. The assumptions are that the measurements are sufficiently far apart for the residuals to be uncorrelated and normally distributed.

(ii) Mean Squared Residual Test - In this test, confidence bounds are put on these measurement residuals and if a significant number of measurements lie outside this region then the hypothesis would be rejected. If the measurements are closely spaced then the number of degrees of freedom can be reduced.

(iii) Spatial Structure Test - If there is some correlation between the measurement residuals, then it is possible to check whether or not the measurement residuals have a statistically, stationary spectral density, by passing the residuals through a spatial whitening filter. The output of this should be an uncorrelated series of adjusted measurement residuals, if the hypothesis H_0 that the residuals are independent is true.

The mean residual test checks for systematic biases, while the mean squared residual test checks for overall fit and the spatial structure test checks for more subtle spatial features. The authors note that these tests can be applied to all available measurements or to selected subsets such as all measurements taken at a particular time or along a particular transect. They caution, that this range of possibilities complicates the task of reaching an unequivocal yes or no conclusion about the results of a model validation.

This introduces considerable ambiguity in the model validation. As the authors themselves state, a particular method relies on some assumptions which can not be readily justifiable, such as knowledge of means, variances and correlation scales. If the uncertainties in soil property statistics that are used to compute the covariances and other quantities are taken into account, the validation confidence intervals will widen and the tests will become less stringent. These kind of tests need a lot of data which may be hard to obtain.

Model verification, according to Recknow et al. (1990), aims for a quantitative statement that the model adequately describes observed behavior so that it can be used as a prediction tool. They propose some statistical tests which augment the evaluation procedures which were used before, like graphical comparisons, professional reputation of models and also the judgement of the modelers. They state that as hypothesis testing is basically a decision process about the acceptance or rejection of a proposed hypothesis, it should be used together with other tools. For example, if the data are highly variable or the sample size is small or the residuals are also highly variable, then it can result in statistics that would favor the acceptance of null hypothesis. Graphical comparisons will indicate the likely cause of the hypothesis results like a good fit or inadequate data. If the sample data size is small, even though the statistical tests are favorable, the small data size will be apparent on a graph and indicate inadequacies in the testing approach.

The assumptions considered in these statistical tests are that the data have the properties of normality, equality of variances and independence. As for normality, it is generally believed that some natural data, such as contamination data, can be described

with a lognormal distribution. The lognormal transformation is generally recommended. Many tests are robust to mild violations of equality of variance. But the statistical procedures are not robust to the violation of independence assumption.

The tests recommended are the t-test, Wilcoxon test, regression test and Kolmogorov-Smirnov test. The t-test has limited robustness to violations of normality and equality of variances while there will be problems if the observations are dependent. The Wilcoxon test is designed to test the hypothesis that two random samples are drawn from identical continuous distribution with the same center against the alternative hypothesis that they are offset but otherwise identical. The Wilcoxon test is relatively powerful, and while not requiring normality, violations of independence is serious.

For the intercept, α, a hypothesis test with H_0: $\alpha=0$, could indicate a bias (constant overprediction or underprediction) in the predictions if the null hypothesis is rejected. For the slope β, a hypothesis test with H_0: $\beta=1$ could indicate increasing or decreasing error in the predictions if the null hypothesis is rejected. An important assumption for regression is the lack of covariance in the error term. In case of positive autocorrelation, the regression slope is inflated leading to false results. The authors argue that for the Kolmogorov-Smirnov test, there is no restrictive assumption of normality.

While it is desirable to run these tests along with graphical analysis and the judgement of the modelers, these tests suffer a number of limitations. First of all, it is up to the user to decide on the level of significance to conduct the tests. Secondly, the tests generally require a large sample size. It might be irrelevant to predict annual runoff, sediment, etc., and then compare it to the predicted value for conducting these tests.

Thirdly, when the assumptions outlined in these tests no longer hold, the alternative is not very clear. Nevertheless the authors make significant contribution towards the traps to be avoided in evaluating models.

Martinec and Rango (1989) emphasize three criteria used to evaluate hydrologic models. The criteria used are (i) The Nash-Sutcliff coefficient, R^2 (ii) Coefficient of gain from daily means, DG, and (iii) The volumetric difference between the total measured and computed runoff, D_v. For evaluation purposes, the authors compared nine rainfall runoff models.

The Nash-Sutcliff coefficient, R^2 is

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Q_i - Q_i^i)^2}{\sum_{i=1}^{n}(Q_i - \overline{Q})^2} \qquad (2\text{-}1)$$

where Q_i is measured daily discharge, Q_i^i is computed daily discharge, n is the number of daily discharge values and $\overline{Q}$ is average measured discharge.

When the R^2 values are compared for a wet and dry year, the R^2 value for dry year is lower than the wet year. The reasoning advocated by the authors is that $\overline{Q}$ is low for the dry year. DG is given by

$$DG = 1 - \frac{\sum_{i=1}^{n}(Q_i - Q_i^i)^2}{\sum_{i=1}^{n}(Q_i - \overline{Q}_j)^2} \qquad (2\text{-}2)$$

where $\overline{Q}_i$ is the average measured discharge from past years for each day of the period.

D_v is given by

$$D_v\ [\%] = \frac{V - V'}{V} x\ 100 \qquad (2\text{-}3)$$

where V is the measured yearly or seasonal runoff volume and V' is the computed yearly or seasonal runoff volume.

The analysis of R^2 is done by using different time periods and different seasons. Thus in method 1, the average value $\overline{Q}$ consisted of all the years in question. For method 2, the average value is only for the year considered. The R^2 values for method 2 is consistently less in drier years than in wetter years from method 1. The authors conclude that use of proper yearly values (method 2) gives a more realistic R^2.

Similarly the interrelation between R^2 and DG was explored minutely using different models and for different years for a basin. DG compared favorably in most of the occasions which can be attributed to the fact that the model results are compared to $\overline{Q}_i$. Finally the authors use all three criteria of model performance, R^2, DG and D_v to indicate the maximum inaccuracies of the individual models.

But the refrain is that there are numerous possible combination of yearly values that can be considered in a model evaluation which can lead to manipulation of evaluation results. Models where the underlying physical structure is as important as the output results can be misleadingly ranked by these statistical test. Furthermore the tests can confuse a user when the visual plot of observed and measured values can be comfortingly

close but when the statistical tests show that the model is not good enough, i.e. the test results are inadequate.

Along these lines Thomann (1982) also proposes some statistical tests to illustrate model verification. Those are (i) regression analysis, (ii) relative error, (iii) comparison of means, and (iv) root mean square error.

In regression analysis, the square of correlation coefficient, r^2, the standard error of estimate (representing the residual error between model and data), slope (b) and intercept (a) are used. Thomman notes that the evaluation of r^2, b and a together with residual standard error of estimate, can provide an additional level of insight into the comparison of model and data.

Relative error is given by $e = | \bar{x} - \bar{c} |$, where $\bar{x}$ is the observed mean and $\bar{c}$ predicted mean. Aggregations of the relative error can be made across space or time. Also the cumulative frequency of error over space or over time can be computed. One problem with this statistic is the relatively poor behavior at low values of x and the fact that it does not recognize the variability in the data.

The comparison of means is given by

$$t = \frac{\bar{d} - \delta}{S_d} \qquad (2\text{-}4)$$

in which δ is the true difference between model and data, $\bar{d}$ is the average and S_d is the standard deviation of the difference given by a pooled variance of observed and model variability.

$$S_d = \sqrt{2S_{\bar{x}}} \tag{2-5}$$

where $S_{\bar{x}}$ is the standard error of estimate of the observed data and equal to S_x^2/N .

Root mean square (rms) error is given by $e_r = \sqrt{\frac{\sum (x_i - c_i)^2}{N}}$ and it provides a direct measure of model error . If it is expressed as a ratio of the mean value, it represents a second type of relative error. The disadvantage, according to author, is that the rms error does not readily lend itself to pooling across variables to assess overall model credibility.

The problem with these above tests is that they do not determine whether a model is considered verified. For this, the specification of given criteria would be required without which evaluations of models are very subjective. The issue of model evaluation often boils down to single measures of verification on which too much reliance is placed. It might happen that model credibility is relegated to such things as .. this model has a correlation coefficient of this much and the median relative error is n and .. the root mean square of this model is better than that one .. and so it is good. A modeler's judgement always has a role to play in model evaluation.

Reckhow and Chapra (1983) stress that the tests used for evaluation/validation should be different considering the characteristics of prediction (mean, extreme values etc.) and whether the model is descriptive or predictive, etc.. They also advocate the use of sensitivity analysis in the confirmation and evaluation of simulation models. They list some of the common statistical tests used for model confirmation for deterministic and stochastic modeling.

These authors note the need for looking for autocorrelation in a data series of some models. They list some of the steps to be taken to quantify the autocorrelation like the prewhitening process of the Box-Jenkins method. Some of the tests mentioned for model evaluation are relative error between observed and predicted values, the squared error and 't' test, along with graphical tests of goodness of fit. Box plots are particularly useful in model results dealing with order statistics. For stochastic models, Chi-square and Kolmogorov-Smirnov tests might also be used. Finally the authors caution that proposed confirmation criteria may not be feasible for all models. Therefore along with these tests, the modelers judgement and intuition might also be used in model analysis.

Loague and Green (1991) review model evaluation efforts in three steps: (1) An overview of various aspects of mathematical modeling focused upon solute transport models, (2) An introduction to statistical criteria and graphical displays that can be useful for model evaluation, and (3) An illustration of evaluation using the PRZM model. According to the authors, complete model evaluation requires both operational and scientific examination. The operational component consists of assessment of accuracy and precision of model results. The scientific component of model evaluation is the

assessment of consistency between model predicted results and the prevailing scientific theory.

The statistical tests proposed are maximum error, root mean square error, coefficient of determination, modeling efficiency and coefficient of residual mass. Some of the statistical tests are sensitive to a few large errors especially in small data sets. The authors concede that the standards for model evaluation using these tests have not yet been established. The graphical displays that can be used for solute transport model are (1) the comparison of observed and predicted concentration profiles, (2) comparison of ranges and medians of integrated values of predicted and observed data, (3) comparison of matched predicted and observed integrated values, and (4) comparison of cumulative distribution functions for integrated values. The first graphical technique can be used to judge the quality of model performance at specific sites. The remaining methods can be used to evaluate model performance for several sites at once and are, therefore, not one-to-one tests. Systematic error in the form of over- or under- prediction can be detected from (2) and (3) while spatial variation in observation and model prediction are represented by (4).

The authors note that the application of these tests on PRZM show that the model is not up to the standard. In the absence of standards or hypothesis testing, this opinion is questionable. Even in the case of graphical displays, the question remains to be asked as to how good is the fit. The assumptions of independence and equality of variance are not discussed by the authors. The tests are also not conducted on different models for comparison purposes.

Pennel et al. (1990) evaluated five pesticide simulation models (CMLS, MOUSE, PRZM, GLEAMS, LEACHCMP) using a comprehensive data set from a single study. Model evaluations were based on water mass balance, the transport of a non-reactive tracer (bromide) and the transport and degradation of a reactive solute (aldicrab). They kept model calibrations to a minimum. The objective criteria used to validate and compare the models included the Root-Mean-Square Error (RMSE), Normalized Objective Function (NOF) and Reduced Error Estimate (REE). Besides these, graphical comparisons were also made. The test statistics are given by

$$RMSE = \sqrt{\frac{1}{n_t}\sum_{i=1}^{n_t}\frac{1}{n_i}\sum_{i=1}^{n_i}(M_{ti}-P_i)^2} \qquad (2\text{-}6)$$

$$NOF = \frac{RMSE}{\overline{M_{ti}}} \quad where \ \overline{M_{ti}} = \frac{1}{n_t}\sum_{t=1}^{n_t}\frac{1}{n_i}\sum_{i=1}^{n_i}M_{ti} \qquad (2\text{-}7)$$

$$REE = \frac{RMSE}{\sqrt{\frac{1}{n_t}\sum_{i=1}^{n_t}\frac{1}{n_i}\sum_{i=1}^{n_i}(M_{ti}-\overline{M_{ti}})^2}} \qquad (2\text{-}8)$$

where M is the measured value, P is the predicted value, n_t is the number of sampling dates and n_i is the number of measured values. The RMSE is the overall sum of squares of differences normalized to the number of observations. The NOF is the RMSE

normalized to the overall mean which yields a term similar to the coefficient of variation. REE is the RMSE normalized with respect to a term similar to the standard deviation.

GLEAMS, MOUSE and PRZM were minimally calibrated. On the basis of the observed and predicted data, parameters like the SCS curve number and evapotranspiration parameters were calibrated.

On the basis of graphical comparisons and objective functions analysis, CMLS, PRZM and LEACHCMP predicted similar bromide, aldicrab and TSR leaching. The NOF indicated that these models predicted these outputs within approximately 30, 45 and 70 percent of the measured values respectively.

The authors conclude that as far as statistical tests are concerned, RMSE has the advantage of retaining units of measure, but can be overwhelmed by a single large difference between measured and predicted data. RMSE is only normalized with respect to number of observations, so there is difficulty in comparing across the different data sets. The authors contend that the ability of models to predict measured values of several compounds can be evaluated using NOF. They also observe that the REE criteria might correct for the differences in the variability of measured data. But if the variability of solutes is similar, the advantage of REE over NOF is lost. The authors caution that the use of these different objective functions should be taken with knowledge of limitations and along with other tests like graphical evaluation.

Chiew et al. (1993) also compared six hydrologic models with different approaches using objective functions and graphical comparisons. The two objective functions used were

$$OBJ1 = \sum_{i=1}^{N}(SM_i - REC_i)^2 \quad (2\text{-}9)$$

$$OBJ2 = \sum_{i=1}^{N}(SM_i^{0.2} - REC_i^{0.2})^2 \quad (2\text{-}10)$$

where SM_i and REC_i are the simulated and recorded stream flows over period i and n is the number of time periods simulated. OBJ1 places more importance on the high flows and is useful in reflecting the ability of the models to estimate catchment yields. OBJ2 provides weighting to reflect the simulation of low flows as well as high flows.

The authors note that it is difficult to find a true optimum. First, discontinuities are common in the response surface of rainfall-runoff models caused by the use of constraints to prevent parameters from taking unrealistic values and an optimization run may get trapped at one of the discontinuities to form a local optimum. Second, there is usually interdependence between various parameters. Third, the least squares assumptions of error terms (SM_i - REC_i) is that they have zero mean and constant variance, are mutually uncorrelated and are normally distributed, are seldom satisfied. The exponent 0.2 used in the objective ensures that the error term has a constant variance (values of $SM_i^{0.2}$ - $REC_i^{0.2}$ are similar for all flow values). Also the ratio of objective functions for six modeling approaches for different catchments, relative to the lowest value obtained for that simulation, were plotted. The plots were more useful than a direct comparison of the objective function as these values are dependent on flow volumes and can differ by several orders of magnitude.

In a series of papers originating from Virginia Polytechnic and State University very interesting studies on model evaluations were discussed. Zacharias and Heatwole (1993) evaluated the model 'OPUS' on the basis of its prediction of runoff, sediment loss and pesticide movements in three steps. Runoff volume and sediment loss predicted by the model were compared with observed data. They used the actual runoff volume and sediment loss measured at the field in subsequent steps to calibrate the soil water and chemical components of OPUS. In the second step these field measured runoff volumes and sediment losses were input to the model. The third step involved the use of field measured pesticide dissipation half-life to represent degradation of soil instead of literature values. The evaluation of model performance was based on graphical displays and statistical techniques. The quantitative techniques provide an objective assessment by quantifying the difference between observed and predicted values.

To evaluate predicted pesticide concentration distribution in soil, the factor of 2 criteria is used. The null and alternative hypothesis are :

H_0 : Model predicts pesticide concentration in the soil profile within a factor of 2 of the observed data for all sampling dates and depths.

H_a : Model does not predict concentrations within a factor of 2 for all sampling dates and depths.

This was tested by a non parametric method based on confidence intervals. The confidence interval corresponding to the median of the i^{th} date-depth combination is denoted by L_i^* and U_i^*. For these combinations the corresponding confidence internals are $(½)\mu_{pi}$ and $2\mu_{pi}$, where μ_{pi} represents the model predicted value for the i^{th} date-depth

pair. The hypothesis is rejected if any case results in either $U_i^* < (1/f)\mu p_i$ or $L_i^* > f\mu_{pi}$ for f equal to 2.

The model capacity index C_i^* is defined as

$$C_i^* = \{ L_i^* / \mu_{pi} , \text{ if } \mu_{pi} < L_i^* \qquad (2\text{-}13)$$

$$1, \quad \text{if } L_i^* \leq \mu_{pi} \geq U_i^*$$

$$\mu_{pi} / U_i^*, \quad \text{if } \mu_{pi} > U_i^* \}$$

The hypothesis is rejected in all depth-date pairs when $C_i^* > 2$. The overall model performance over the study period can also be expressed in terms of the number of percentage of date-depth pairs, where the hypothesis was not rejected.

The authors note that this method takes into account the variability in the observed data. The limitation is that where the lower limit is zero, the C_i^* is not defined, which was treated as rejected.

As for the results, the model grossly overpredicted both the runoff volume and sediment loss, even after changing the curve numbers using the observed rainfall-runoff data. The soil water distribution was predicted fairly well at the site. The hypothesis was rejected for both atrazine and metolachlor in the two simulations involving literature and field dissipation half-lives. The authors speculate that the lack of agreement between observed and predicted pesticide concentration may be due to the fact the model did not represent the rapid movement of pesticides following large rainfall events early in the season.

Parrish and Smith (1990) discussed the hypothesis testing as outlined by Zacharias and Heatwole(1993). Parrish and Smith (1990) illustrate model validation by using a

multivariate case using PRZM model. They note that it is desirable to test the models predictive ability with respect to an array of parameters in space or time. Then the hypothesis would be,

H_0 : Model predicts concentrations in the soil profile within a factor of 2 for all depths.

H_a : Model does not predict within a factor of 2 at all locations in the soil profile.

A confidence interval is computed for each mean at a specific time-depth, so that taken jointly the confidence level is controlled at a specific value. The lower L_i and upper U_i confidence intervals are given by

$$L_i = \bar{X}_i - \frac{Ts_i}{n^{1/2}} \qquad (2\text{-}14)$$

$$U_i = \bar{X}_i + \frac{Ts_i}{n^{1/2}} \qquad (2\text{-}15)$$

where $\bar{X}_i$ and S_i are sample mean and standard deviation of the i^{th} parameter, based on multivariate sample size n and $T = t_{1-\alpha/2k,n-1}$ where k is the number of parameters.

The capacity index was given earlier (equation 2-13). If any C_i exceeds the acceptability criterion of being within a factor of two, then the null hypothesis would be rejected. A single index C_{max}, could be defined as the maximum of the C_i values. When this procedure was applied for the PRZM model the C_i values calculated were 1.01 for day 20, 1.69 for day 48 and 1.28 for day 86. But on day 83, and for third depth, the index of overprediction was 6.83 so the hypothesis was rejected.

The authors caution that the choice of outputs actually determine the specific model needs. Sometimes, as in groundwater leaching models, the depth would be of importance, where as sampling time may be critical in some cases. Sample size should be carefully chosen so that the test has a good chance of detecting a situation for which the null hypothesis is false.

Garrick et al. (1978) proposed two criteria for evaluating the efficiency of conceptual rainfall-discharge models. The first assesses the model as a means of converting the input factors into discharge by comparison with a forecast based only on the seasonal regime of the river. The second criteria expresses the efficiency of the model under the assumption that it is to be used with an updating procedure to provide a forecast of discharge over a prescribed lead time.

When these criteria are applied to the SSARR model and a seasonal forecast based only on date is made, the result is that the SSARR model is less efficient than the simple seasonal prediction. The authors do not make any effort to check the site specificity of the model involved, and the fact that part of data was used in calibrating the model makes the results all the more suspect.

Zacharias et al. (1993) analyzed the model OPUS using the same principal proposed by Parrish and Smith (1990). They have adapted non parametric methods so that when the data distribution is non-Gaussian or unknown, it can be applied to model validation.

The authors note that comparing simulated values against the data distribution may be more appropriate when the output variable is pesticide concentration, as it takes into

account the large variability in the data. If the underlying structure is non-Gaussian, the sample median may be a more appropriate measure of location than the sample mean and the measure of dispersion should be the range, inter-quartile range or median absolute deviation.

The Median Absolute Deviation (MAD) is given by

$$S^* = 1.4826 \text{ x median } \{ |x_i - \bar{x}| \quad i = 1,2 \ldots n\} \tag{2-16}$$

where S^* is the median absolute deviation, x_i is the i^{th} observation, $\bar{x}$ is the sample median, n is the sample size and 1.4826 is for consistency with the Gaussian distribution.

The method computes the confidence interval based on the rank based on the sign statistic instead of the t-statistic. The sign statistic assumes neither normality nor symmetry.

For the univariate case, if j is such that $P(x \leq j) = \alpha/2$ from the binomial table, B(n, 0.5), then the $(1-\alpha)$ 100% confidence interval for the population median is given by equations (2-17) and (2-18).

$$L^* = X(j+1) \tag{2-17}$$

$$U^* = X(n-j) \tag{2-18}$$

where n is the sample size, $X(j+1)$ is the $(j+1)^{th}$ smallest observation sample. Using this, C^* max (equation 2-13) can be found and used to test the hypothesis. Along with this, other quantitative methods proposed by the authors are, Median Absolute Error (MdAE), Coefficient of Determination (CD^*) and Modeling Efficiency (EF^*).

$$MdAE = \sum_{i=1}^{n} \frac{|P_i - O_i|}{n} x\left(\frac{100}{\overline{O}}\right) \quad (2\text{-}19)$$

$$CD^* = \frac{\sum_{i=1}^{n} |O_i - \overline{O}|}{\sum_{i=1}^{n} |P_i - \overline{O}|} \quad (2\text{-}20)$$

$$EF^* = \frac{\sum_{i=1}^{n} |O_i - \overline{O}| - \sum_{i=1}^{n} |P_i - \overline{O}|}{\sum_{i=1}^{n} |O_i - \overline{O}|} \quad (2\text{-}21)$$

where O_i are the observed values and P_i are the predicted values, n is the number of samples and $\overline{O}$ is the median of the observed data.

According to the authors, a field study can be carried such that a large field is subdivided into several sites for modeling purposes and hypothesis testing carried out. When the model is used to simulate the whole set of the large field, then a model can be used in a probabilistic mode.

In yet another paper, Zacharias et al. (1993) evaluated models GLEAMS and PRZM for their ability to predict pesticide leaching. The comparisons of simulated versus observed data were made considering (1) bromide, atrazine and metolachlor concentration distributions in the root zone, (2) mass of atrazine and metolachlor remaining in the root zone, (3) depth of solute peak concentration, and (4) depth of solute center of mass.

The authors contend that the first output option would help to evaluate the appropriateness of model theory and assumptions in describing field situations while the third and fourth goals assess the ability of the model to simulate pesticide leaching.

The authors follow the quantitative measures as described by Zacharias et al. (1993) (reviewed earlier) for evaluating chemical concentration predicted by the model at different sampling depths and dates. The evaluation of the mass remaining in the root zone and the depth of solute center of mass was based on the root mean square error (RMSE) and normalized objective function (NOF) as outlined by Green and Stephenson (1986).

As for the model simulation results, the hydrology results with the uncalibrated model indicate that both models overpredicted the observed monthly runoff. Both models underpredicted the leaching of bromide, atrazine and metalachlor. To remedy this, leaf area index, curve numbers in GLEAMS and the parameter ANTED in PRZM along with curve number were calibrated. After this run, it was noted by the authors that GLEAMS had predicted chemical concentration profile and pesticide prediction better than PRZM.

Finally the authors conclude that both models are adequate for management purposes. They do not back this with solid statistical criteria. Although the results of the RMSE, NOF and other statistical test results are given for individual results, it is not concluded with any degree of confidence using statements like ..since this figure is better than the other, the model can be concluded to predict this output well...

Likewise Mamillapalli et al (1994) have also validated GLEAMS (nutrient component) using a variety of statistical tests. They also report calibration results are not

particularly satisfying. To test whether the model has achieved better results after calibrating, the authors use different criteria as outlined by other authors whose work is also reviewed earlier.

The majority of the work reviewed in this chapter deals with model evaluation where observed data were compared with predicted data. Some researchers use part of the observed data to calibrate the model and then model simulations are compared with another part of observed data. There is a scarsity of work on model evaluation for the case where observed data are lacking. This study is an attempt to lay a basic foundation for model evaluation where observed data are missing or scarse.

CHAPTER III

OUTLINE OF THE STUDY

OBJECTIVE

The objective of this study is to evaluate a statistical model evaluation protocol. EPIC (Erosion Productivity Impact Calculator) and AGNPS (AGricultural NonPoint Source) models were chosen for this evaluation. The models are explained in greater detail in the next chapter. It is to be recognized that a complete model evaluation protocol requires the comparison of observed data with predicted values. The model evaluation procedure outlined by Haan et al. (1993) and used in this study is an effort to evaluate these models in some applications where observed data are lacking and thus get an estimate of the model accuracy under these conditions. This is not an attempt to evaluate the models in some specific application.

It is to be recognized that a complete model evaluation requires a critical assessment of the algorithms involved and model runs involving many field settings, among other things. This study does not attempt to evaluate models in this sense. Rather

it is an attempt to apply a particular model evaluation procedure to assess the suitability of a model for use in a situation where calibration data do not exit.

PROCEDURE

The evaluation starts with sensitivity analysis of the model. This is to identify the input parameters that have the greatest impact on model predictions. Either absolute or relative sensitivity coefficients can be used. These coefficients are defined as

$$S = \frac{\partial O}{\partial I} \qquad S_r = \frac{\partial O}{\partial I}\frac{I}{O} \tag{3-1}$$

where S is the absolute sensitivity, S_r is the relative sensitivity (dimensionless), O represents a particular output and I represents a particular input. Relative sensitivity gives the percent change in O for a one percent change in I (Coleman and DeCoursey, 1976). When the 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 under study. For this study six or seven important sensitive physical parameters will the receive bulk of the attention.

The next step is to generate probability distributions of these sensitive parameters. Equations describing the probability of occurrence of random events are known as probability density functions (pdf) or cumulative distribution functions (cdf). A pdf can be used to evaluate the probability of a random event in a specified interval. A cdf can be used to evaluate the probability of an event less than or equal to a given value (Haan

et al., 1993). The uncertainty associated with the parameters of a model can be quantified in the form of a pdf. The pdf of an input parameter provides information on the variability of an input parameter and the sensitivity coefficient provides information on the impact of this variability on model predictions.

The next step is to generate output pdf's by either of two techniques, Monte Carlo Simulation (MCS) and First Order Analysis (FOA). FOA has been shown to produce good estimates of the mean and variance of a model response if the coefficient of variation of the input parameter is small and the model response is linear with respect to the parameter in the range of interest (Stevens, 1993). When FOA is not appropriate, 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. For MCS, the output pdfs will be based on the input pdfs.

The output pdfs can then be used to place confidence intervals (CIs) on model predictions. The width of the CIs depend on the level of significance and the applicable pdf. The comparison of model predictions with measured watershed response is performed at this stage. These data are plotted on the pdf of the model response and compared to the CIs. If the measured data fall within the CIs, the model may be judged to have performed satisfactorily from a statistical point of view. CIs that are so wide as to judge the model predictions of little use, even though the predictions are within the CIs, indicates that the model structure and uncertainty in input parameters combine in such a way as to render the model predictions too uncertain. Thus it is possible for a statistically acceptable solution to be unacceptable in application (Haan et al., 1993).

There is also uncertainty associated with the measured response 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.

The above model evaluation protocol is based on statistical procedures designed to minimize personal bias and to help distinguish between uncertainties associated with parameter estimation and problems associated with the structure of the model (Haan et al., 1993). This procedure was followed for the evaluation of EPIC and AGNPS and recommendations developed regarding the predictive ability of these two models. Uncertainty in measured response was not considered.

CHAPTER IV

DESCRIPTIONS OF MODELS AND THE DATASET

DESCRIPTIONS OF THE DATASET

The data used in this study are from a research field in northwestern Arkansas (lat. 36^0 N long. 94^0 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 four fields namely RA, RB, WA, WB. The model simulations in this study were done using the data from the field WA. The crop cover for this field is predominantly tall fescue. The details of the field are given in the Table 4.1.

The area of the field is 1.46 ha and it has predominantly 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).

The field WA was used for both grazing and hay production during the study period. The field was grazed from September 1991 through January 1992 and from September through December 1992. It was also cut for hay on July 7, 1992. Inorganic fertilizer (ammonium nitrate) was surface applied on March 23, 1992, at 138 kg N/ha and

April 13, 1993, at 226 kg N/ha. Phosphorous was not applied on any occasion. There were no erosion control practice in the field (Edwards et al., 1993).

Edwards et al. (1993) also outlined the steps taken to monitor the rainfall events. Tipping bucket rain gauges were used and data logging software were used to record rainfall occurring during five minute increments. The daily maximum and minimum temperatures were also recorded. The output data collected were runoff volume, sediment yield, NO3 in surface runoff, organic N loss with sediment and P loss in sediment and runoff. The total time period for which the data were collected was from September 1, 1991, to April 30, 1993. The parameters used in Edwards et al. (1993) are also used in this simulation study (Table 4.1).

DESCRIPTION OF THE MODELS

Erosion Productivity Impact Calculator

Erosion Productivity Impact Calculator (EPIC) (Sharpley and Williams, 1990) was developed by USDA-ARS in cooperation with Texas Agricultural Experiment Station, Texas A & M University.

Table 4.1. Parameters and their values used in model simulations.

PARAMETERS	VALUES
Area (ha)	1.46
Curve Number	79
Distance from outlet to furthest point (m)	194
Channel slope m/m	0.04
Channel roughness factor	0.24
Surface roughness factor	0.24
Average elevation (m)	460
Latitude	96.6
Organic Carbon (%)	1.0
Labile P, ppm	393
Slope length (m)	194

This model is composed of physically based components for simulating erosion, plant growth and related processes and economic components for assessing the cost of erosion and developed to be a particularly helpful tool for determining optimal management strategies.

EPIC is a comprehensive model consisting of hydrology, weather, an erosion/production relationship, soil temperature, tillage, economics, nutrients and plant environmental control components. It was developed specifically for application to the erosion/productivity problem. The management components that can be changed are crop rotation, tillage operations, irrigation scheduling, nutrient and pesticide application rates and timing.

EPIC operates on a daily step basis. The drainage area considered by the model is generally small because soil and management are assumed to be spatially homogeneous. In the vertical direction, the model is capable of working with a variation in soil properties and the soil profile is divided into a maximum of ten layers. When erosion occurs on the first layer and it is removed, the second layer thickness is reduced by the amount of eroded thickness, and the top layer properties are adjusted by interpolation and this process is carried on to subsequent layers (Williams et al., 1984).

EPIC Model Algorithm

This section contains the details of the model components along with outputs and the processes that are involved in the model. Emphasis is given to the outputs that are used in this study. The majority of this discussion is taken from Williams et al. (1984).

Hydrology

Runoff, percolation, lateral subsurface flow and snow melt are simulated.

Runoff : The runoff model simulates surface runoff volume and peak runoff rates, given daily rainfall amounts. Runoff volume is estimated by using a modification of the Soil Conservation Service (SCS) curve number (CN) technique (Soil Conservation Service, 1972).

Runoff volume, Q, is given by

$$Q = \frac{(R - 0.2S)^2}{R + 0.8S} \qquad \text{when } R > 0.2S \tag{4-1}$$

$$Q = 0.0 \qquad \text{when } R \leq 0.2S \tag{4-2}$$

where Q is the daily runoff, R is the daily rainfall and S is the retention parameter. The parameter S is related to CN by

$$S = 254\left(\frac{1000}{CN} - 10\right) \tag{4-3}$$

The constant 254 gives S in millimeters. CN is the curve number for antecedent moisture condition 2 and represents an average curve number which can be obtained for most areas in the US from SCS handbooks.

EPIC assumes that the handbook values for CN are appropriate for a 5% slope. Equations for adjusting that value for other slopes are contained in the model. Fluctuation in soil water content causes the retention parameter to change. The retention parameter depends on the field capacity and wilting point among other parameters.

Peak runoff rate : Peak runoff rate prediction is based on the proportion of total rainfall that occurs during the time of concentration, runoff volume and area of the watershed.

Percolation : The percolation component of EPIC uses a storage routing technique combined with a crack-flow model to predict flow through each soil layer in the root zone. It is based on the percolation rate through a layer, soil water content at the beginning of the day, travel interval (24 h) and travel time.

The travel time is dependent on hydraulic conductivity, field capacity and soil water content. The flow through a soil layer may be reduced by a saturated lower soil layer. If the layer immediately below the layer being considered is saturated, then no flow can occur regardless of the percolation rate calculated from upper layer.

Evapotranspiration : This component is based on daily solar radiation, albedo and slope of the saturation vapor pressure curve at the mean air temperature. The albedo is evaluated considering the soil, crop and snow cover.

The model computes soil and plant evaporation separately. Actual soil evaporation is completed in two stages. In the first stage it is equal to the potential soil evaporation. Stage two is predicted with a square root function of time.

Weather

The weather variables necessary for the model are precipitation, air temperature, solar radiation and wind. There is provision in the model to input daily precipitation, minimum and maximum temperature and solar radiation data directly. Otherwise it can be generated stochastically.

Air temperature and solar radiation : The residuals of daily maximum and minimum temperature and solar radiation are generated from a multivariate normal distribution. The means and coefficients of variation for each variable should be input. As these variables are affected by rainfall, the means and coefficients of variation must be input separately for wet and dry days. The wind simulation model uses two variables. They are average daily velocity and daily direction. Wind direction is expressed in radians from north in a clockwise direction and is generated from an empirical distribution specific for each location.

Erosion

Water erosion : The water erosion component of EPIC uses a modification of USLE. This equation's energy factor is composed of both rainfall and runoff variables. It is given by

$$Y = (0.646\ EI + 0.45\ (Q)\ (q_p)^{0.833})\ (K)\ (CE)\ (PE)\ (LS),\ Q > 0 \qquad (4\text{-}4)$$

$$Y = 0,\ Q \leq 0 \qquad (4\text{-}5)$$

where Y is the sediment yield in t/ha, EI is the rainfall energy factor in metric units, Q is the runoff volume in mm, q_p is the peak runoff rate in mm/h, K is the soil erodibility factor, CE is the crop management factor, PE is the erosion control practice factor and LS is the slope length and steepness factor and is calculated with the equation

$$LS = \left(\frac{\lambda}{226}\right)^{\xi} (65.41S^2 + 4.56S + 0.065) \qquad (4\text{-}6)$$

where S is the land surface slope in m/m, λ is the slope length in m, ξ is the parameter dependent on slope and is given by

$$\xi = 0.6(1 - \exp(- 35.835S)) \quad (4\text{-}7)$$

The crop management factor is evaluated for all days when runoff occurs using the equation

$$CE = (0.8 - CE_{mn,j}) \exp(- 0.00115\ cv) + CE_{mn,j} \quad (4\text{-}8)$$

where $CE_{mn,j}$ is the minimum value of the crop management factor for crop j and cv is the soil cover (above ground biomass plus residue). The factors Q and q_p are supplied by the hydrology component.

The erosion caused by applying irrigation water in furrows is estimated with the Modified Universal Soil Loss Equation (MUSLE). Wind erosion depends on the climatic factor, soil ridge roughness factor, field length, quantity of vegetative cover and soil erodibility index.

Nutrients

The model simulates nitrogen and phosphorous fertilization, transformations, crop uptake and nutrient movement. Nutrients can be applied as mineral fertilizers, in irrigation water or as animal manures.

Nitrate loss in surface runoff : The amount of NO_3-N in runoff is estimated by considering the top soil layer only. The average concentration can be obtained by integrating the exponential function (which simulates the decrease in NO_3-N concentration) to give NO_3-N yield and dividing by the volume of water leaving the layer. The resulting relationships are

$$VNO_3 = WNO_3[1 - \exp(-\frac{QT}{VL})] \quad (4\text{-}9)$$

$$C_{NO_3} = \frac{VNO_3}{QT} \quad (4\text{-}10)$$

where WNO_3 is the weight of NO_3-N contained in the soil layer at the start of a day, QT is the total water lost from the first layer, VL is the upper limit of water storage in the layer, VNO_3 is the amount of NO_3-N lost from the first layer and C_{No3} is the concentration of NO_3-N in the first layer.

Organic N transport by sediment : The loading function for estimating organic N loss is given by

$$YON = 0.001\ (Y)\ (C_{on})\ (ER) \quad (4\text{-}11)$$

where YON is the organic N runoff loss kg/ha, C_{on} is the concentration of organic N in the top soil layer in g/t, Y is the sediment yield in t/ha and ER is the enrichment ratio. The enrichment ratio is the concentration of organic N in the sediment divided by that of the soil.

Denitrification : This depends on temperature, water content and organic carbon content in the soil and is considered a microbial process.

Mineralization : This model considers fresh organic N associated with crop residue and microbial biomass and the stable organic N associated with the soil humus pool as sources of mineralization. Immobilization is also an important process as it determines the residue decomposition rate which has an important effect on erosion. The daily

amount of immobilization is computed by subtracting the amount of N contained in the crop residue from the amount assimilated by the microorganisms.

Soluble Phosphorous loss in surface runoff : The EPIC approach to P loss is based on the concept of partitioning phosphorus into solution and sediment phases. Soluble P in runoff can be expressed as

$$YSP = 0.01(C_{LP1})\frac{(Q)}{kd} \qquad (4\text{-}12)$$

where YSP is the soluble P in Kg/ha lost in runoff volume Q in mm, C_{LP1} is the concentration of labile P in soil layer one in g/t and kd is the P concentration in the sediment divided by that of the water.

P transport by sediment : P loss in sediment is simulated by

$$YP = 0.001\ (Y)\ (Cp)\ (ER) \qquad (4\text{-}13)$$

Where YP is the sediment phase P loss in runoff in Kg/ha and Cp is the concentration of P in the top soil layer in g/t and ER is the amount of residue. Mineralization, immobilization and crop uptake are other P outputs in EPIC and are similar to that of N loss.

EPIC Dataset Description

This section describes the parameters used in building the data file for EPIC. Some of the important parameters like CN and Slope are taken from Edwards et al. (1993) which is described in the third chapter.

For this model the number of years of simulation is taken as four, starting in 1990. This enables the model to simulate fully grown grass at the start of study period (from Sept 1, 1991) which is actually the case. The simulation is started from January 1, 1990.

The maximum and minimum temperature and rain are input into the model. There is a provision for including the file containing the weather data at the end of the data file in ASCII format. The format is specified in the help option for the weather parameters. The rest of the parameters like solar radiation and wind are generated stochastically as those data were not available. Since weather data is available from Sept. 1, 1991 to April 30, 1993, for the rest of the simulation period the weather data from year 1992 are used (for corresponding periods) to fill in the gaps for which the data is not available. For the analysis part, only the data from Sept. 1, 1991 to April 30, 1993 are used.

For other weather parameters like maximum and minimum air temperature, average monthly precipitation, probability of wet day after dry day, etc., EPIC command called 'locweat' is used. The user has to give the latitude and longitude along with the command. A list of weather stations which are close to the field will appear on the screen. Eureka Springs (36.4^0 L latitude and 93.75° W longitude) is used. Various wind parameters are also accessed by this command. Likewise the soil parameters like field capacity, bulk density, soil albedo, etc. can be obtained by the command called 'getsoil' along with the soil number. The soil numbers are given in the user manual. Linker Loam A corresponds to the soil number 412. The labile P value was changed to 393 ppm

and organic Carbon was changed to 1.0 %, which are field measured values, rather than using the model default values.

For tillage practices, a four-year crop rotation was assumed. For simulation, it is assumed that grass is planted on April 1, 1990. The clastil.dat file is used as the tillage file. Similarly clascrop.dat is used for crop parameters. In that file grass is listed as range. At the end of the data file, the file containing weather parameters is listed. The complete list of input parameters for EPIC is given in Appendix A.

AGricultural Non Point Source

The AGNPS model was developed by the Agricultural Research Service (ARS) in cooperation with the Minnesota Pollution Control Agency and the Soil Conservation Service (SCS). The model was developed to analyze and provide runoff water quality from agricultural watersheds ranging in size from few hectares to upwards of 20,000 ha (Young et al., 1989).

AGNPS is event based. It operates on a cell basis. Cells are uniform square areas subdividing the watersheds allowing analysis near any point within the watershed. Potential pollutants are routed through cells from the watershed divide to the outlet in a stepwise manner so that flow at any point between the cells may be examined. All watershed characteristics and inputs are expressed at the cell level. Accuracy of results can be increased by reducing the cell size, but this increases the time to run the model (Young et al., 1989).

The model simulates runoff, sediment and nutrient (N and P) movement in soil. Model components are hydrology, erosion and sediment and chemical transport. The model also considers point sources of sediment from gullies and input of water, sediment, nutrients and chemical oxygen demand from animal feedlots, springs and other point sources.

AGNPS Model Algorithm

Hydrology

Runoff volume and peak flow rate are calculated in this part of the model. Runoff volume estimates are based on SCS curve number method as explained in EPIC hydrology component. In AGNPS there is a provision to input the state of the antecedent condition for an event. Peak runoff rate is based on drainage area, channel slope, runoff volume and watershed length-width ratio parameters.

Erosion and sediment transport

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

$$SL = (EI)\ KLSCP\ (SSF) \qquad (4\text{-}14)$$

where SL is the soil loss, EI is the rainfall energy-intensity, K is the soil erodibility factor, L is the topographic factor, C is the cover and management factor and SSF is factor to adjust for slope shape within the cell.

Using a steady-state continuity equation the detached sediment is routed from cell to cell through the watershed to the outlet. The sediment discharge at the downstream end of a channel reach depends on lateral sediment inflow rate, downstream distance, reach length, channel width and the deposition rate.

Chemical transport

The chemical transport part of the model estimates transport of N, P and COD throughout the watershed. Chemical transport calculations are divided into soluble and sediment adsorbed phases. Nutrient yield in the sediment absorbed phase is calculated using total sediment yield from a cell as given by

$$Nut_{sed} = (Nut_f)\ Q_s(x)\ ER \qquad (4\text{-}15)$$

where Nut_{sed} is N or P transported by sediment, Nut_f is N or P content in the field soil and ER is the enrichment ratio, $Q_s(x)$ is the sediment yield.

Soluble nutrient estimates consider the effects of nutrient levels in rainfall, fertilization and leaching. Soluble nutrients contained in runoff are estimated by

$$Nut_{sol} = C_{nut}\ Nut_{ext}\ Q \qquad (4\text{-}16)$$

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.

AGNPS Dataset Description

For simulation purposes the entire 3.61 acres is considered as a single cell. This simplifies the sensitivity analysis and the simulations in that multiple cells would require multiple parameter sets.

Since AGNPS is an event based model, a precipitation event of 3.76 inches on July 30, 1992 is used in the model. 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 a CN value of 70 is used which is the average of CN values at CN(I) and CN(II) conditions. CN(I) may be computed based on CN(II) from Haan et al. (1994) as

$$CN(I) = \frac{4.2\ CN(II)}{10 - 0.058\ CN(II)} \qquad (4\text{-}17)$$

From Edwards et al. (1993) the CN(II) value is 79.

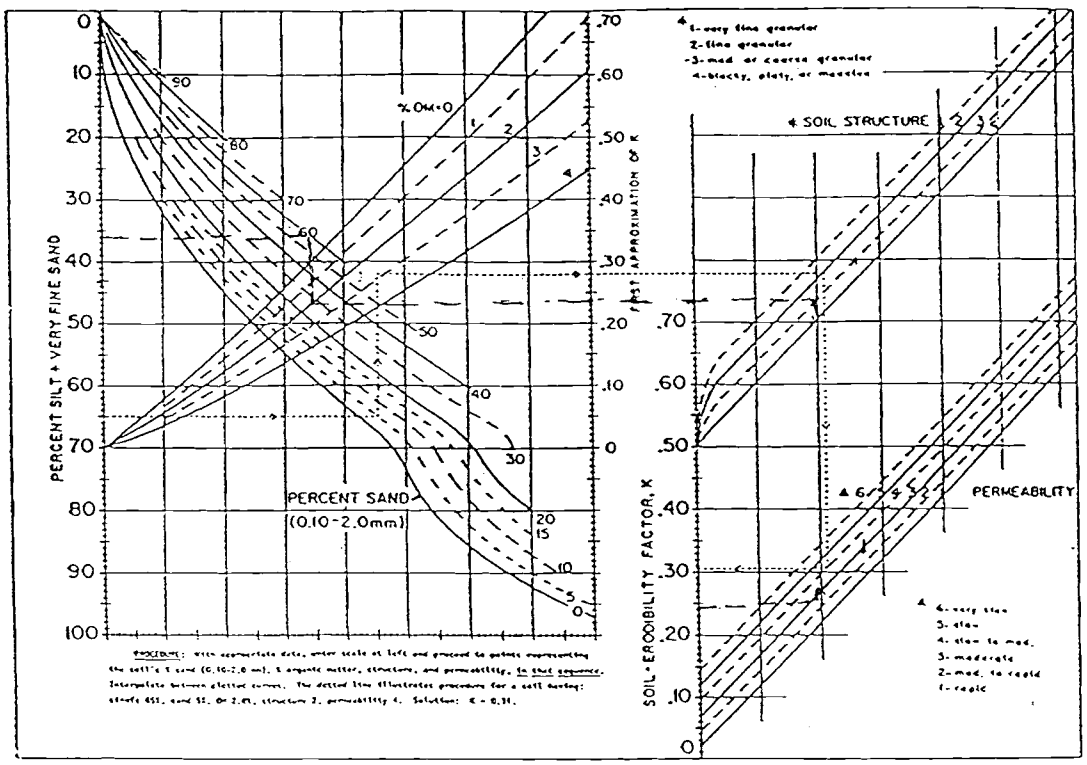
$$CN(I) = \frac{4.2 * 79}{10 - 0.058 * 79} = 61.74$$

The average value of these two conditions is 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. For soil parameters, the K factor is estimated from the soil erodibility nomograph of Agriculture Handbook number 537, "Predicting Rainfall Erosion Losses" (Wishmeir and Smith, 1978). The percentage of soil particles are obtained from the EPIC data file. The percentage of silt is 35.6. The very fine sand particle percentage 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 parameters the K value is derived as 0.24 (Fig 4.1).

From Table 10 (Agriculture Handbook 537, Wishmeir and Smith, 1978) for "tall weeds or short bushes" category and a percent cover of 50 % and percent ground cover of 80 %, the C value is assumed to be 0.012 for type G (grass) (Table 4.2).

For the surface condition constant, good pasture is assumed with a value of 0.22. For the COD factor, the pasture value of 60 is input. The soil texture number is 3 for 56 percent of sand and 35 percent of silt and the soil triangle is given as fig 4.2. For this soil texture a number of default values regarding the N and P coefficients were accessed. The soil P value was 0.0005 lb P/lb soil. The approximate actual field measured value is 0.0004 and test run indicated that there is not much difference in the P outputs. There are no point sources or impoundments in the field. The channel type is taken as the one without a definitive channel. The complete list of AGNPS dataset is given in Appendix C.



The soil-erodibility nomograph. Where the silt fraction does not exceed 70 percent, the equation is $100\ K = 2.1\ M^{1.14}\ (10^{-4})\ (12 - a) + 3.25\ (b - 2) + 2.5\ (c - 3)$ where $M = (\text{percent silt} + \text{vfs})\ (100 - \text{percent c})$, a = percent organic matter, b = structure code, and c = profile permeability class.

FIGURE 4.1 The soil erodibility factor nomograph

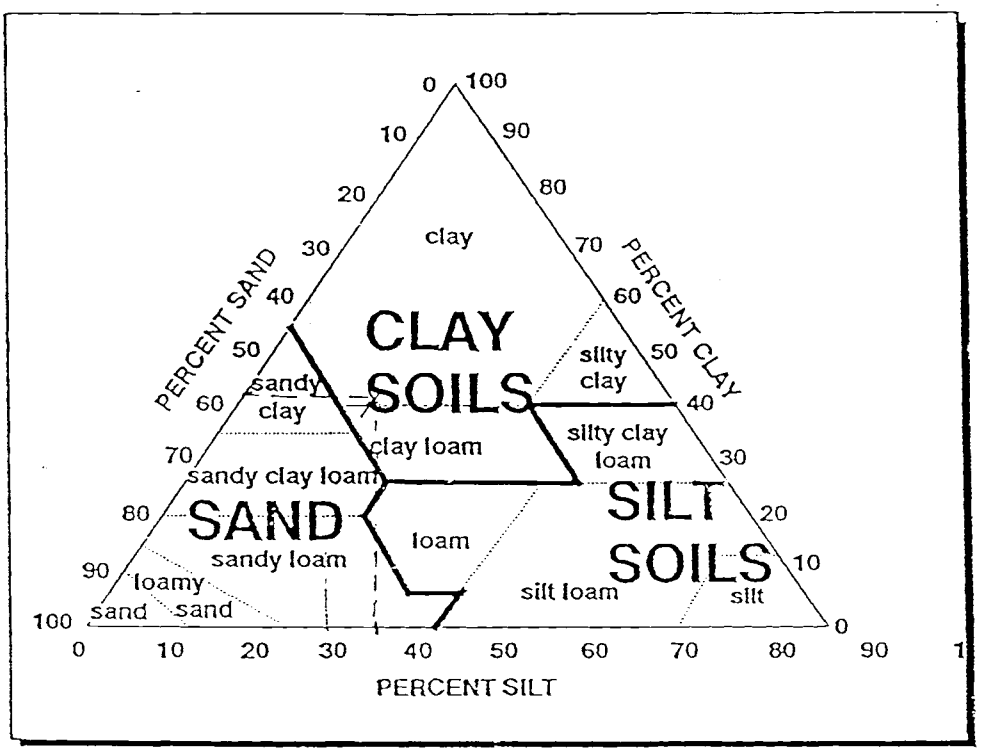


FIGURE 4.2 The soil triangle

TABLE 4.2 Factor C for permanent pasture, range, and idle land

Vegetative canopy		Cover that contacts the soil surface						
Type and height[2]	Percent cover[3]		Percent ground cover					
		Type[4]	0	20	40	60	80	95+
No appreciable canopy		G	0.45	0.20	0.10	0.042	0.013	0.003
		W	.45	.24	.15	.091	.043	.011
Tall weeds or short brush with average drop fall height of 20 in	25	G	.36	.17	.09	.038	.013	.003
		W	.36	.20	.13	.083	.041	.011
	50	G	.26	.13	.07	.035	.012	.003
		W	.26	.16	.11	.076	.039	.011
	75	G	.17	.10	.06	.032	.011	.003
		W	.17	.12	.09	.068	.038	.011
Appreciable brush or bushes, with average drop fall height of 6½ ft	25	G	.40	.18	.09	.040	.013	.003
		W	.40	.22	.14	.087	.042	.011
	50	G	.34	.16	.08	.038	.012	.003
		W	.34	.19	.13	.082	.041	.011
	75	G	.28	.14	.08	.036	.012	.003
		W	.28	.17	.12	.078	.040	.011
Trees, but no appreciable low brush. Average drop fall height of 13 ft	25	G	.42	.19	.10	.041	.013	.003
		W	.42	.23	.14	.089	.042	.011
	50	G	.39	.18	.09	.040	.013	.003
		W	.39	.21	.14	.087	.042	.011
	75	G	.36	.17	.09	.039	.012	.003
		W	.36	.20	.13	.084	.041	.011

[1] The listed C values assume that the vegetation and mulch are randomly distributed over the entire area.

[2] Canopy height is measured as the average fall height of water drops falling from the canopy to the ground. Canopy effect is inversely proportional to drop fall height and is negligible if fall height exceeds 33 ft.

[3] Portion of total-area surface that would be hidden from view by canopy in a vertical projection (a bird's-eye view).

[4] G: cover at surface is grass, grasslike plants, decaying compacted duff, or litter at least 2 in deep.

W: cover at surface is mostly broadleaf herbaceous plants (as weeds with little lateral-root network near the surface) or undecayed residues or both.

CHAPTER V

SENSITIVITY ANALYSIS

Sensitivity analysis identifies the parameters that have the greatest impact on model predictions. A number of methods have been employed by researchers for the purpose of 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.

They extend the sensitivity analysis to parameter estimation by means of so called addictive 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 the total variance can be found. This will lead to identify parameters which require more accurate determinations of their value.

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. They used regression models to estimate probability distributions, as very few samples of parameters were available. They did not use some of the parameters in the model in their study as those parameters were derived from other parameters, and thus are correlated.

Deer-Ascough and Nearing (1994) calculated sensitivity analysis on the WEPP model using parameters for three soil types and three different management practices. They used deterministic sensitivity analysis (which is outlined later in the chapter). 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 vadose zone models for important parameters using sensitivity and uncertainty analysis. They defined the sensitivity coefficient, S, as

$$S = \frac{\partial O}{\partial I} \tag{5-1}$$

where O represents the output of interest and I represents the input parameter. If the model output can be written in a symbolic form, the sensitivity can be applied by differentiating O symbolically. If the models are too complex for this approach, the sensitivity can be calculated by using the difference equation

$$S = \frac{\Delta O}{\Delta I} \tag{5-2}$$

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

$$S_r = \frac{\Delta O}{\Delta I} * \frac{I}{O} \tag{5-3}$$

The relative sensitivity is a measure of the relative change in model output, corresponding to a relative change in the input parameter. S_r gives the percentage change in model response for one percent change in an input parameter. If the absolute value of S_r is greater than one, the absolute value of the relative change in model output will be greater than the absolute value of the relative change in input parameter. If the absolute value of S_r is less than one, the absolute value of the relative change in model output will be less than the absolute value of the relative change in input. Here the sensitivity coefficients reflect the change in output function due to a single input

parameter. Uncertainty analysis is used to incorporate simultaneous changes in more than one parameter and variability of the parameters (Nofziger et al., 1993).

SENSITIVITY ANALYSIS OF EPIC

Sensitivity analysis of EPIC was conducted using all parameters except weather parameters. There were a total of 43 parameters. The percent change in input parameters was one percent across the base value. The outputs studied are runoff, sediment, nitrogen in sediment and runoff and phosphorous in runoff. The most sensitive parameters were chosen for the study and are given below along with their relative sensitivities for a particular output. The complete sensitivity analysis is given in Appendix B.

TABLE 5-1. Relative sensitivity values for runoff for EPIC

Parameter	Rel. sen.
Curve number	5.19
Field capacity	0.28
Slope	0.19

TABLE 5-2. Relative sensitivity values for sediment for EPIC

Parameter	**Rel. sen.**
Curve number	5.29
Slope	1.8
P- factor	1.11
Silt	0.52

TABLE 5-3. Relative sensitivity values for N loss in sediment for EPIC

Parameter	**Rel. sen.**
Curve number	4.30
slope	1.68
P - factor	1.05
Org. N	0.97
silt	0.47

TABLE 5-4. Relative sensitivity values for NO3 loss in surface runoff for EPIC

Parameter	**Rel. sen.**
Curve number	11.38
Bulk density	3.44
Field capacity	0.57
Slope	0.48

TABLE 5-5. Relative sensitivity values for P loss in runoff for EPIC

Parameter	**Rel. sen.**
Curve number	7.68
Bulk Density	1.54
Field Capacity	0.37
Slope	0.29

SENSITIVITY ANALYSIS OF AGNPS

Sensitivity analysis of AGNPS model was conducted using 28 parameters. Even though precipitation was found to be a sensitive parameter, it is not used in simulations. In AGNPS some of the input parameters had to be changed more than one percent, because of program input limitations. The input parameters of AGNPS used for sensitivity analysis and the percent changes are given in Appendix C. As in EPIC, tables 5-6 to 5-10 contain the relative sensitivity index of the parameters used in the study. The complete list of sensitivity analysis of the model is given in Appendix D.

TABLE 5-6. Relative sensitivity values for runoff for AGNPS

Parameter	Rel. sen.
Curve number	5.17

TABLE 5-7. Relative sensitivity values for sediment yield for AGNPS

Parameter	Rel. sen.
Curve number	2.5
Land slope	5
K - factor	1.25
C - factor	1.25
P - factor	1.25

TABLE 5-8. Relative sensitive values for N loss in sediment for AGNPS

Parameter	Rel. sen.
Curve number	1.56
Land slope	4.17
K - factor	1.17
C - factor	1.17
P - factor	1.17
soil N	2.18

TABLE 5-9. Relative sensitive values for N in runoff for AGNPS

Parameter	Rel. sen.
Curve number	10
N extr. runoff	3.33
N extr. leaching	3.33

TABLE 5-10. Relative sensitive values for P in sediment for AGNPS

parameter	Rel. sen.
Land slope	4.17
k - factor	1.56
C - factor	1.56
P - factor	1.56

CHAPTER VI

DISTRIBUTIONS OF THE PARAMETERS

The sensitivity analysis of EPIC indicates the curve number, bulk density, field capacity, slope, percentage silt, organic nitrogen and erosion control practice factor are the most sensitive parameters. For AGNPS, besides curve number, slope and the erosion control practice factor, the other important factors are soil erodibility factor, cover and management factor, soil nitrogen, nitrogen extraction coefficient for runoff and nitrogen extraction coefficient for leaching. For the Monte Carlo simulation, there is need to find the distribution of these variables. The choice of a distribution to represent a physical system is generally motivated by an understanding of the nature of the underlying phenomenon and is verified by the available data. After a distribution is chosen, its parameters must be determined. Also for the MCS it is very important to determine if there is correlation among the input parameters. Using the limited data available, the correlations among the various input parameters were investigated. Although data were insufficient for rigorous testing, independence among the parameters was assumed.

There are a number of different types of probability distributions. Prominent among them is the normal distribution. The lognormal (LN), exponential, gamma and Weibul are other types of distributions which can describe hydrologic and physical

variables. The Central Limit Theorem states the general result that if X is mad
the sum of the many small effects, then X might be expected to be normally distr
Similarly if X is equal to the product of many small effects, then lnX can be exp
be normally distributed (Haan, 1977).

Data published in the literature were used to determine appropriate pdfs
various parameters. Also the data used in fitting the distribution were chose
different sources. Even for the same soil, the samples were taken from differe
An Analysis of Variance (ANOVA) was used to test whether datasets from differ
can be grouped together. The hypothesis tested is that the means of the different
do not differ significantly from each other. The probability distributions of the
either be tested by plotting them on probability paper and comparing the data
the best fit commulative distribution or using standard tests like the Kolmogorov-
or Chi square test.

Bulk density and percentages of sand and clay, along with saturated con
and water content are some of the soil properties that have received a lot of
from researchers. One widely quoted study was done by Nielsen et al. (1973)
the above soil properties were extensively studied. Another comprehensive lo
area was by Jury (1986). He compiled information regarding the mean and
of the soil properties. Courtin et al. (1983), Rawls et al. (1982), Cassel a
(1975), Vauclin et al. (1983) and Gajem et al. (1981) have also done extensive
this subject. Much of the work was to quantify the lateral variability of
properties and the sample size required to measure the variables. Haan an

(1987) and Hjelmfelt (1981) have studied the distribution of the retention parameter, S, which is a transform of the curve number (CN).

CURVE NUMBER

The curve number is a very sensitive parameter for many of the outputs that are considered.

The SCS uses the relationships

$$Q = \frac{(R-0.2S)^2}{R+0.8S} \qquad R > 0.2S \qquad (6\text{-}1)$$

$$Q = 0.0 \qquad R \leq 0.2\ S$$

$$S = \frac{25400}{CN} - 254 \qquad (6\text{-}2)$$

where Q is runoff volume, R is rainfall volume and S is initial abstraction.

Equation (6-1) can be arranged as

$$S = 5R + 10Q - 10\sqrt{Q^2 + 1.25Q} \qquad (6\text{-}3)$$

For several rainfall - runoff data pairs, Haan and Schulze (1987) estimated, the corresponding value for S from this relationship. The differences in S were attributed to different antecedent conditions prevalent at the time of precipitation. Hjelmfelt et al. (1981) have also studied the S values for two watersheds in Iowa for many rainfall - runoff values. They found that the lognormal distribution described the data. Haan and

Schulze (1987) found that S has a coefficient of variation, C_v, averaging 0.5 for the watersheds they investigated. Using this C_v and assuming the value of the curve number obtained from tables for the existing soils and cover as the mean value, the variance can be found.

For other soil variables, data are extremely limited. The following data have been drawn from many sources. For the purpose of fitting a distribution, a sample size of at least 20 is needed. Reports of this many observations from the same site and from the same soil are hard to find. ANOVA tests were used to group the data from different sites and for the same soil. This is illustrated using the bulk density (BD) values for Cecil soil from Watkinsville, GA (Bruce et al., 1983).

BULK DENSITY

There are six sites with BD values ranging in number from 5 to 8 as given in Table 6-1. It can be noted that the mean values are close to each other. To determine if they are statistically different, ANOVA was performed on this data set. The result is given in the Table 6-2.

The F ratio for this is 3.727 which has a 99.2 % significance level. This is greater than the Table value of F (3.68 for degree of freedom (df) 5 (n) and 38 (d) at 99% Confidence limit)(Cumulative F Distribution table, Haan (1977)) which is unacceptable. By removing the third group, the F-ratio was reduced to 1.243 which is

below the table value of 4.02 (for df of 4 and 31). The same procedure is adapted for the layer of 6 to 11 cm also.

TABLE 6-1. Bulk density values for Cecil soil from Watkinsville, GA

g/cm^3	plot 1	plot 2	plot 3	plot 4	plot 5	plot 6
0-6 cm	1.38	1.49	1.23	1.30	1.30	1.53
	1.40	1.48	1.23	1.42	1.56	1.65
	1.46	1.31	1.35	1.45	1.42	1.37
	1.48	1.33	1.34	1.23	1.38	1.32
		1.31	1.22	1.25	1.65	1.34
		1.39	1.24	1.23	1.31	1.31
		1.39	1.28	1.27	1.45	
Mean	1.432	1.375	1.259	1.340	1.438	1.433
Var.	0.002	0.006	0.004	0.006	0.014	0.017

TABLE 6-2. ANOVA table for the BD values from the Cecil soil data

WEIGHTED MEANS MODEL
ANALYSIS OF VARIANCE

SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
X	0.189	5	0.038	3.727	0.008
ERROR	0.385	38	0.010		

LEAST SQUARES MEANS.

			LS MEAN	SE	N
X	=	1.000	1.432	0.045	5
X	=	2.000	1.375	0.036	8
X	=	3.000	1.259	0.036	8
X	=	4.000	1.340	0.036	8
X	=	5.000	1.438	0.036	8
X	=	6.000	1.433	0.038	7

TABLE 6-3. K-S test results for BD values of Cecil soil

DIST.	K-S TEST
Gamma	0.105
Lognormal	0.106
Weibull	0.174
Normal	0.202

The K-S test results are indicated in table 6-3 for 0 - 6 cm depth. The tabular value at a significance level of 0.2 is 0.18 (Table E.9 Haan (1977)), so the gamma and lognormal distributions will qualify. The similar analysis for 7 to 11 cm layer bd values indicate the K-S test ranks the lognormal distribution as first (test value is 0.009). Here gamma is ranked as first in terms of fit. This gives an idea of the need for caution when few data are analyzed for purpose of fitting a probability distribution. Table 6-4 gives a range of values for C_v and means from different sources.

The Cecil data are from Bruce et al. (1983) and is for the first and second layers of the soil. Sharma and Rogowski (1983) and Carcel et al. (1988) observed that the C_v for soil properties such as bd and total porosity is less than 0.15. This seems to be substantiated by the range of values from the Table 6-4.

Table 6-4. The C_v values of BD

MEAN (Mg /m^3)	C_v (%)	FIELD SIZE (ha)	NO OF SAMPLES	REFERENCE
1.36	7	150	120	Nielson et al. (1973)
1.30	7	15.0	64	Gumma (1978)
1.20	26	3.80	30	Courtin (1983)
1.47	9	1.30	192	Cassel (1975)
1.26	6	0.50	144	Cassel (1975)
1.65	3	0.34	5	Babalola (1978)
1.39	7	-	36	Cecil data
1.59	18	-	36	Cecil data
1.20	15	40	36	Stockton (1971)

The weighted mean average of C_v with the number of samples is calculated as 8 which is a good estimate. Sharma and Rogowski (1985) also observed that soil properties exhibiting larger C_v (> 0.40) are frequently found to have a lognormal distribution, while those with lower C_v (< 0.40) may be adequately fitted with a normal distribution. Rogowski (1972) found that a random sample of soils from the northeastern United States to be normally distributed. Tiscareno-Lopez et al. (1993) also used normal distribution for bulk density. Thus normal distribution was selected for this study. A plot of normal distribution for the Cecil soils are given in figure 6-1 and it indicates a straight plot, thus justifying normal distribution.

FIELD CAPACITY

For the field capacity the data is much more limited. The available literature on soil properties do not have much on field capacity. The field capacity is not a precisely defined parameter. In this study the field capacity will be taken as volumetric water content at 100 cm or 0.15 bar (Haan, 1994a). The data used to examine distributional forms are for Bethany, Tipton and Konawa soils. Each soil had data from different sites ranging in number from 3 (Tipton) to 6 (Bethany) with 4 sites for Konawa (Nofziger et al, 1983). Each site had about 6 readings. The volumetric water content readings were usually at potentials of -93 and -106 cms. Interpolation of the data were done to calculate the volumetric water content at a potential of -100 cm.

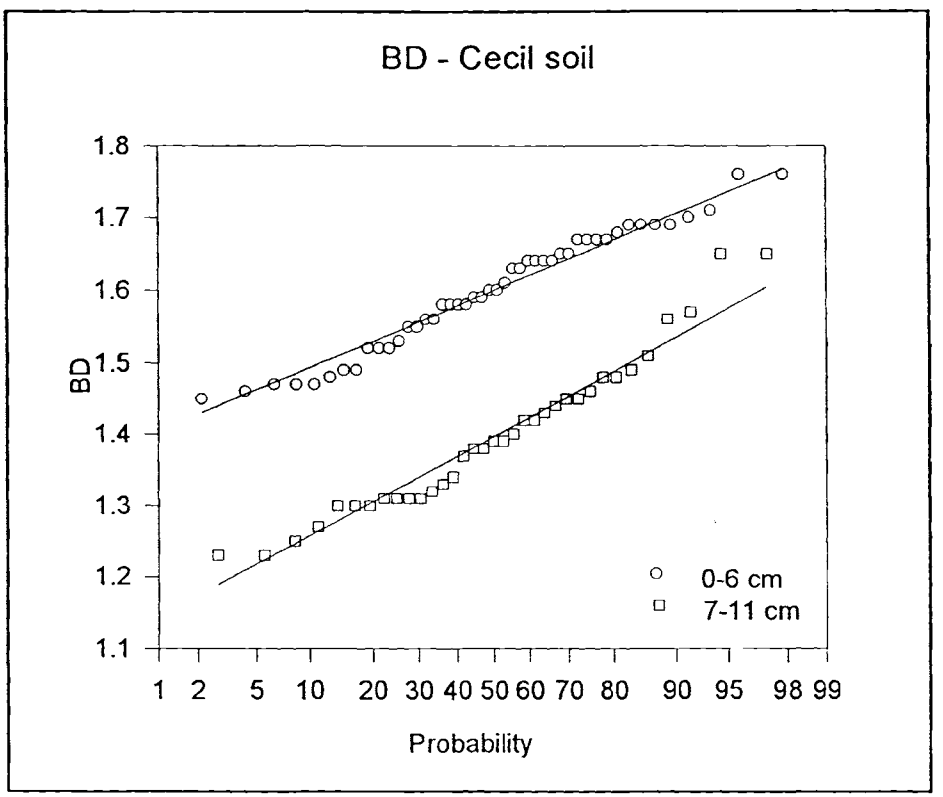


Figure 6-1. Normal distribution plot of BD of Cecil soil values.

An ANOVA for testing the hypothesis that the data from different sites have the same field capacity was conducted. As a result of that test, the data from Bethany soil is divided into two groups and data for the Tipton soil is considered as a single group. The Konawa soil can not be grouped according to this test. The result of initial ANOVA test for the Bethany soil is given in table 6-5.

When the first three datasets are grouped together and ANOVA is conducted again. The decision regarding the grouping of the first three datasets is taken based on the observed closeness of the LS MEAN of these three groups. Similarly the last three datasets are also grouped together. The ANOVA test result for the first three datasets grouping is given in table 6-6.

The K-S test results which indicate different distributions as the best fitting distributions and C_v values of these data are given in table 6-7. This dataset has very low C_v values. Proposing a value of C_v based on this small data may not be appropriate. Carcel et al. (1988) also conducted more extensive studies on variability of field capacity. Some of the results are given in table 6-8.

The difference in the C_v from the two studies, may be attributed to measurement of the field capacity in different plots. For the earlier study it is probable that the plots are closer together and the variability in the plots are limited. The Carcel et. al (1988) study involved data from different parts of Ohio and reflect the variability in the fields better. Thus Carcel data were given more importance and the C_v(%) value can be taken as 40.5 (from the weighted mean with the sample size) as representative of the field capacity. Since this value is close to the limit of $C_v = 0.4$ as suggested by Sharma and

Rogowski (1983), the lognormal distribution can be used as the distribution. A plot of lognormal distribution of the three soils used in the analysis is given in figure 6-2. It can be seen that data plotted straight, thus justifying lognormal distribution assumption.

The other soil properties like percentage slope and percentage silt are taken from Rawls' database (Rawls et al., 1982). Even though this database had a lot of soils in its list, there were very few soils with a large number of sample values. The soils examined are Rayne, Coshoct, Berks and an unnamed soil. The number of observations was 15 for Coshoct, 22 for Rayne, 17 for Berks and 16 for Unnamed soil.

PERCENTAGE OF SILT

Normal, Weibul, gamma and lognormal distributions were tested. All of them qualify for the best fit category when the hypothesis test was conducted. Tiscareno-Lopez et al. (1993) had assumed normal distribution as the best fitting distribution. The K-S test values are given in Table 6-9 for the soils considered with the sample size. The mean and C_v values from a number of sources are given in Table 6-10.

The plot of normal distribution is given in figure 6-3 for some soils from the Rawls' database. It can be seen that for the most part the data plotted as a straight line thus justifying the assumption of normal distribution.

TABLE 6-5. ANOVA test for Bethany soil

WEIGHTED MEANS MODEL
ANALYSIS OF VARIANCE

SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
X	0.024	5	0.005	12.788	0.000
ERROR	0.011	30	0.000		

LEAST SQUARES MEANS.

			LS MEAN	SE	N
X	=	1.000	0.316	0.008	6
X	=	2.000	0.310	0.008	6
X	=	3.000	0.318	0.008	6
X	=	4.000	0.361	0.008	6
X	=	5.000	0.359	0.008	6
X	=	6.000	0.376	0.008	6

Table 6-6. ANOVA test for three Bethany soils

WEIGHTED MEANS MODEL
ANALYSIS OF VARIANCE

SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
X	0.000	2	0.000	0.167	0.848
ERROR	0.010	15	0.001		

LEAST SQUARES MEANS.

			LS MEAN	SE	N
X	=	1.000	0.316	0.010	6
X	=	2.000	0.310	0.010	6
X	=	3.000	0.318	0.010	6

TABLE 6-7. K-S test results for FC values of various soils.

SOIL TYPE	C_v (%)				
Bethany 1	7	**DIST.**	Weibul	Normal	Gamma
		K-S TEST	0.101	0.311	0.322
Bethany 2	3.3	**DIST.**	Gamma	Normal	
		K-S TEST	0.133	0.160	
Tipton	4.3	**DIST.**	Normal	Gamma	
		K-S TEST	0.160	0.163	

TABLE 6-8. C_v values of FC for several soils (Carcel et al., 1988)

SAMPLE SIZE	MEAN	C_v(%)
52	11.8	78
459	19.5	42
371	22.4	35
230	24.1	38

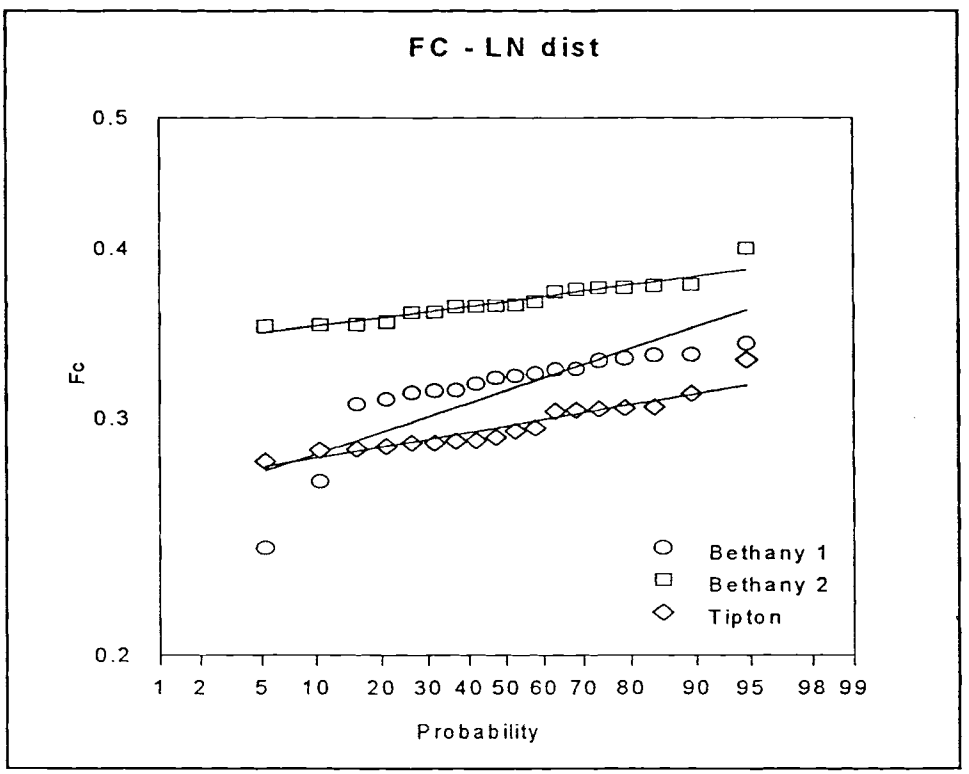


Figure 6-2. Lognormal distribution of FC of three soils.

Table 6-9. K-S test values of LN and Normal distribution for some of the soils for percentage of Silt.

SOIL	SAMPLE SIZE	LOG NORMAL	NORMAL
Berks	17	0.09	0.13
Coshoct	15	0.165	0.14
Rayne	22	0.14	0.11
Unnamed	16	0.11	0.20

Table 6-10. The Mean and C_v values of Percent Silt from number of sources

MEAN	C_v (%)	REFERENCE
7.20	44.4	Vaclin et al. (1983)
8.50	16.5	Babalola (1978)
26.8	25.0	Neilson et al. (1973)
64.9	7.0	Coshoct soil*

* Rawls database

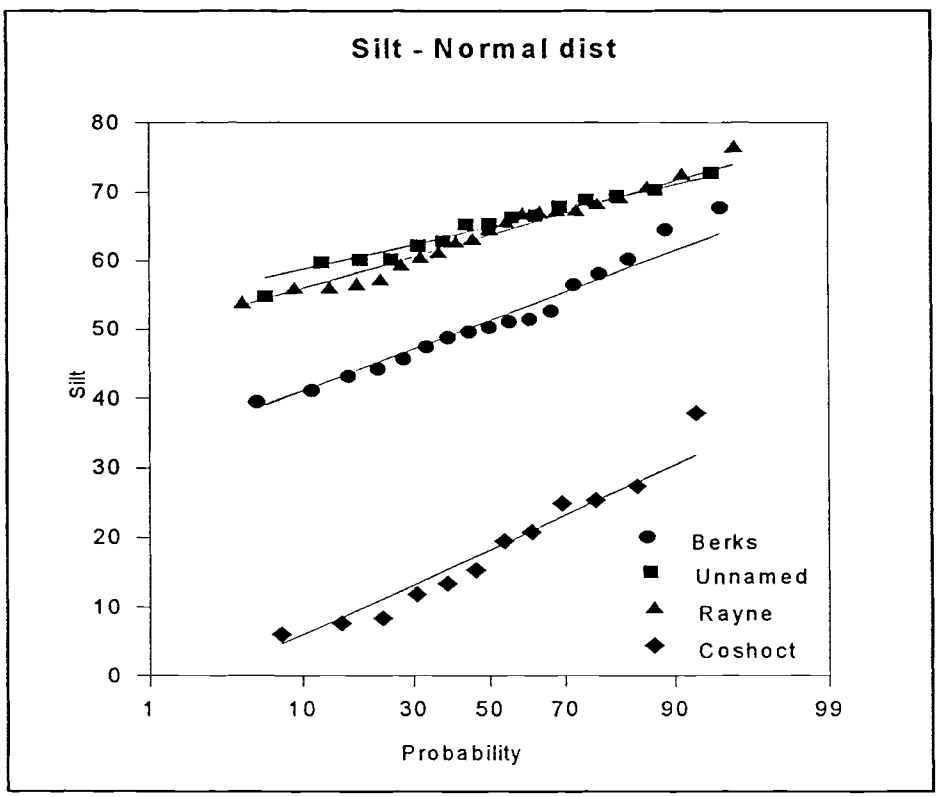


Figure 6-3. Normal distribution of percent silt for several soils from Rawls database.

Carcel et al. (1988) have analyzed several soils to determine C_v values for percent sand and clay. Their data indicate that there is not much difference between the standard deviation values for percent sand and clay. It is not unreasonable to assume, that the standard deviation for the percent silt is also approximately equal to that for sand and clay. Since the total of percent sand, silt and clay would be equal to 100, the mean values for percent silt can be deduced. The standard deviation values for the percent silt are taken as the average of figures for sand and clay. These are given in table 6-11. The C_v value for percent silt used by Tiscareno-Lopez et al. (1993) was 14.6 %. This value is from a single watershed. Considering the values in table 6-11, with most values ranging from 15 to 36, a value of 25% as C_v would be a reasonable estimate and normal distribution can be taken as the best fitting distribution.

SLOPE

The lognormal distribution seems to be a good choice for the distribution for slopes for three out of four soils analyzed from Rawls database. The K-S test values for the lognormal distribution and C_v values are given in table 6-12. A C_v value of about 0.35 would be a good estimate.

The lognormal distribution of the four soils from Rawls database are plotted in the figure 6-4. Although this plot indicate that lognormal distribution is justified, this plot cannot be taken as a sole indicator of the best fit of a distribution. This can be taken as an aid in illustration of the best of the distributions.

TABLE 6-11. C_v values deduced from mean and standard deviation values of silt percentage of different soils (Carcel et al., 1988).

MEAN (%)			STANDARD DEVIATION (% SILT ASSUMED)			C_v
SAND	CLAY	SILT	SAND	CLAY	SILT	SILT
14.9	55.2	29.9	10.7	10.9	10.8	36.12
29.8	32.6	37.6	5.9	3.7	4.8	12.76
40	19.7	40.3	6.5	5.2	5.8	14.51
80.9	6.4	12.7	3.8	3.2	3.5	27.55
5.8	9.5	84.7	4.5	2.7	3.6	4.2
6.1	46.3	47.6	4.5	4.9	4.7	9.8
47.5	41	11.5	3.9	4.5	4.2	36.52
54.3	27.4	18.3	7.3	4.0	5.6	30.87
63.4	11.1	25.5	7.9	4.8	6.3	24.90

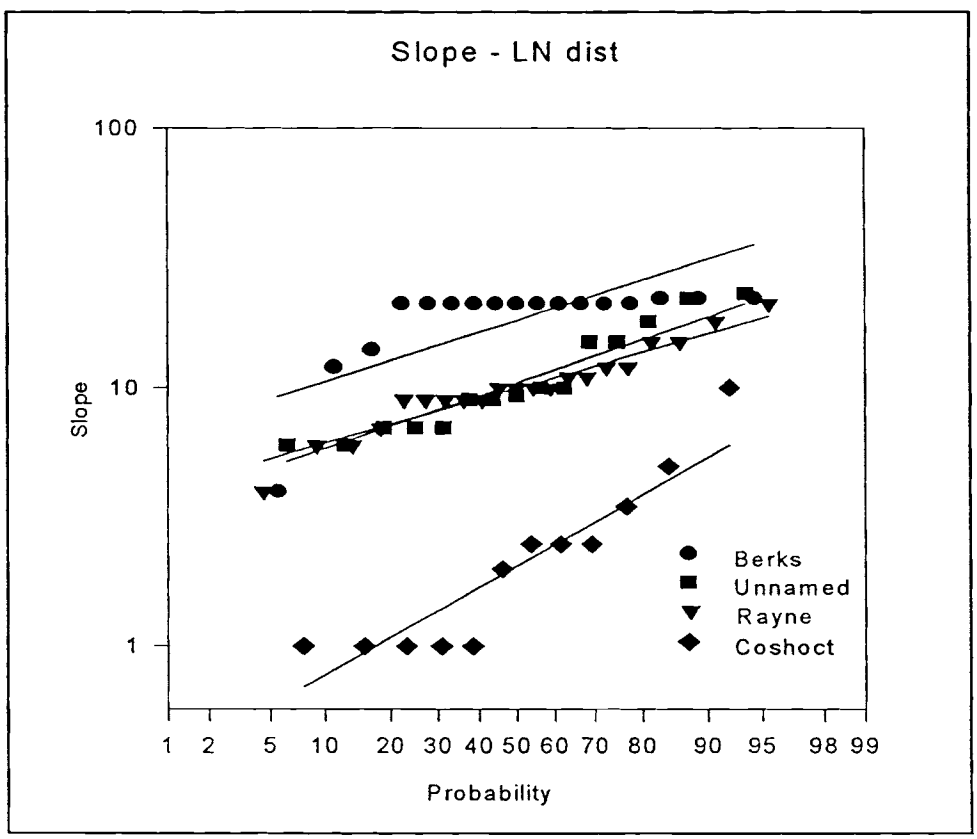


Figure 6-4. Lognormal distribution of slope of four soils from Rawls database.

Table 6-12. K-S values for LN distribution of slope for three Rawls database soils along with Mean and C_v

SOIL	MEAN (%)	C_v	K-S TEST
Berks	19.23	24.9	0.39
Coshoct	11.55	49.2	0.25
Rayne	10.61	37.6	0.18

The soil nitrogen and the nitrogen coefficients for runoff and leaching are assumed to be lognormally distributed with a C_v value of 0.5. The other parameters were considered to be from triangular distributions. The data for those parameters were taken from the tables, so the triangular distribution is convenient. The triangular distributions has the advantage of restricting the values on the left and right. These ranges are deduced from the nature of the parameters and the data. For the soil erosion control practice factor, P, which is equal to one (Edwards et al., 1993), the range is defined as 0.8 to 1. For organic nitrogen the range is assumed to be from 20 to 574 g/t. For other parameters the range is given in Table 6-13.

The First Order Analysis requires the variance of the input parameters. The variance of the parameters having triangular distributions can be calculated from

$$Var(x) = E(X^2) - E^2(X) \tag{6-4}$$

$$E(X) = \int_{-\infty}^{\infty} x\, p_x(x)dx \tag{6-5}$$

Since the triangular distribution is limited in left and right ranges, the ∞ will be replaced by the value to the right and -∞ will be replaced by the left value. The $p_x(x)$ will be representing the equation of the line which makes up the trianglular distribution. The variance of the parameters which are represented by triangular distributions are given in Table 6-14. Appendix F shows the equations for E(X) and Var(X).

In conclusion, the various parameters, their distributions and C_v's are given in Tables 6-15 and in 6-16 for EPIC and AGNPS models.

TABLE 6-13. The Mean and Ranges of triangular distribution parameters.

PARAMETER	MEAN	LEFT	RIGHT
Organic Nitrogen, g/t	297	20	574
Erosion Control Practice Factor (P)	0.93	0.8	1
Soil Erodibility Factor (K)	0.25	0.18	0.36
Cover and Management Factor (C)	0.012	0.006	0.018

TABLE 6-14. The standard deviation of the parameters which are triangular distributed

PARAMETER	STD DEV.
Organic Nitrogen, g/t	113.08
Erosion Control Practice Factor (P)	0.041
Soil Erodibility Factor (K)	0.037
Cover and Management Factor (C)	0.002

TABLE 6-15. Distributions and C_v values for input parameters for EPIC model.

PARAMETER	DISTRIBUTION	COEF VAR.
Retention parameter (S)	Log normal	0.5
Bulk density	Normal	0.08
Field capacity	Log normal	0.4
Slope	Log normal	0.3
P - factor	Triangle	0.05
Silt	Normal	0.25
Organic Nitrogen, g/t	Triangle	0.38

TABLE 6-16. Distributions and C_v values for input parameters for AGNPS model

PARAMETER	DISTRIBUTION	COEFF. VAR.
Retention parameter (S)	Log normal	0.5
Slope	Log normal	0.3
K - factor	Triangle	0.14
C - factor	Triangle	0.20
P- factor	Triangle	0.05
Soil Nitrogen, lbs/ac	Log normal	0.5
Nit. runoff coeff.	Log normal	0.5
Nit leaching coeff.	Log normal	0.5

CHAPTER VII

MONTE CARLO AND FIRST ORDER ANALYSIS

MONTE CARLO ANALYSIS

The Monte Carlo analysis is useful in characterizing the uncertainties due to the parameters. Here the variability or uncertainty in the system is quantified in terms of the variance and pdfs of the input distribution and the model outputs. In Monte Carlo Simulation (MCS) the input distributions and the number of simulation runs are very important.

Monte Carlo simulation has been used widely to characterize uncertainty by a number of researchers. Coy et al. (1986) used MCS to characterize the propagation of error. They assigned an error distribution for each recognized error source and calculated the effects of the several sources of error on true values. After assigning the true value, random numbers were generated to pick input values within the range of concern. The corresponding error was then calculated for the source affecting the output determination. The resulting discrete error was added to or subtracted from the true value and the resultant used as input to the distribution for the second occurring error source. Contributions from sources operating simultaneously were calculated and

summed simultaneously. The process was then repeated to include all the sources and results in a single output value corresponding to the single random number chosen. Carcel et al. (1988) used the PRZM model for making a regional assessment of pesticide leaching incorporating MCS. They calculated 90th, 95th and 99th percentiles of the amount of aldicrab residues moving past various depth as a function of sample size. These half-width of confidence intervals were used to provide a measure of uncertainty of interval estimates. A relative uncertainty value was constructed by dividing the half-width of the 95 % confidence interval for a given percentile by the value of the percentile estimate. They, however, caution that as the MCS procedure uses generalized distributions for soil characteristics, the probabilities calculated with this procedure may sometimes underestimate or overestimate some measurements.

They gave an example of corn cultivation with the output as leaching potential. As yield of some crops on lighter textured soils is poor, these crops are not usually grown on soils where leaching potential is highest. In this case, the assessment procedure may overestimate the probability of significant pesticide movement. According to the authors, the MCS technique provides little insight into cause and effect relationships.

O'Neill et al. (1980) used triangular distributions for MCS specified by minimum, mean and maximum values. They claim that the triangular distribution represents a least-biased assumption when the true distribution is unknown. They set the maximum and minimum values of all parameters equal to $\pm$ 10 % of the mean with a C_v value of 4.1%. The integrated error was calculated as the sum of squares of the differences between the calculated and expected states. They tested the acceptability of each MCS by defining

an upper and lower limit as a percent deviation from the expected value. Simulation values which lay outside these limits were eliminated. According to the authors, the limits represent the measured variance of field data which the model was expected to match.

Simulation Procedure

The routine for the generation of random numbers was adapted from Press et al., (1986). For curve number (CN), the retention parameter (S) was first generated from a lognormal distribution and then converted to the curve number using

$$CN = \frac{1000}{S+10} \tag{7-1}$$

For all parameters which have lognormal distributions, random observations first were generated from a normal distribution and then converted to the lognormal distribution. For lognormal distribution the expected value and the variance was estimated from equation 7-2 and 7-3 (Haan, 1977)

$$\overline{Y} = \ln(\overline{X}^2/(C_v^2 + 1))/2 \tag{7-2}$$

$$S_y^2 = \ln(C_v^2 + 1) \qquad (7\text{-}3)$$

where C_v is the coefficient of variation of the original data and $\overline{X}$ is the expected value of the original data. For triangular distributions, the minimum and maximum values were specified and random numbers were generated within this interval. An example of computer program for the generation of random numbers is given in Appendix E for normal, lognormal and triangular distributions for AGNPS.

A number of simulation runs were conducted for both EPIC and AGNPS. To determine the required number of runs, simulations involving only curve numbers were conducted. The CN was chosen for this simulations because it is the most significant parameter as defined by the sensitivity analysis. The means of these runs were determined. The results based on runoff are given in figures 7-1 for EPIC and 7-2 for AGNPS. For other output parameters similar patterns were detectible. For EPIC the same observed rainfall and daily temperature was used for all simulations. As mentioned in chapter III, the outputs from September 1, 1991 to April 30, 1993 were used in calculating these results. The outputs correspond to the total values for this period. For AGNPS as it is an event based model, the analysis was confined to a single event of 3.76 inches precipitation on July 30, 1992. Based on these results, it was decided that 1500 simulations are adequate to define the output distributions.

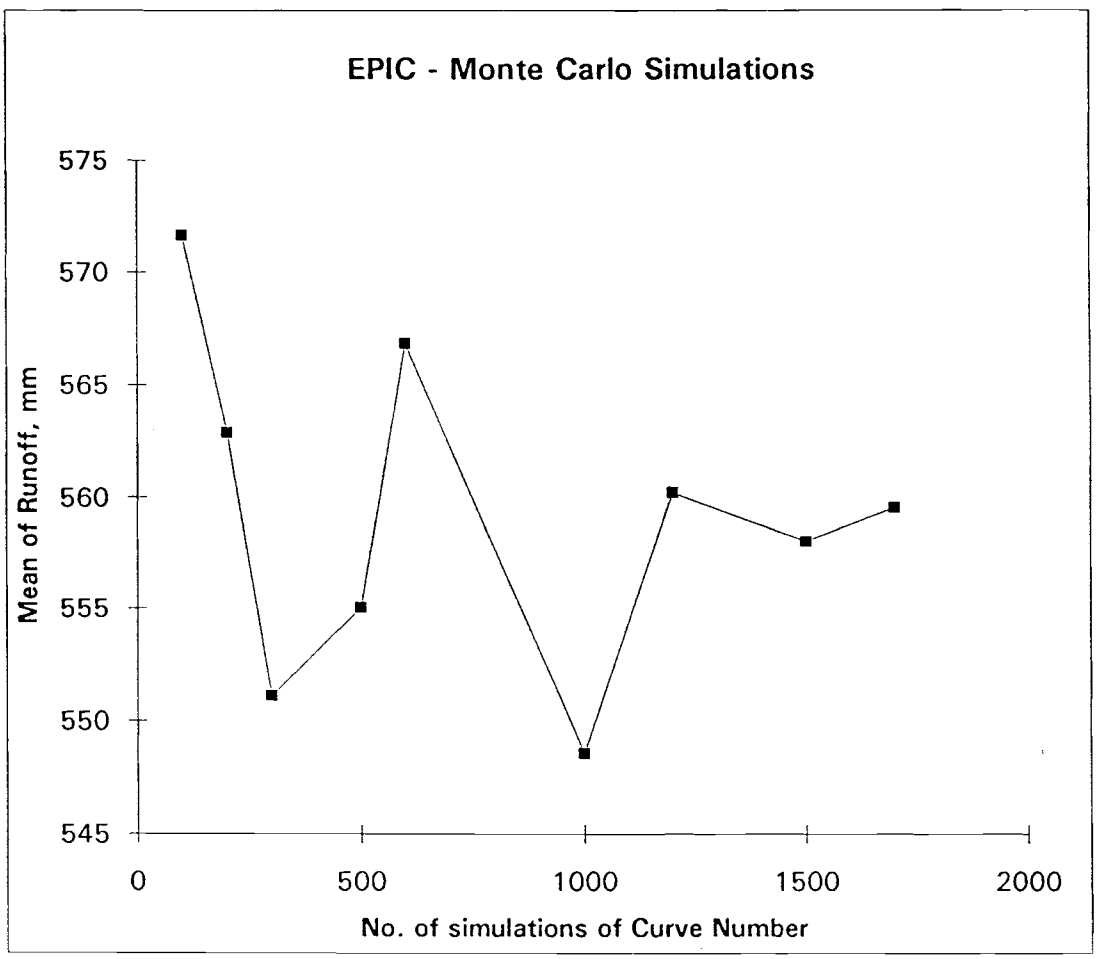


FIGURE 7-1. The Mean simulated values of runoff with CN as random variable for EPIC.

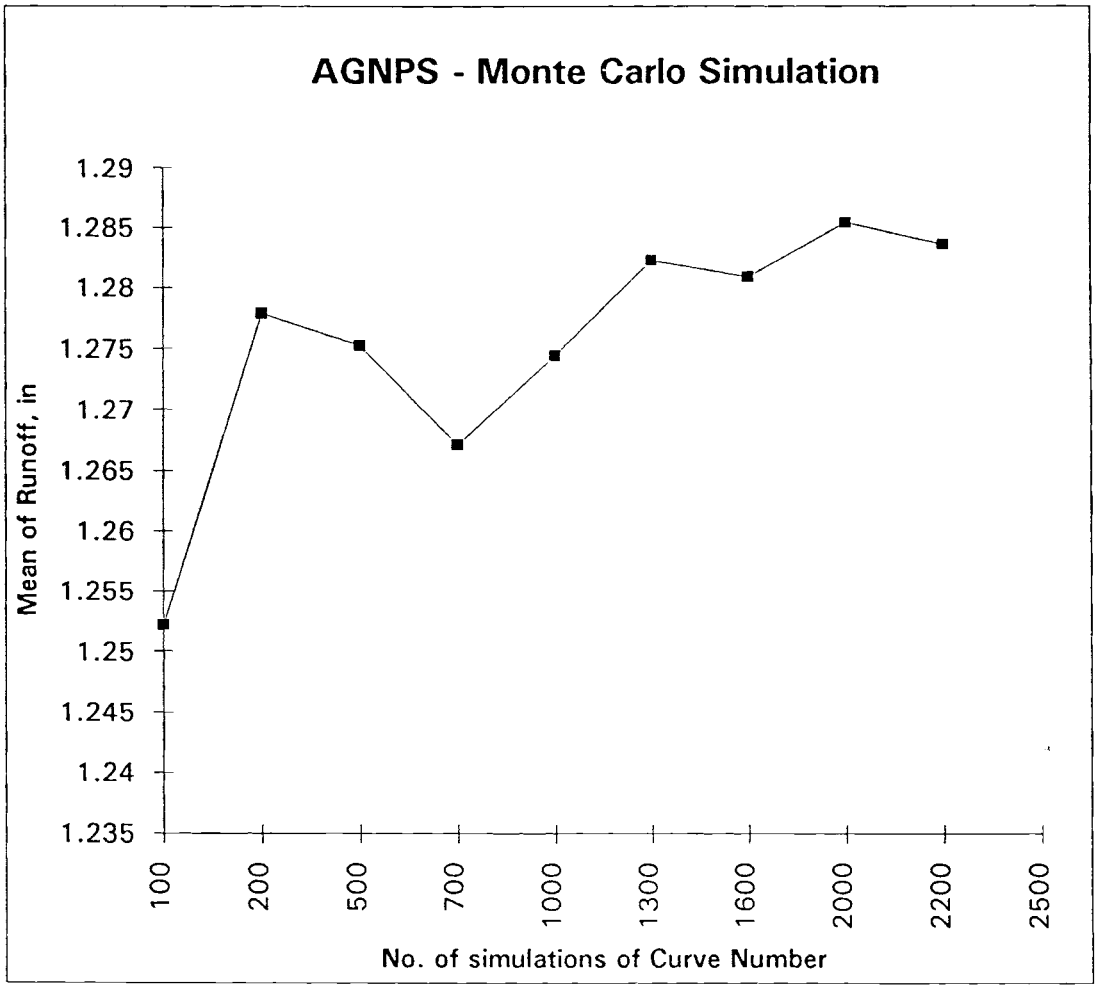


FIGURE 7-2. The Mean simulated values of runoff with CN as random variable for AGNPS.

The next step was to take all of the parameters shown in Tables 6-15 and 6-16 as random and perform 1500 simulation runs. The parameters were simultaneously changed, using the random observations generated from the respective distributions. The expected values for the input parameters used in the simulations were taken from the mean of the field values as given in Edwards et al. (1993) and are presented in Appendices A and C. Descriptive statistics are given for the EPIC simulation outputs are given in Table 7-1 and for AGNPS it is given in Table 7-2.

Simulation Results

The output results of the 1500 simulation runs were tested for goodness of fit for various distributions. The Chi-square goodness of fit test was used. This test makes a comparison between the actual number of observations and the expected number of observations (expected according to the distribution under test) that fall in various class intervals (Haan, 1977). The Chi-square test statistics for lognormal and normal distributions are given for the EPIC outputs in Table 7-3 and for AGNPS it is given in Table 7-4.

The output distribution is chosen on the basis of the lowest Chi-square value. For both the models the output distribution is the same i.e for runoff it is normal; sediment, nitrogen in runoff and sediment it is lognormal; for phosphorus in runoff it is normal; and for phosphorus in sediment it is lognormal.

Frequency histograms and best fitting distributions are shown in figures 7-3 through 7-7 for EPIC and figures 7-8 through 7-12 for AGNPS.

TABLE 7-1. Descriptive Statistics for the EPIC Simulation outputs.

STATS	RUNOFF, mm	SED., ton/Ha	SED. N, Kg/Ha	RUNOFF N, Kg/Ha	RUNOFF P, g/Ha
MIN	28.57	0.0	0.0	0.56	219.47
MAX	1305.5	5.64	2.57	19.1	8515.51
MEAN	541.48	1.47	0.55	2.53	3150.05
VAR	6.39 E 04	0.73	0.135	3.56	3.4 E 06
STD DEV	252.78	0.85	0.37	1.89	1839.1
C_v	0.46	0.58	0.67	0.75	0.58
SKEW	0.35	1.52	1.54	3.57	0.59

TABLE 7-2. Descriptive Statistics for the AGNPS Simulation outputs.

STATS	RUNOFF, inches	SED., tons	RUNOFF N, lbs/Ac	SED. N, lbs/Ac	SED. P, lbs/Ac
MIN	0.0	0.0	0.0	0.0	0.0
MAX	2.97	1.48	12.37	2.82	0.89
MEAN	1.28	0.28	1.11	0.45	0.23
VAR	0.29	0.03	2.19	0.11	0.014
STD DEV	0.54	0.18	1.48	0.33	0.12
C_v	0.42	0.64	1.33	0.73	0.52
SKEW	0.06	2.06	2.75	2.42	1.46

TABLE 7-3. Chi-square test Statistics for EPIC outputs.

OUTPUTS	NORMAL	LOGNORMAL
RUNOFF, mm	3.35 E -04	1.34 E -03
SEDIMENT, tons/ha	3.711	0.027
RUNOFF N., Kg/Ha	17.90	0.015
SEDIMENT N., Kg/Ha	1.87 E 09	0.091
RUNOFF P., g/Ha	1.81 E -04	2.03 E -04

TABLE 7-4. Chi-square test Statistics for AGNPS outputs.

OUTPUTS	NORMAL	LOGNORMAL
RUNOFF, inches	0.211	2.61
SEDIMENT, tons	33.53	3.88
RUNOFF N., lbs/Ac	1.3 E 03	0.28
SEDIMENT N., lbs/Ac	4.9	1.28
SEDIMENT P., lbs/Ac	18.74	6.74

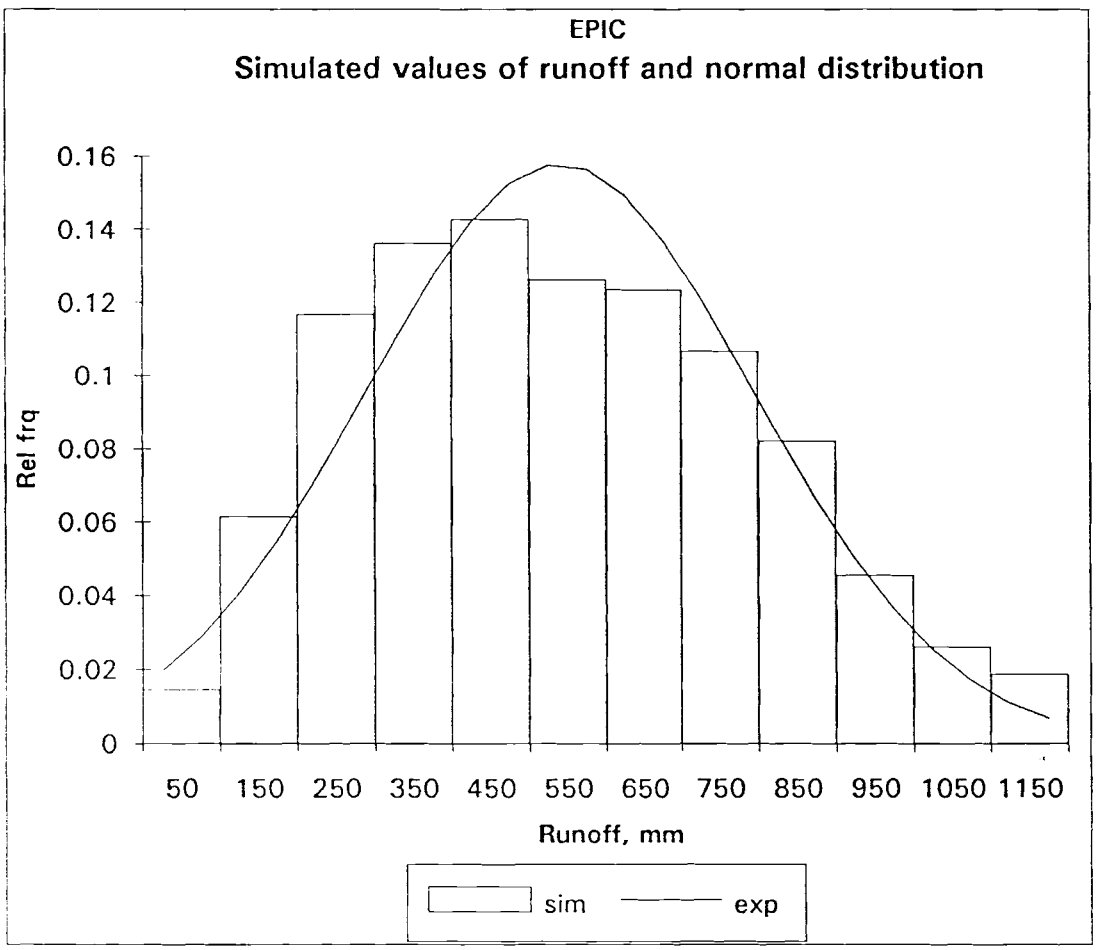


FIGURE 7-3. Expected normal distribution and simulated relative frequencies for runoff using EPIC.

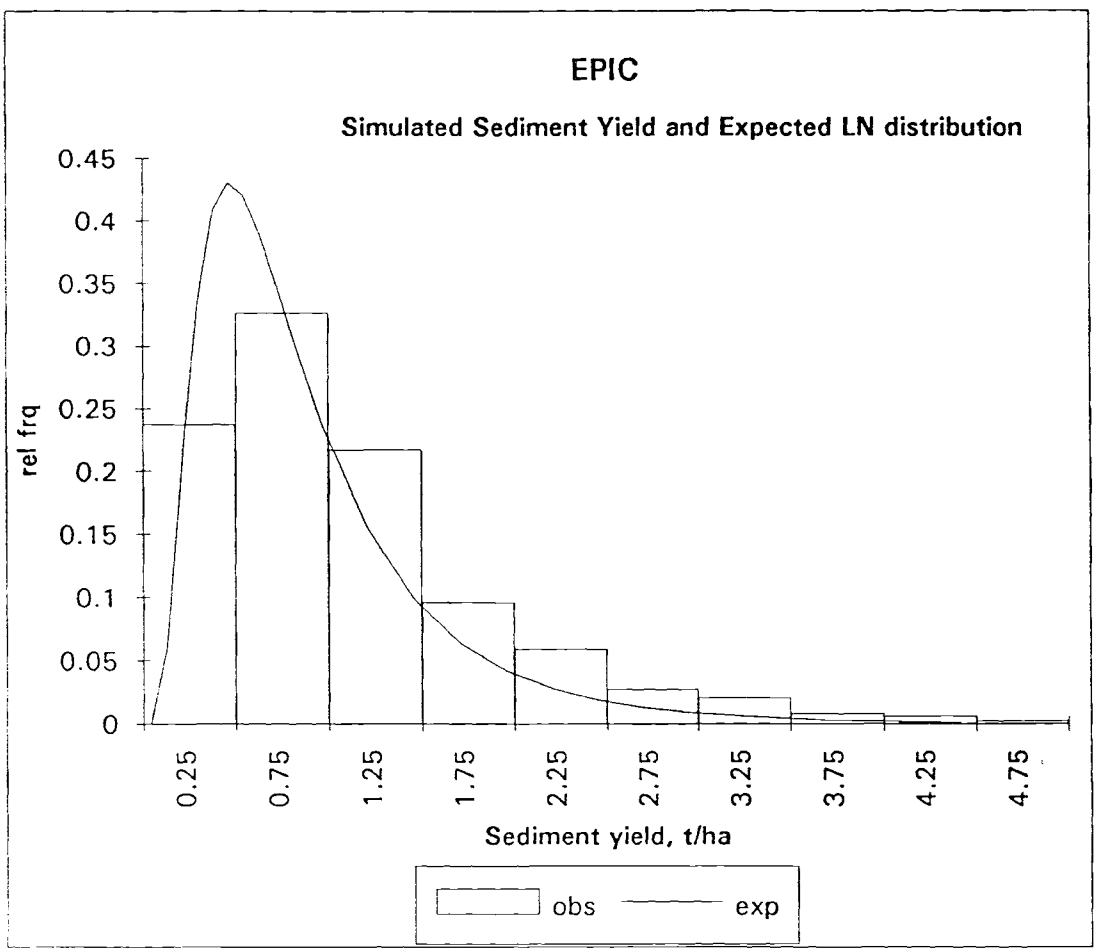


FIGURE 7-4. Expected lognormal distribution and simulated relative frequencies for sediment using EPIC.

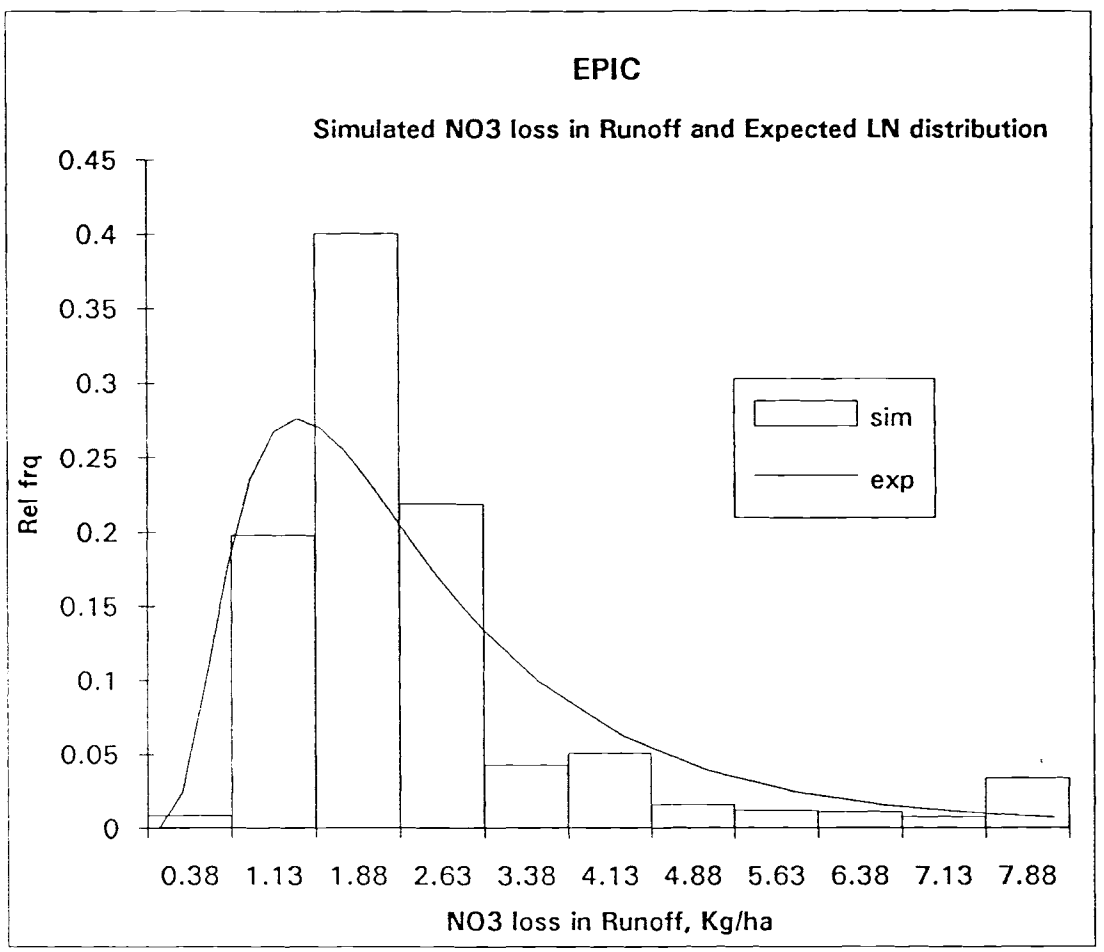


FIGURE 7-5. Expected lognormal distribution and simulated relative frequencies for nitrogen in runoff using EPIC.

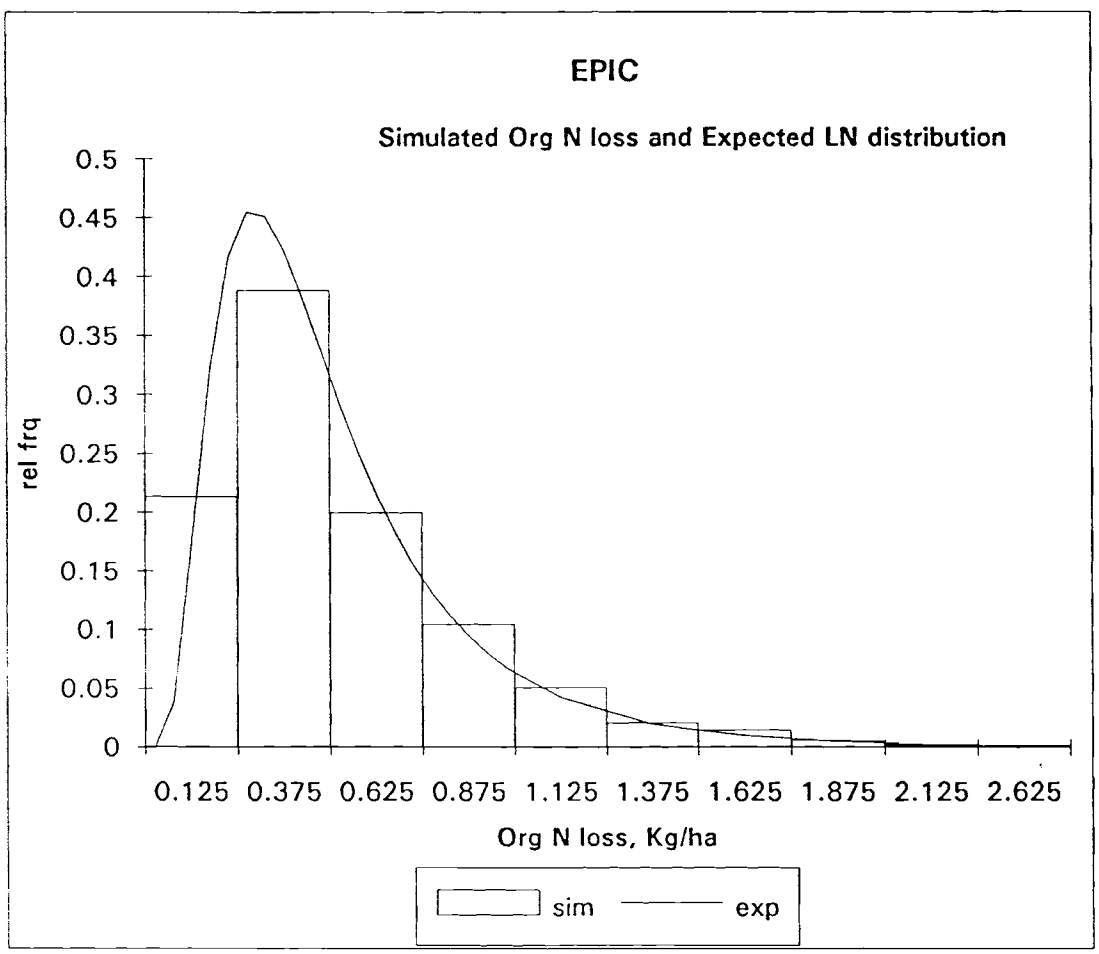


FIGURE 7-6. Expected lognormal distribution and simulated relative frequencies for nitrogen in sediment using EPIC.

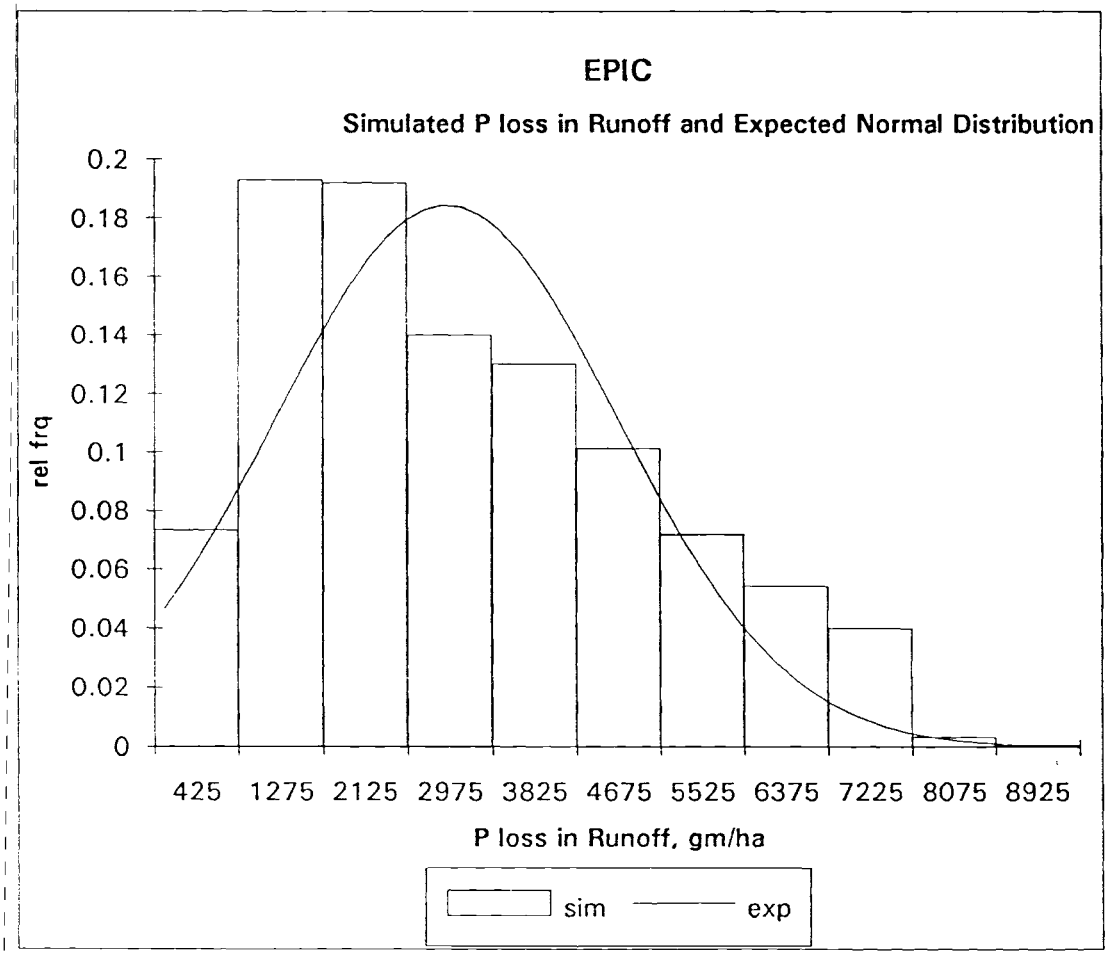


FIGURE 7-7. Expected normal distribution and simulated relative frequencies for phosphorus in runoff using EPIC.

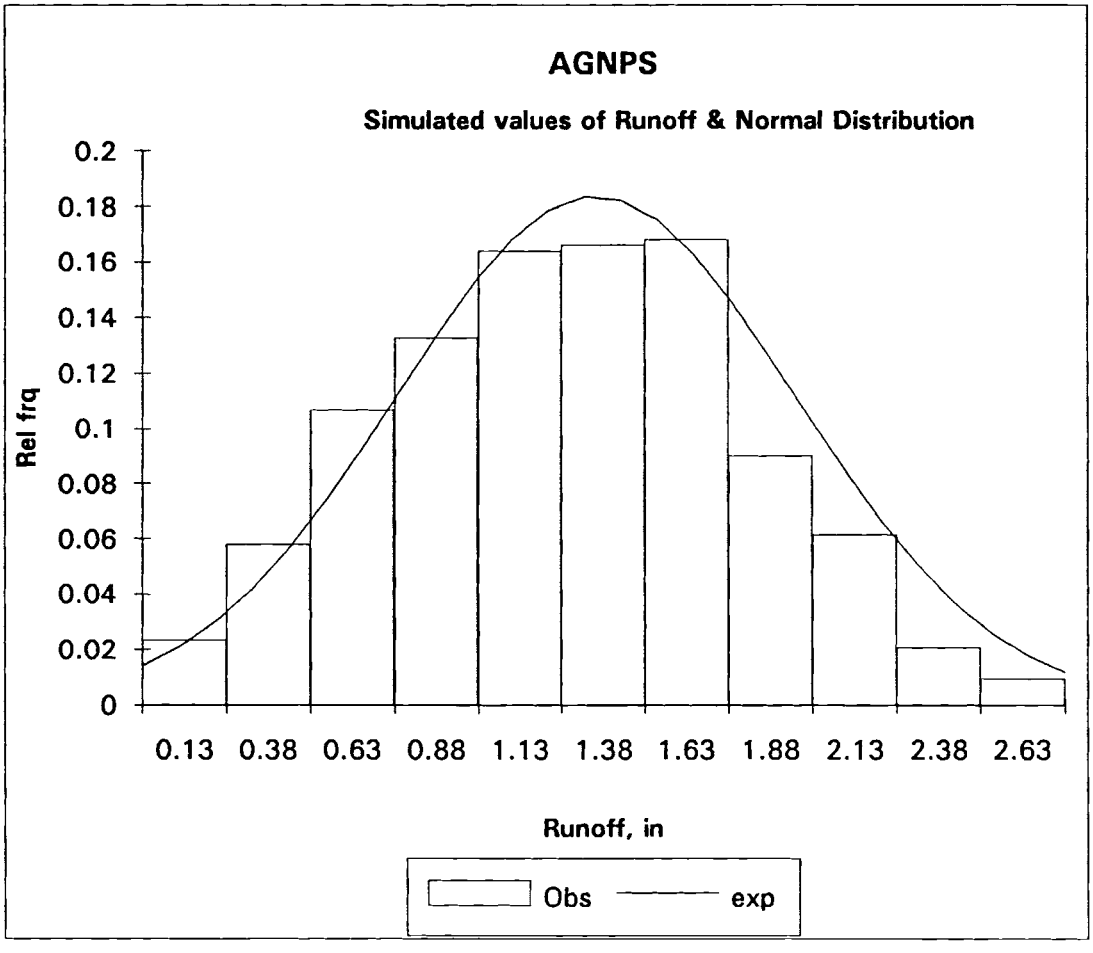


FIGURE 7-8. Expected normal distribution and simulated relative frequencies for runoff using AGNPS.

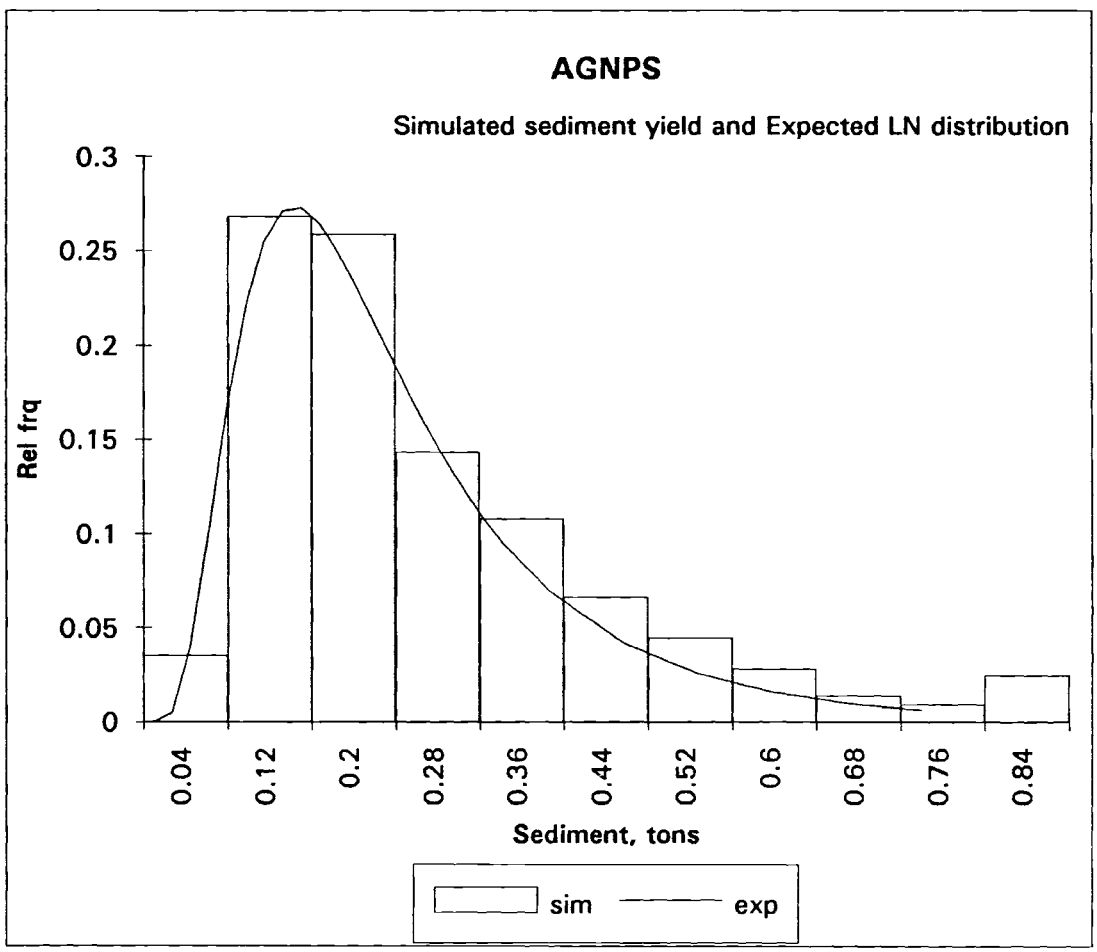


FIGURE 7-9. Expected lognormal distribution and simulated relative frequencies for sediment using AGNPS.

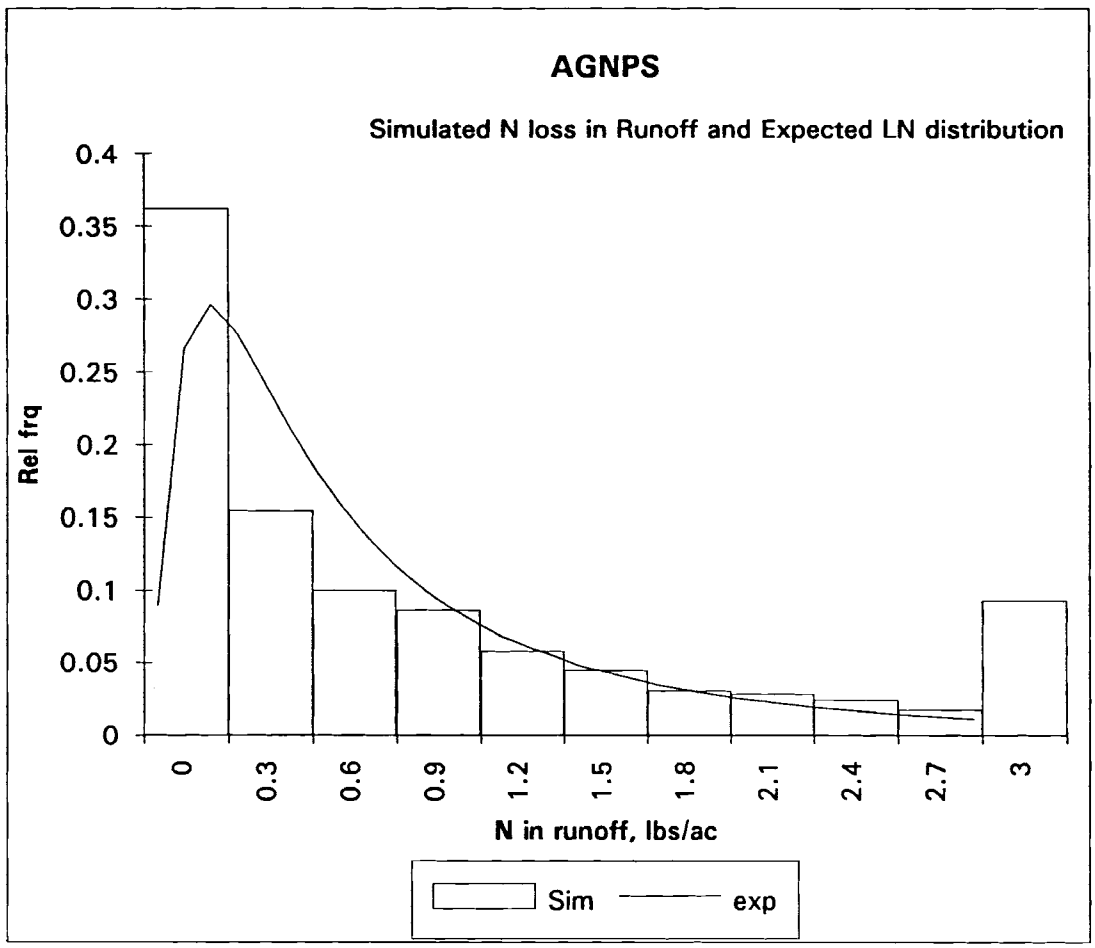


FIGURE 7-10. Expected lognormal distribution and simulated relative frequencies for nitrogen in runoff using AGNPS.

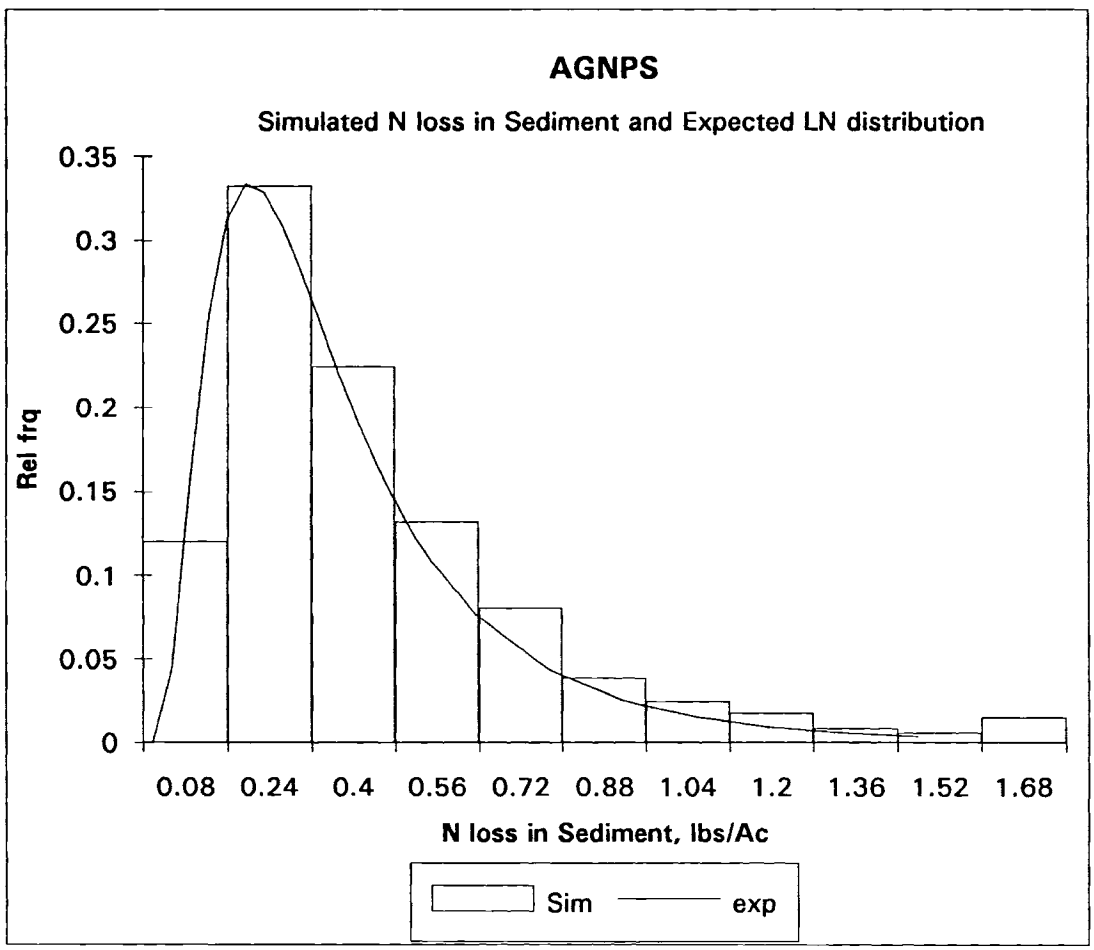


FIGURE 7-11. Expected lognormal distribution and simulated relative frequencies for nitrogen in sediment using AGNPS.

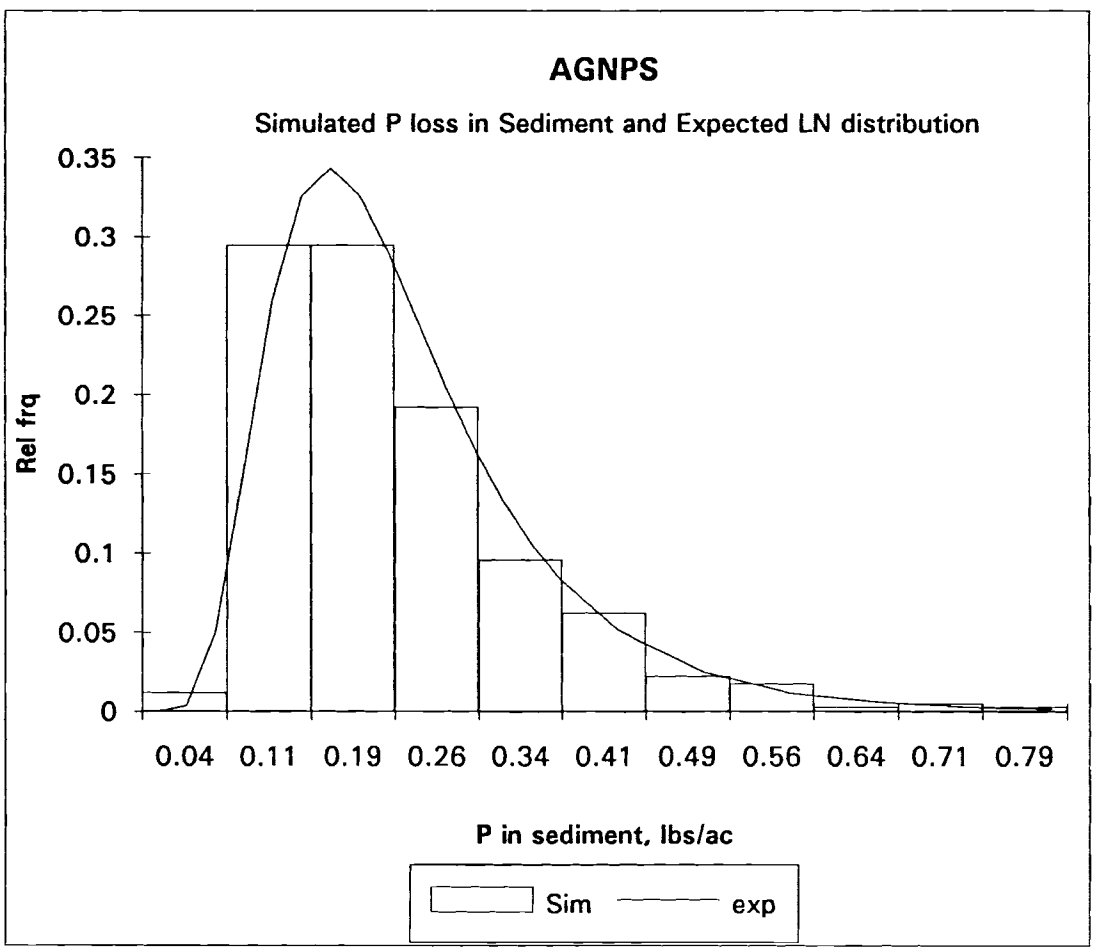


FIGURE 7-12. Expected lognormal distribution and simulated relative frequencies for phosphorus in sediment using AGNPS.

Analysis of the Simulation Results

If one assumes the model is valid and the uncertainty in model outputs is due to uncertainty in input parameters, confidence intervals (CI) can be computed such that a given percent of the output distribution is included within these CIs. Letting 100(1-α) be the confidence interval in percent, the upper, u, and lower, l, confidential limits can be computed from

$$\frac{\alpha}{2} = \int_{-\infty}^{l} p_x(x)dx \tag{7-4}$$

and

$$\frac{\alpha}{2} = \int_{u}^{\infty} p_x(x)dx \tag{7-5}$$

where $p_x(x)$ represents the pdf of the output x in question. For bounded distributions, $-\infty$ and ∞ are replaced by the lower and upper bounds of the distribution respectively.

For the normal distribution, l and u can be determined from

$$l = \bar{x} - z_{1-\alpha/2}\ \sigma_{\bar{x}} \tag{7-6}$$

$$u = \bar{x} + z_{1-\alpha/2}\ \sigma_{\bar{x}} \qquad (7\text{-}7)$$

where $z_{1-\alpha/2}$ is the value of Z from standard normal distribution such that the area to the right of Z is $\alpha/2$ and $\bar{x}$ is the mean and σ_x is the standard deviation of the population (Haan, 1977).

The 90% and 95% CI are given in Table 7-5 for the EPIC and Table 7-6 for AGNPS results.

As a next step the observed values i.e, the actual watershed responses measured from the field are also tabulated and given in table 7-7. The complete list of the observed field responses is given in Appendix G. These observed values are analyzed to determine whether they fall within the CIs. The results are shown in figure 7-13 through 7-17 for EPIC and 7-18 through 7-22 for AGNPS.

From figure 7-13, It can be seen that the observed total runoff falls within both CIs. It can be inferred in a statistical sense that EPIC predicts the runoff satisfactorily. However the CIs can be seen to be very wide indicating that the model structure and the uncertainty in input parameters combine in such a way as to render the EPIC model predictions regarding the runoff quite uncertain. Loosely interpreted, one might state they are 90% confident that the runoff lies between 124 and 959 mm. Such a wide interval may render the results too uncertain for a particular application. If this is the case, the uncertainty in the model input parameters must be reduced.

TABLE 7-5. CIs for EPIC model outputs.

OUTPUTS	95 % lower	95 % upper	90 % lower	90 % upper
RUNOFF, mm	45.98	1036.99	124.35	958.62
SED. tons/ha	0.25	3.37	0.31	2.75
RUNOFF N., Kg/ha	0.14	1.50	0.16	1.24
SED. N., Kg/ha	0.55	7.48	0.68	6.08
RUNOFF, P., g/ha	-454.57	6754.68	115.54	6184.56

TABLE 7-6. CIs for AGNPS model outputs

OUTPUTS	**95 % lower**	**95 % upper**	**90 % lower**	**90 % upper**
RUNOFF, inches	0.21	2.32	0.38	2.16
SED. tons	0.067	0.76	0.081	0.66
RUNOFF N., lbs/ac	0.10	4.83	0.12	3.53
SED. N., lbs/ac	0.09	1.31	0.11	1.07
SED. P., lbs/ac	0.07	0.55	0.09	0.45

TABLE 7-7. Measured total watershed response values from the field WA.

OUTPUTS	OBSERVED VALUES
RUNOFF, mm	297.23
SED. tons/ha	0.26
RUNOFF N., Kg/ha	6.40
SED. N., Kg/ha	8.97
RUNOFF, P., g/ha	5055

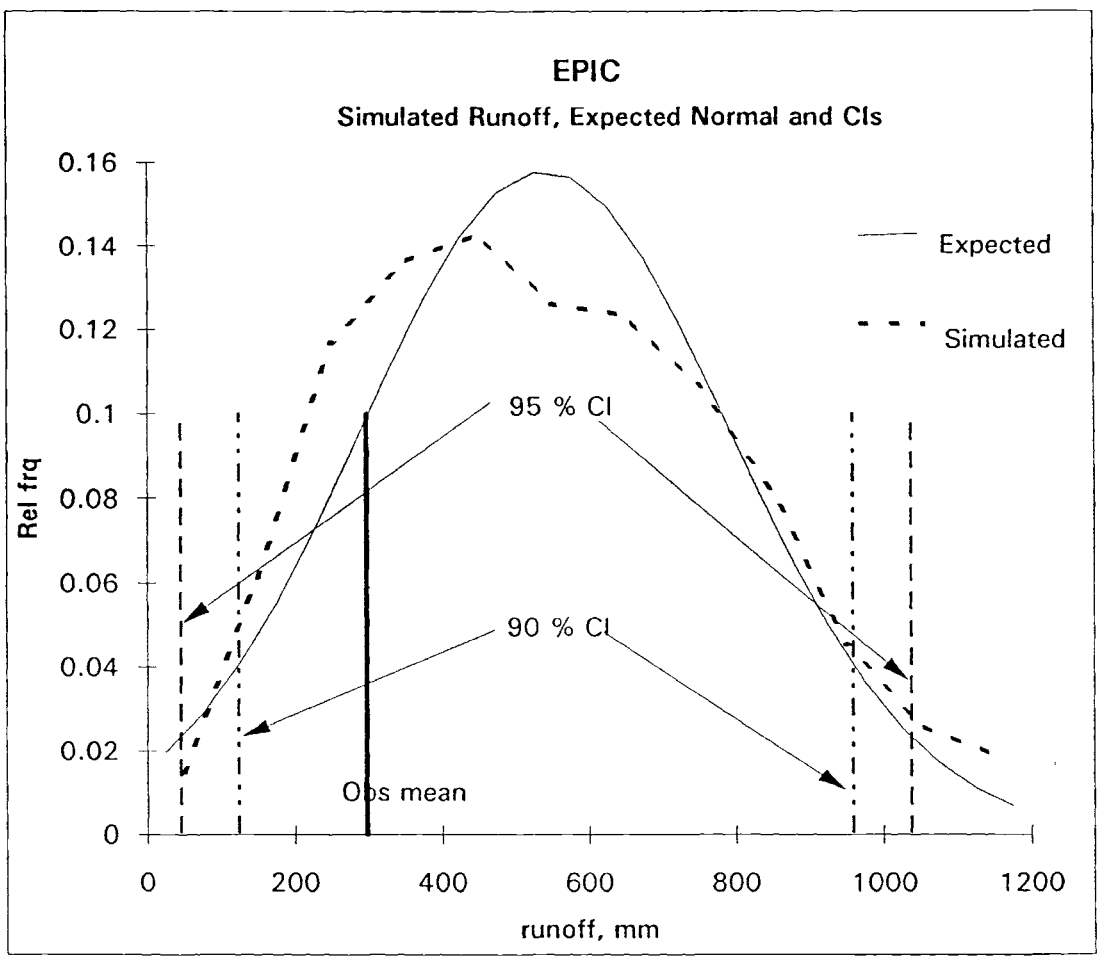


FIGURE 7-13. The simulated values, observed total, expected normal distribution and CIs of runoff using EPIC.

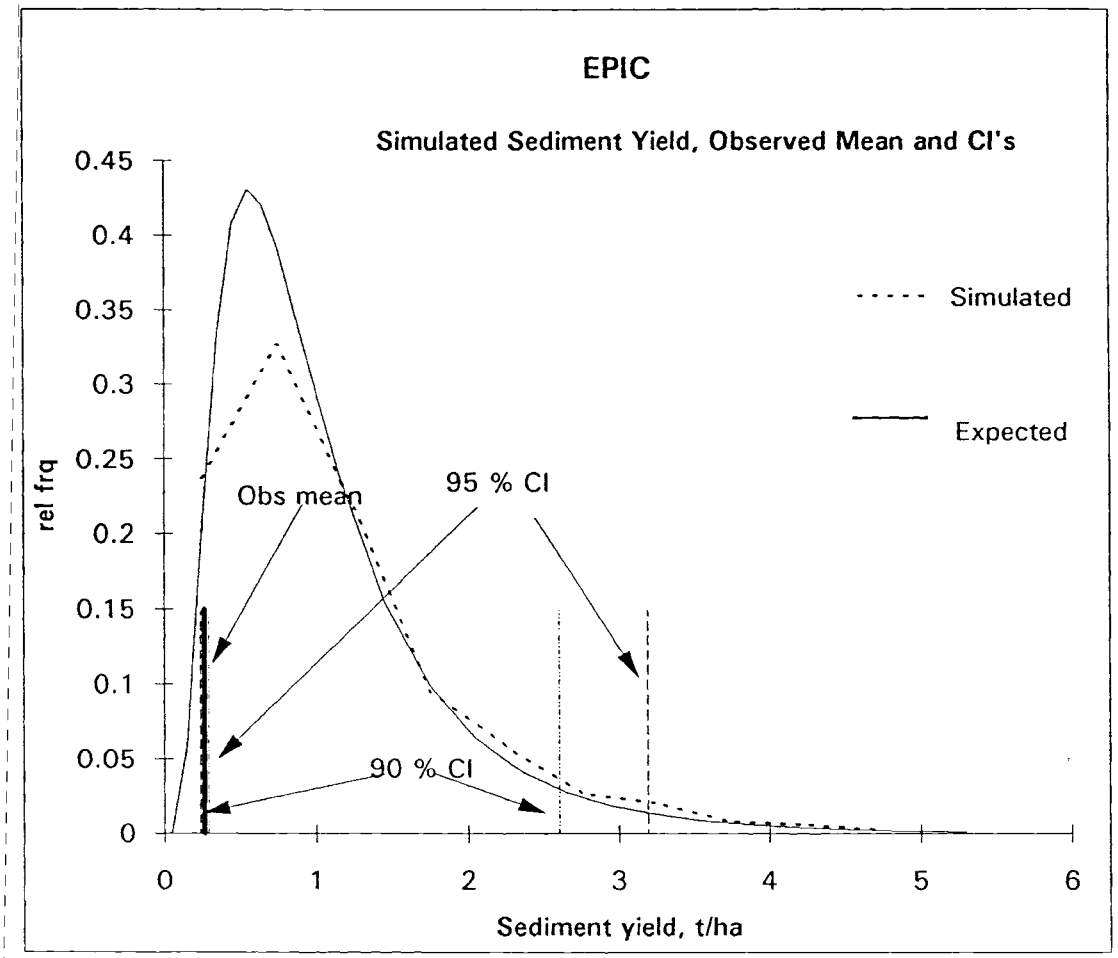


FIGURE 7-14. The simulated values, observed total, expected lognormal distribution and CIs of sediment using EPIC.

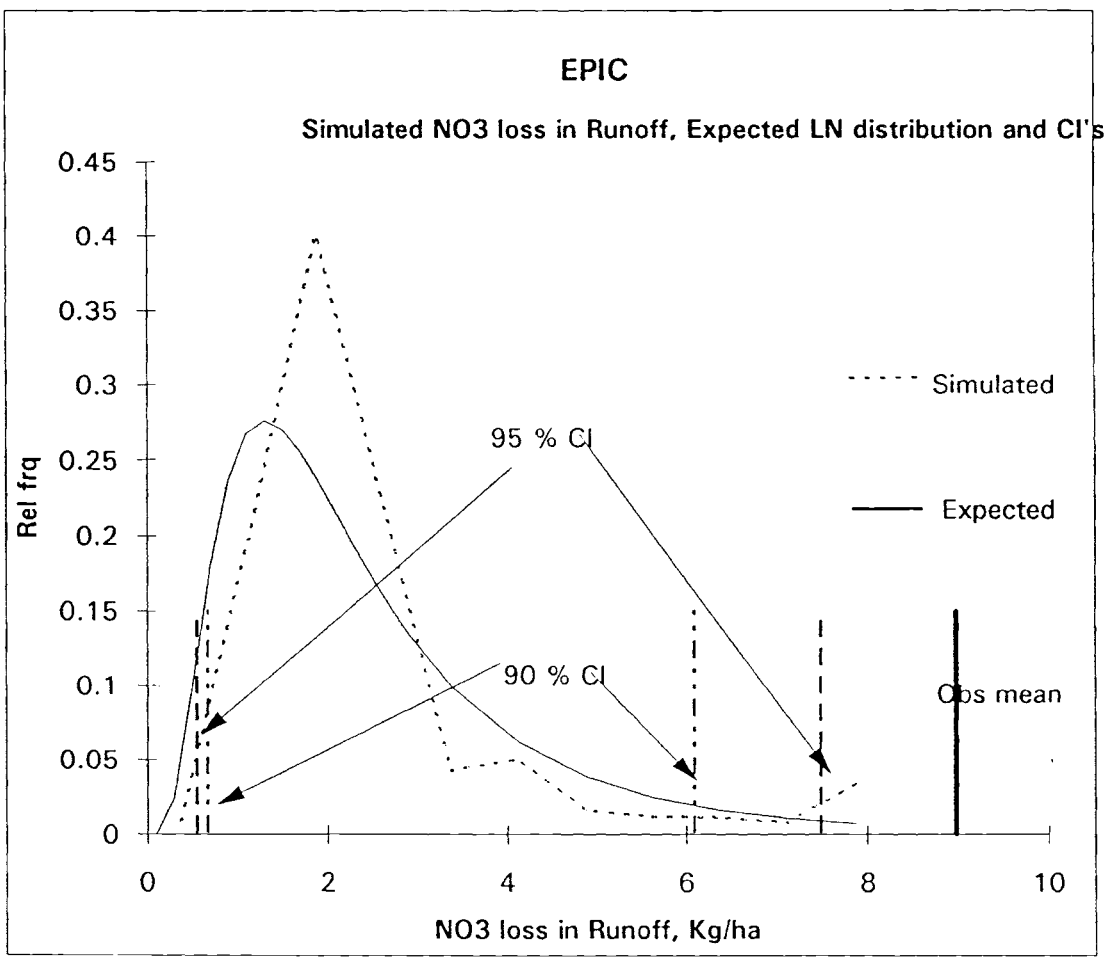


FIGURE 7-15. The simulated values, observed total, expected lognormal distribution and CIs of nitrogen in runoff using EPIC.

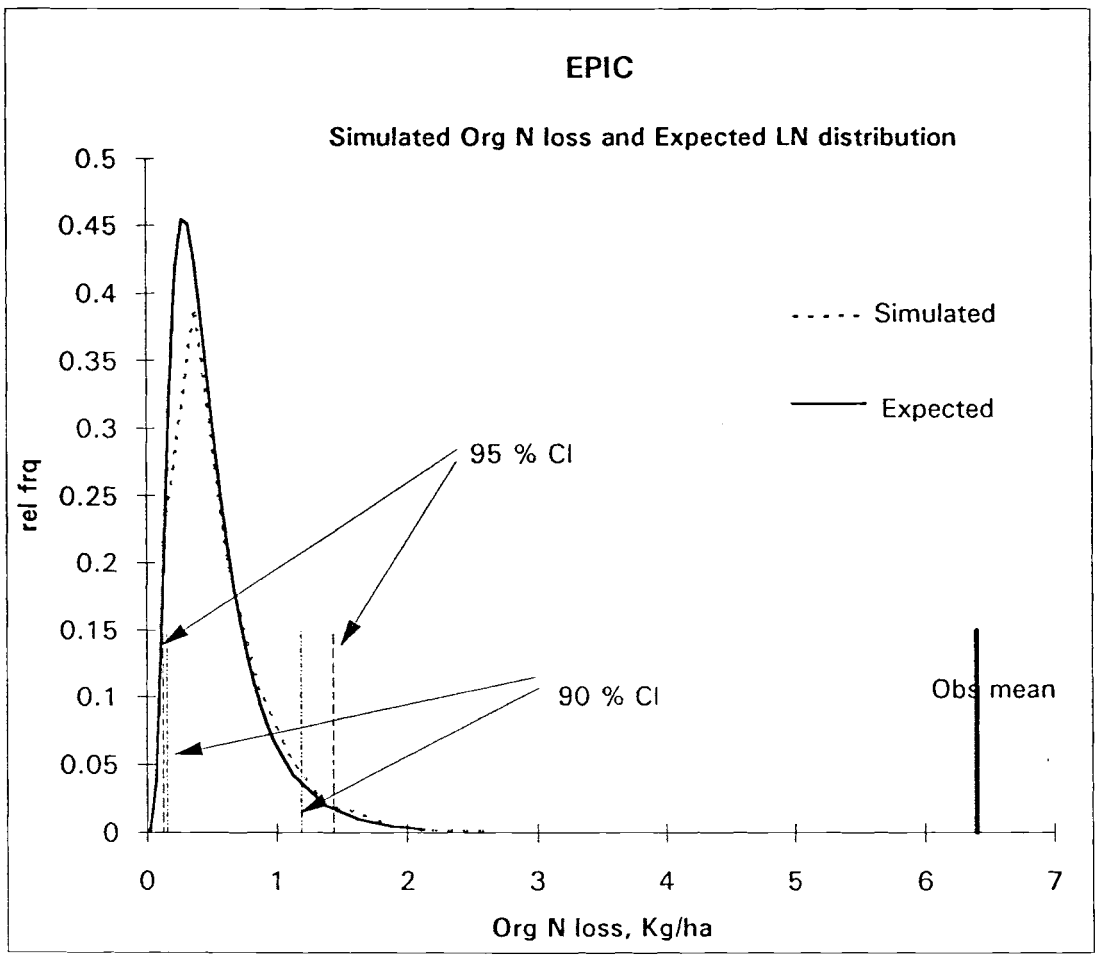


FIGURE 7-16. The simulated values, observed total, expected lognormal distribution and CIs of nitrogen in sediment using EPIC.

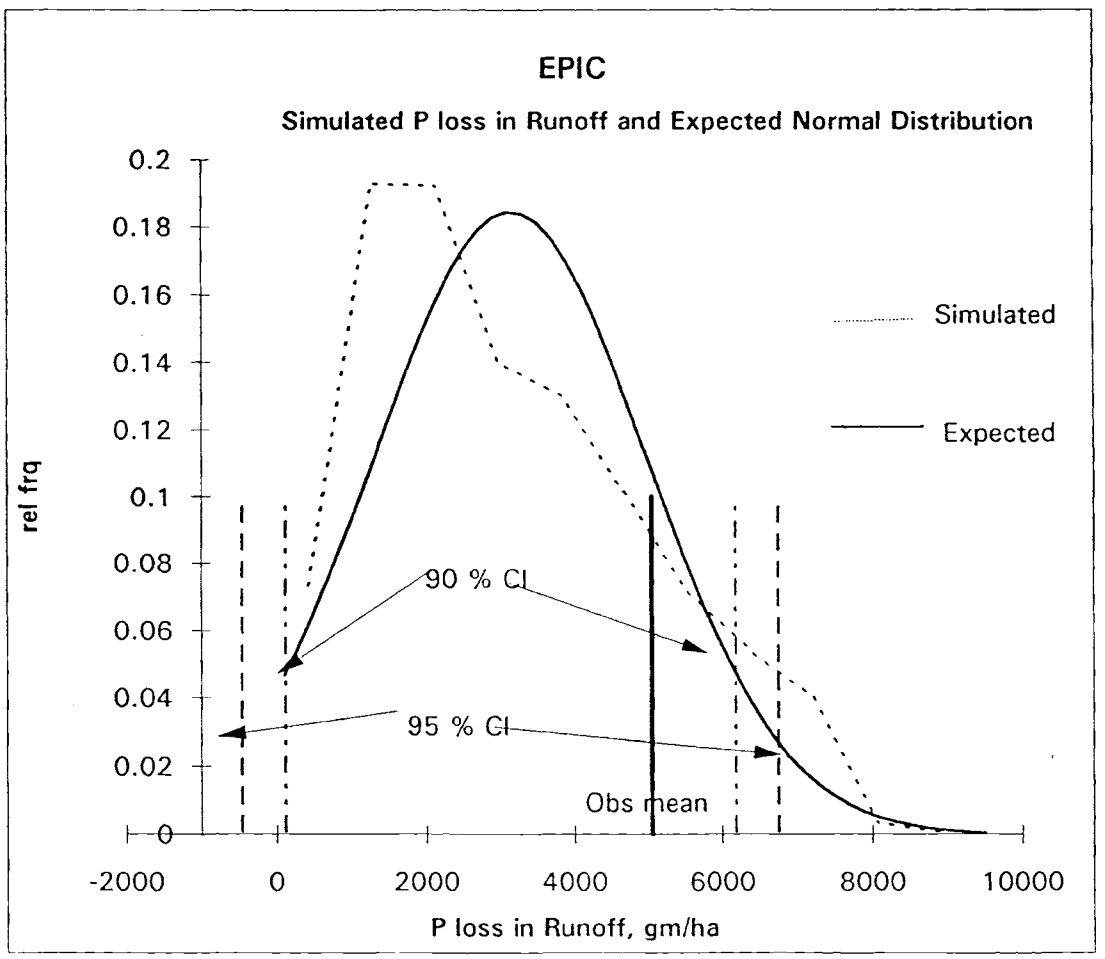


FIGURE 7-17. The simulated values, observed total, expected normal distribution and CIs of phosphorus loss in runoff using EPIC.

Figures 7-14, 7-15, 7-16 illustrate that the observed watershed responses fall outside both the 95 percent and 90 percent CIs. This indicates that either model algorithm inadequacies or parameter estimation problems for predicting the sediment yield, nitrogen in runoff and sediment if there exists no data for model calibration.

It can be noted that in case of P loss in runoff, even though the observed mean falls within the CIs, the CIs are so wide as to make the confidence in the results less than desirable. Thus the P loss in runoff while statistically satisfactory, needs the uncertainty in the model parameters to be reduced.

A similar analysis was conducted for AGNPS model. As AGNPS is an event based model, the observed field response used is from a single rainfall event of 3.74 inches and is given in Table 7-8.

TABLE 7-8. The observed mean of a single event response from field WA.

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

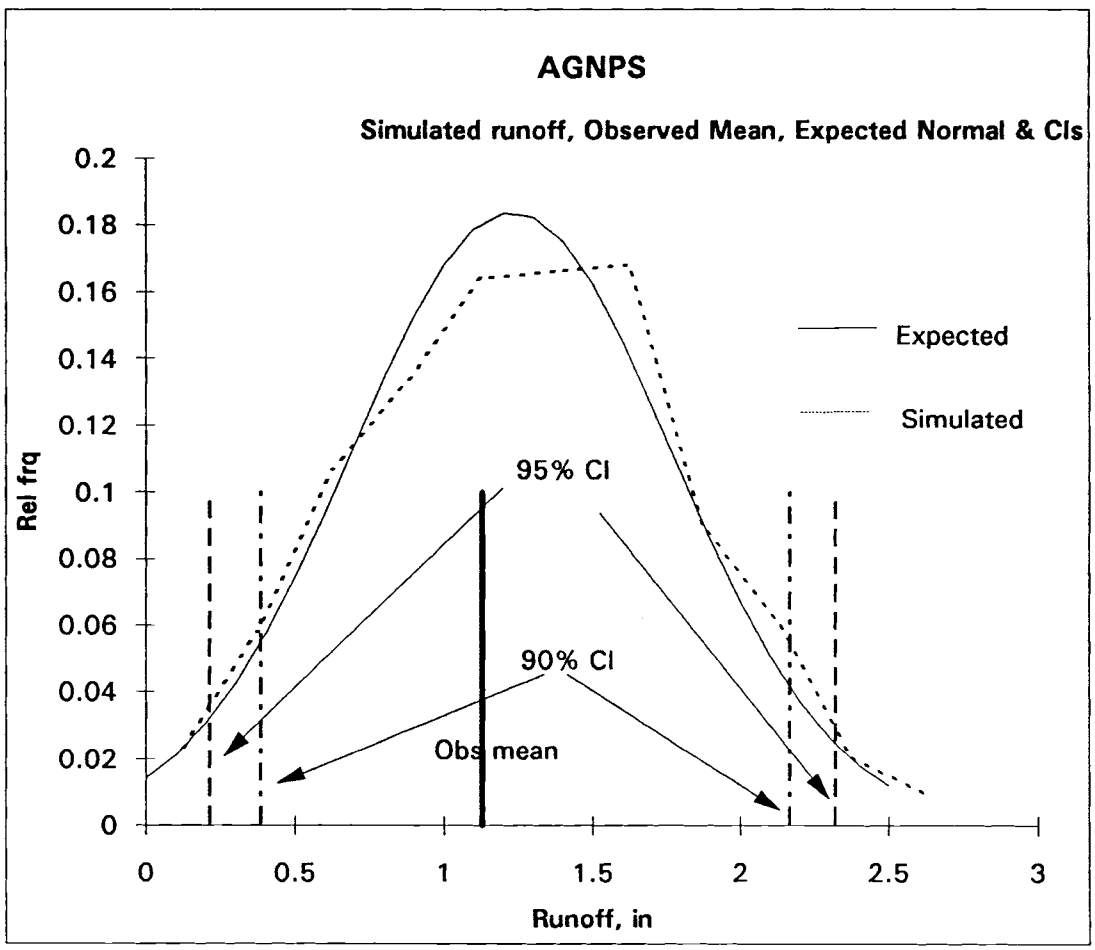


FIGURE 7-18. The simulated values, observed mean, expected normal distribution and CIs of runoff using AGNPS.

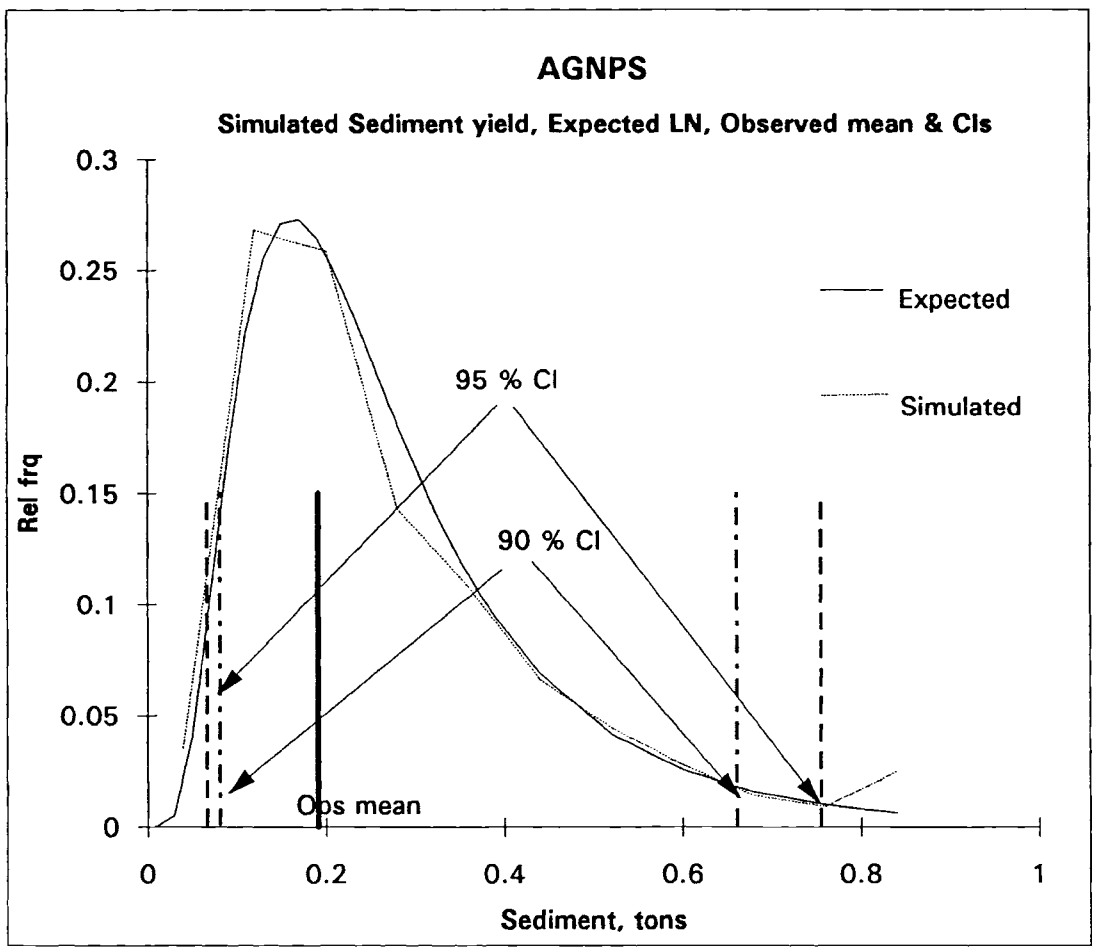


FIGURE 7-19. The simulated values, observed mean, expected lognormal distribution and CIs of sediment using AGNPS.

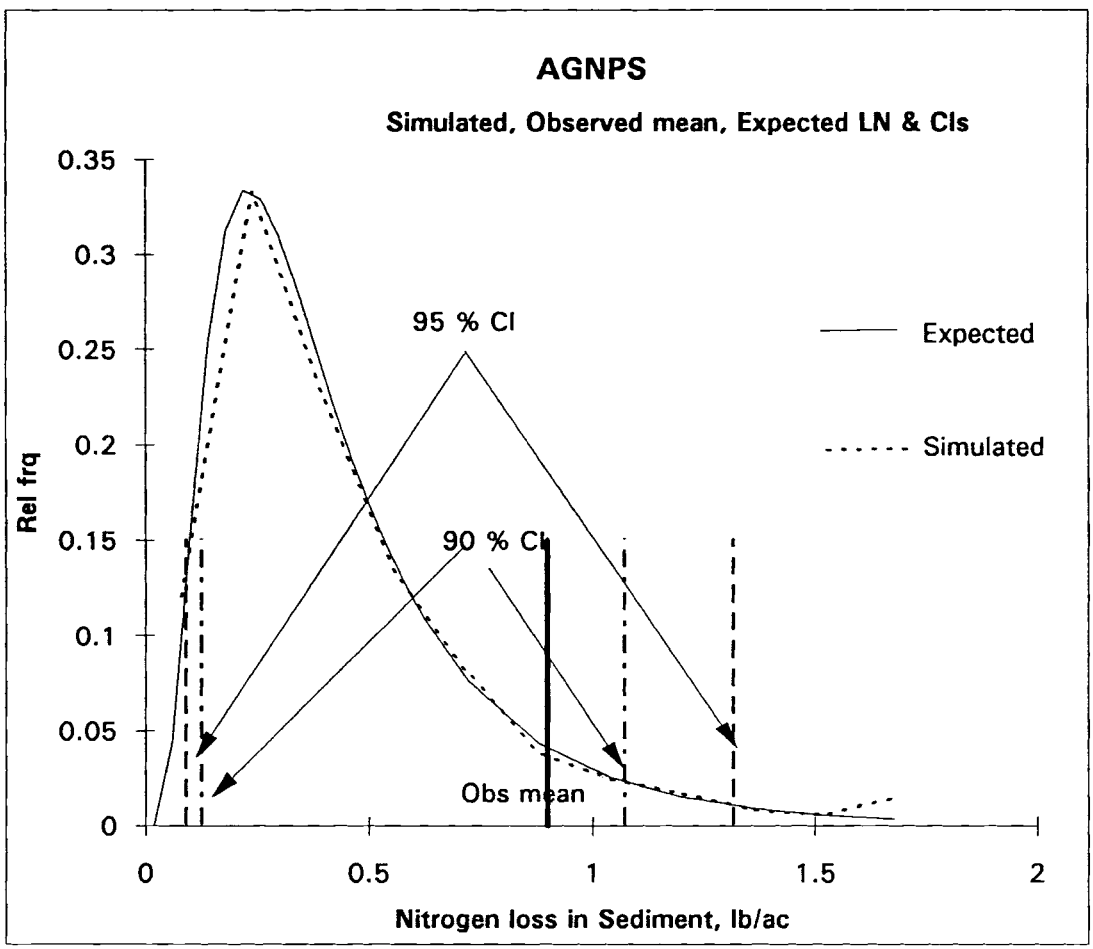


FIGURE 7-20. The simulated values, observed mean, expected lognormal distribution and CIs of nitrogen in sediment using AGNPS.

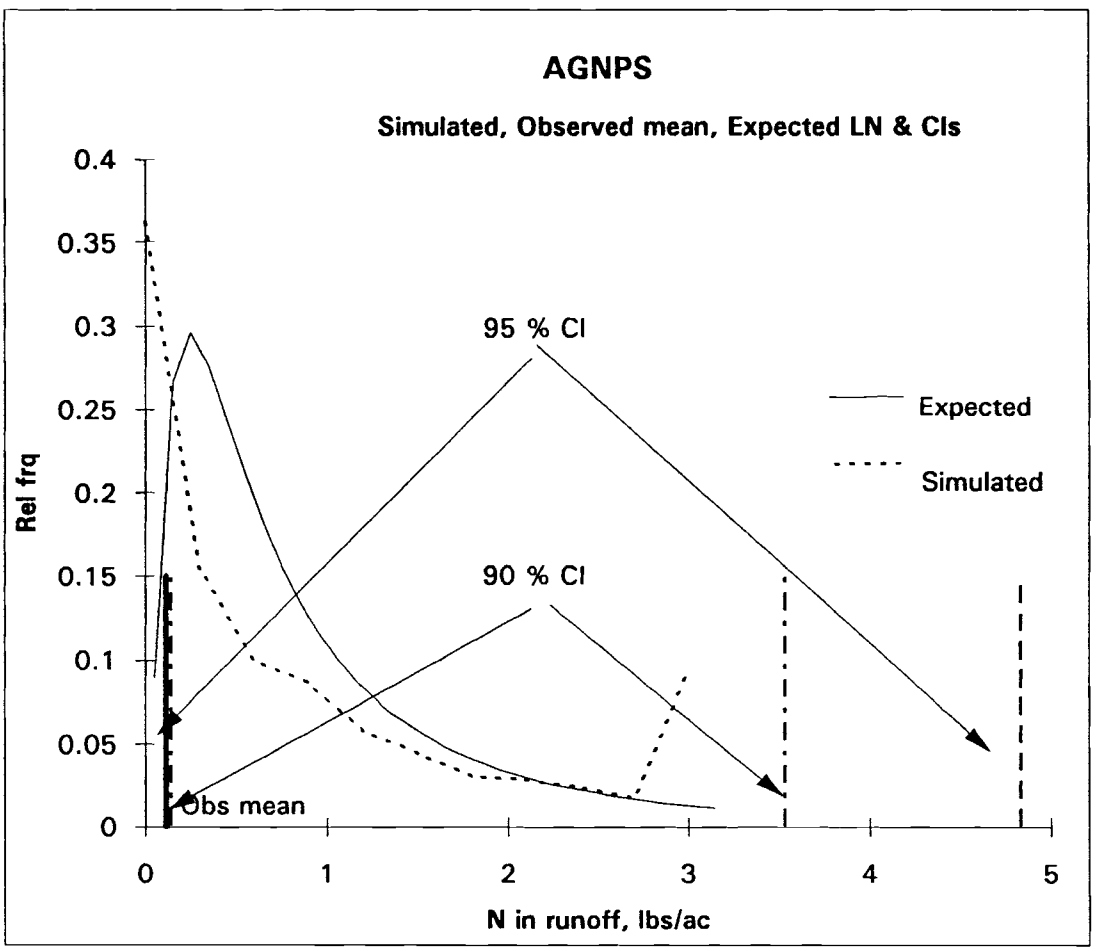


FIGURE 7-21. The simulated values, observed mean, expected lognormal distribution and CIs of nitrogen loss in runoff using AGNPS.

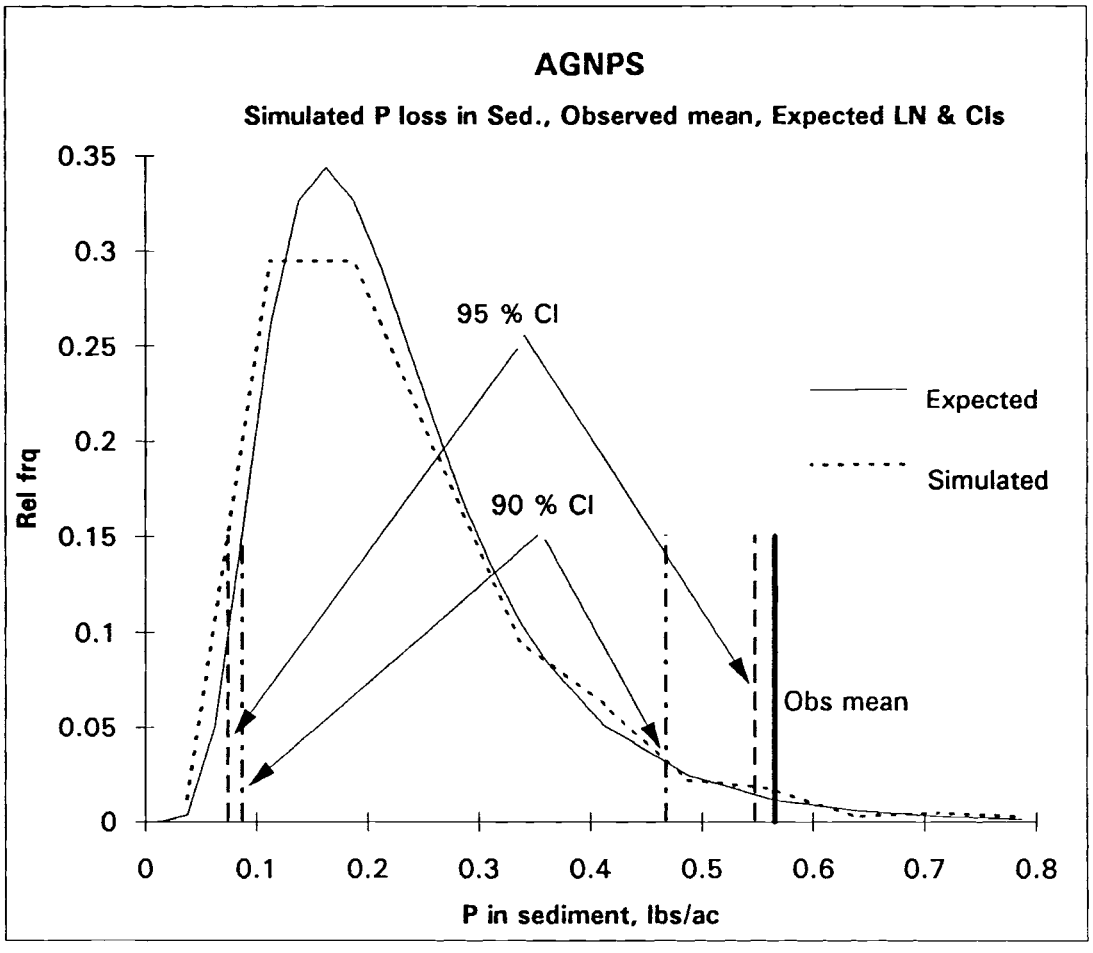


FIGURE 7-22. The simulated values, observed mean, expected lognormal distribution and CIs of phosphorus loss in sediment using AGNPS.

It can be noted that for runoff, sediment, and nitrogen loss in sediment; the observed mean falls within both the 95 and 90 percent CIs (figures 7-18 through 7-20). Figure 7-16 indicates while for EPIC the observed total nitrogen loss was way over simulated values. In the case of AGNPS it is seen that the observed mean just falls over the lower 95 percent limit. In figure 7-22 for phosphorus in sediment the observed mean value falls outside both the CIs. It can be inferred that the model algorithm is not satisfactory in predicting this output.

FIRST ORDER ANALYSIS

First Order analysis (FOA) has been shown to produce good estimate of the mean and variance of model response if the coefficient of variation of the input parameter is small and the model response is linear with respect to the parameter in the range of interest. Sensitivity coefficients provide an indication of the linearity in that a linear response yields an absolute sensitivity coefficient that is constant over a range of values for the input parameter and a relative sensitivity coefficient that approaches unity as the intercept term of the linear relation becomes small. Once the expected value and the variance are estimated, the parameters of an assumed two parameter distribution can be determined thus specifying the output distribution (Haan et al., 1993). In this study a first order analysis was conducted involving all the parameters that were used in the MCS approach. Stevens (1993) outlined the procedure for calculating the output variance given as equation 7-6

$$var[y] \approx \sum_{i=1}^{p}\left(\frac{\partial g}{\partial x_i}\Big|_{\bar{x}_i}\right)^2 Var[x_i] + 2\sum_{i=1}^{p}\sum_{j=1, j\neq i}^{p}\frac{\partial g}{\partial x_i}\Big|_{\bar{x}_i}\frac{\partial g}{\partial x_j}\Big|_{\bar{x}_j} Cov[x_i, x_j] \qquad (7\text{-}6)$$

Since the parameters are assumed uncorrelated, the covariance between the input parameters is zero. The variance of the input parameter is estimated using the C_v. The expected value of the output parameter is estimated from

$$E[y] = E[g(\bar{x})] + \sum_{i=1}^{p}\frac{\partial g}{\partial x_i}\Big|_{\bar{x}} E[(x_i - \bar{x}_i)] \qquad (7\text{-}7)$$

Since the expected value of $(x_i - \bar{x}_i)$ is zero, this reduces to $E[y] \approx g(\bar{x})$.

The function g($\bar{x}$) is calculated by running the models using the expected values of the parameters. The var(y) or the variance of the outputs is seen to be a function of the $\partial g/\partial x_i$ which are the sensitivity coefficients of equations 5-1. These sensitivity coefficients were calculated for the period Sept. 1, 1990 to Apr. 30, 1992 for EPIC and for the storm of 3.74 in. for AGNPS. The sensitivity coefficients are shown in Table 7-9 for EPIC and in 7-10 for AGNPS. The $\bar{x}_i$ represents the parameter means and the var(x_i) is the parameter variances given for EPIC in Table 7-11 and for AGNPS in table 7-12. The variable p represents the number of the sensitive parameters investigated. The

value for p was 7 for EPIC and 8 for AGNPS. The output variance and expected values are given in Table 7-13 for EPIC and in 7-14 for AGNPS.

TABLE 7-9. The absolute sensitivity coefficient values for FOA for EPIC

PARAMETER	**RUNOFF** mm	**SED.** tons/ha	**RUNOFF** N, Kg/ha	**SED. N** Kg/ha	**RUNOFF** P, g/ha
S	162.59	0.56	2.55	-	1034.02
BD	7.58	-	5.86	-	1141.72
FC	159.09	-	4.13	-	1652.89
SILT	0.01	0.01	-	-	4.21
Org. N.	-	-	-	-	-
SLOPE	2050	50	25	25	12500
P- factor	0.55	1.11	-	-	166.67

TABLE 7-10. The absolute sensitivity coefficient values for FOA for AGNPS

PARAMETER	RUNOFF in.	SED. lbs/ac	RUNOFF N, lbs/ac	SED. N lbs/ac	SED. P, lbs/ac
S	0.14	-	0.093	0.02	0
Land slope	-	0.25	-	0.09	0.04
K factor	-	1.04	-	0.09	0.097
C factor	-	20.83	-	0.11	0.11
P factor	-	0.27	-	-	-
Soil N	-	-	-	-	-
N run coef	-	-	50	-	-
N leach coef.	-	-	6	-	-

TABLE 7-11. The variance and expected values of the input parameters for EPIC used in FOA.

PARAMETER	E(X)	VAR.
Retention parameter (S)	2.66	1.77
Bulk density	1.45	0.013
Field capacity	0.242	0.009
Slope	0.04	1.4 E -04
P - factor	0.9	0.002
Silt (%)	35.6	79.21
Organic Nitrogen	297	12733.1

TABLE 7-12. The variance and expected values of the input parameters for AGNPS used in FOA.

PARAMETER	**E(X)**	**VAR.**
Retention parameter (S)	4.29	4.60
Slope (%)	4.0	1.44
K - factor	0.24	0.0014
C - factor	0.012	6.0 E -06
P- factor	0.9	0.0017
Soil Nitrogen	0.001	2.5 E -07
Nit. runoff coeff.	0.05	6.2 E -04
Nit leaching coeff.	0.25	0.016

TABLE 7-13. Variance and expected values of EPIC outputs for FOA.

OUTPUTS	VAR.	E(X)
RUNOFF, mm	4.7 E 04	463.3
SED. tons/ha	0.94	0.87
RUNOFF N., Kg/ha	9.83	1.78
SED. N., Kg/ha	0.09	0.44
RUNOFF, P., g/ha	1.9 E 06	2459.07

TABLE 7-14. Variance and expected values of AGNPS outputs for FOA.

OUTPUTS	VAR.	E(X)
RUNOFF, inches	0.09	1.16
SED., tons	0.09	0.24
RUNOFF N., lbs/ac	2.16	0.38
SED. N., lbs/ac	0.21	0.42
SED., P., lbs/ac	0.04	0.21

Comparing the variances of outputs from MCS for EPIC (Table 7-1 to Table 7-13), it can be noted that the variances of runoff, sediment, N loss in sediment and P loss in sediment are quite comparable. For AGNPS, the variances comparison (Table 7-2 and Table 7-14) is also quite favorable.

As a next step, for FOA, the distributions of these outputs are assumed to be same as from MCS approach. Based on these distributions, the CIs were calculated. For EPIC, these are given in Table 7-15 and for AGNPS it is given in 7-16.

For EPIC, as in Monte Carlo Simulation results for runoff, the total observed value falls inside both the 95 and 90 percent CIs and the CIs are comparable. For sediment, the confidence intervals of FOA are wider than that from MCS. The observed value falls below the lower limits. For N loss in runoff, the CIs are very wide to be of much use in a particular application. The N loss in sediment has CIs from FOA which are not as wide as that from MCS. Likewise the CIs of both MCS and FOA are comparable for P loss in runoff of EPIC.

The CIs from MCS for runoff of AGNPS are wider than that from FOA. So CIs of FOA do not contain the observed mean value. But for sediment the CIs of FOA are wider than that of MCS and thus contain the observed mean. Like that of EPIC, the CIs of N loss in runoff are very wide. The CIs of both P and N loss in runoff and sediment the CIs of FOA are wider than that of MCS and thus contain the observed mean.

TABLE 7-15. CIs of outputs from FOA for EPIC.

OUTPUTS	**95 % lower**	**95 % upper**	**90 % lower**	**90 % upper**
RUNOFF, mm	35.68	890.98	103.32	823.34
SED. tons/ha	0.62	9.16	0.77	7.41
RUNOFF N., Kg/ha	0.01	2766.03	0.03	1046.5
SED. N., Kg/ha	0.86	2.80	0.94	2.56
RUNOFF, P., g/ha	-249.14	5167.28	179.20	4738.94

TABLE 7-15. CIs of outputs from FOA for AGNPS.

OUTPUTS	95 % lower	95 % upper	90 % lower	90 % upper
RUNOFF, inches	-0.50	0.68	-0.41	0.59
SED. tons	0.6	2.00	0.66	1.82
RUNOFF N., lbs/ac	0.49	155.86	0.77	98.77
SED. N., lbs/ac	0.5	3.04	0.57	2.63
SED. P., lbs/ac	0.69	1.57	0.74	1.48

CHAPTER VII

CONCLUSIONS AND FUTURE RECOMMENDATIONS

This study to illustrates a statistical model evaluation protocol. EPIC and AGNPS models were used for illustration purpose. A major task in modeling is parameter estimation. This study used probability distribution functions to indicate the input parameter uncertainty so that output uncertainty could be quantified. Thus the protocol can be considered as a tool in alerting the modeler towards the need for refinement in parameter estimation and/or improvement in model algorithms. This protocol in fact can be used to distinguish whether model unacceptability is due to model algorithms or parameter estimation. If the input parameter uncertainty is reduced to a minimum and the observed mean prediction still falls outside the CIs, then the model algorithms can be inferred as unsatisfactory.

The protocol can also be used to indicate the degree of confidence on predictive abilities of the models in settings where the observed data are lacking. For example, in case of EPIC, for runoff; the protocol indicated the CIs to be very wide and the observed mean falls within the CIs. This output can be termed as statistically acceptable. But a model user may not be satisfied because of the width of the CIs. For example, the CIs on runoff was 100 mm to 600 mm for this particular study.

This kind of results can be attributed to the uncertainties in the parameters and the model structure combination. The protocol also indicates that for EPIC, in the case of sediment yield, N loss in runoff and in sediment, either the parameter estimation or the modeling approach is not satisfactory. This can be seen by the fact that the observed mean for these outputs fall outside the CIs. A similar trend is discernible for AGNPS. For example, in case of runoff one can tell that parameter estimation process and modeling approach is adequate by the fact that the observed mean falls within the CIs. Likewise in case of N loss in runoff and P loss in sediment the modeling approach and/or parameter estimation technique may be termed as unsatisfactory. The point to be remembered is that AGNPS was run for a single event and also considering the whole area as a single cell which is not the normal case.

There is a need to use these models in different settings and take a comprehensive look at the model algorithms to come to any conclusion regarding the acceptability of the models themselves. Also there are many assumptions including that the field variability can be represented by a particular distribution and its parameters. These assumptions also need to be tested before arriving at a firm conclusion regarding model performance.

The protocol lays basic foundation for research regarding models performance. The strength of the protocol lies in the fact that the observed values were not used during the evaluation stage. Thus the possibility of confounding model evaluation with parameter estimation is avoided. There is scope for making this protocol a regular tool in assessing model performance following further research on the parameter distribution. At least the

protocol gives a feel for the uncertainties involved in model output estimation. Testing of this protocol on many models can be foreseen.

Regarding the simulation techniques, the variances of the MCS and the FOA approach compare favorably. But there is a need for further study to be confident about the use of FOA to make it an effective tool in model simulations. Also it should be noted many assumptions about the use of FOA were violated in this study.

It is also important to remember that the measured values can also be uncertain. If this uncertainty can also be quantified in the form of a pdf and plotted on the model response, the degree of overlap will indicate the predictive ability of the models. Finally an overhaul of the model structure might be needed to better represent the field variability so that input parameters should be represented by a distribution rather than a single value. Model output could then be indicated by a range of values with a degree of confidence indicated on them.

REFERENCES

American Society of Civil Engineers, 1993, "Criteria for Evaluation of Watershed Models", ASCE Task Committee of the Watershed Management Committee, Journal of Irrigation and Drainage Engineering, 119(3), 429-443.

Babalola, O., 1978, "Spacial Variability of Soil Water Properties in Tropical Soils of Nigeria", Soil Sci. 126, 269-279.

Barfield, B. J., C. T. Haan and D. E. Storm, 1989, "Why Model", Proceedings of the CREAMS/GLEAMS Symposium, Sept. 27 - 29, 1989, Athens, GA.

Bruce, R. R., J. H. Dane, V. L. Quinsenburry, N. L. Powel and A. W. Thomas, 1983, "Physical Characteristics of Soils in the Southern Region: Cecil, Southern Cooperative Series, Bul. no. 267, Georgia Ag. Exp. Station and University of Georgia, Athens, GA.

Carcel, R. F., R. S. Parish, R. L. Jones, J. L. Hansen and R. L. Lamb, 1988, "Characterizing the Uncertainty of Pesticide Leaching in Agricultural Soils ", J. Contaminant Hydr., 2, 111-124.

Cassel, D. K. and A. Bauer, 1975, "Spatial Variability in Soils below Depth of Tillage: Bulk Density and Fifteen Atmosphere Percentage" Soil Sci. Soc. Amer. Proc., 39, 247-250.

Chiew, F. H. S., M. J. Stewardson and T. A. McMahon, 1993, "Comparison of Six Rainfall-Runoff Modelling Approaches", Journal of Hydrology, 147, 1-36.

Clarke, R. T., 1973, "A Review of some mathematical models used in Hydrology, with Observations on their Calibration and use", Journal of Hydrology, 19, 1-20.

Coleman, G. and D. G. Decoursey, 1976, " Sensitivity and Model Variance Analysis applied to some Evaporation and Evapotranspiration Models ", Water Resources research, 12(5), 873 - 879.

Courtin, P., M. C. Feller and K. Klimba, 1983, "Lateral Variability in Some Properties of Disturbed Forest Soils in SW British Columbia ", Canad. J. Soil Sci., 63, 529-539.

Coy, D. W., G. A. Kew, M. E. Mullins and P. V. Piserchia, 1986, "Determining Uncertainty in Physical Parameter Measurements by Monte Carlo simulation", Evaluation of Pesticides in Groundwater, Symposium sponsored by the Division of Pesticide Chemistry at the 189th meeting of American Chemical Society, Miami Beach, FL, April 28 - May 3, 1985, pp 39-60.

Decoursey, D. G., 1988, "A Critical Assessment of Hydrologic Modeling", Proceedings International Symposium on Modeling Agricultural, Forest and Rangeland Hydrology. ASAE, Dec 12 - 13, Chicago, IL.

Deer-Ascough, L. A. and M. A. Nearing, 1994, "Sensitivity Analysis in Erosion Prediction Modeling", presented at the ASAE International summer meeting as paper no. 942154, June 19-22, 1994, Kansas City, Missouri.

Ditmars, J. D., E. E. Adams, D. W. Bedford and D. E. Ford, 1987, "Performance Evaluation of Surface Water Transport and Dispersion Models" Journal of Hydraulic Engineering, 113(8), 961-980.

Edwards, D. R., V. W. Benson, J. R. Williams, T. C. Daniel, J. Lemunyon and R. G. Gilbert, 1993, "Use of the Epic Model to Predict Runoff Transport of Surface-Applied Animal Manure Constituents", presented at the ASAE International Summer meeting as paper no. 932075, June 20-23, 1993, Spokane, Washington.

Gajem, Y. M., A. W. Warrick, and D. E. Myers, 1981, "Spacial Variability of Unsaturated Hydraulic Conductivity", Soil Sci. Soc. Amer. J., 36, 847-849.

Garrick, M., C. Cunnane and J. E. Nash, 1978, "A Criterion of Efficiency for Rainfall-Runoff Models", Journal of Hydrology, 36, 375-381.

Green, I. R. A. and D. Stephenson, 1986, " Criteria for Comparison of Single Event Models", Journal of Hydrological Sciences, 31(3), 395-411.

Gumaa, G. A., 1978, "Spacial Variability of *In Situ* Available Water", Ph. D. Thesis, University of Arizona, Tucson (Available as 78-24365 from Xerox University Microfilms, Ann Arbor, MI).

Haan, C. T., 1977, Statistical Methods in Hydrology, Iowa State University Press, Ames, Iowa.

Haan, C. T., B. J. Barfield and J. C. Hayes, 1994b, Design Hydrology and Sedimentalogy For Small Catchments, Academic Press, San Diago, CA.

Haan, C.T. and R. E. Schulze, 1987, "Return Period Flow Prediction with Uncertain Parameters", Transactions of ASAE, 30(3), 665-557.

Haan, C. T., 1994a, Personal Communication, Oklahoma State University, Stillwater, OK.

Haan C. T., B. Allred, D. E. Storm, G. Sabbagh and S. Prabhu, 1993, " Evaluation of Hydrology/Water Quality Models, A Statistical procedure ", presented at the ASAE International Winter Meeting as paper no. 932505. Submitted to Transactions of ASAE for publication.

Hjelmfelt, A. T., L. A. Kramer and R. E. Buswell, 1981, "Curve numbers as Random Variables", In Rainfall-Runoff Relationships, Proc. International Symposium on Rainfall-Runoff Modelling, May 18-21, Mississippi State University, Water Resources Publication, Littleton, CO.

James L. D. and S. J. Burges, 1982, "Selection, Calibration, and Testing of Hydrologic Models", Hydrologic Modeling of Small Watersheds, ed : C. T. Haan, H. P. Jonson and D. L. Brakensiek, ASAE monograph no. 5, ASAE, St. Joseph, Michigan.

Jury W. A., 1986, "Spatial Variability of Soil Properties", Vadose Zone Modeling of Organic Pollutants, editors Stephen C. Hern and Susan M. Melancon, 245-269, Lewis Publishers, Chelsea, Michigan.

Loague, K. and R. E. Green, 1991, "Statistical and Graphical Methods for Evaluating Solute Transport Models: Overview and Application", Journal of Contaminant Hydrology, 7, 51-73.

Loehle, C., 1983, "Evaluation of Theories and Calculation Tools in Ecology", Ecological Modelling, 19, 239-247.

Luis, S. J. and D. McLaughlin, 1992, "A Stochastic Approach to Model Validation", Advances in Water Resources, 15, 15-32.

Majkowski,J., J. M. Ridgeway and D. R. Miller, 1981, "Multiplicative Sensitivity Analysis and its Role in Development of Simulation Models", Ecological Modelling, 12, 191-208.

Mamillapalli, S., B. A. Engel and E. J. Kladivko, 1994, "Validation of GLEAMS Nutrient Component for Midwestern Conditions", presented at the ASAE International summer meeting as paper no. 942090, June 19-22, 1994, Kansas City, Missouri.

Martinec, J. and A. Rango, 1989, "Merits of Statistical Criteria for the Performance of Hydrological Models", Water Resources Bulletin, 25(2), 421-432.

Nielsen, D. R., J. W. Bigger and K. T. Erh, 1973, "Spatial Variability of Field

Measured Soil Water Properties", Hilgardia, 42, 215-259.

Nofziger, D. L., J. R. Williams, A. G. Hornsby, and A. L. Wood, 1983, Physical Characteristics of Soils of the Southern Region, Southern Cooperative Series, Bul. no. 265, Ag. Exp. Station, Oklahoma State University, Stillwater, OK.

Nofziger, D. L., J. Chen and C. T. Haan, 1994, "Evaluation of Unsaturated/Vadose Zone models for Superfund Sites", report from USEPA as EPA/600/R-93/184, Washington, DC.

O'Neil, R. V., R. H. Gardner and J. B. Mankin, 1980, "Analysis of Parameter Error in a Nonlinear Model", Ecological Modelling, 8, 297-311.

Parrish, R. S. and C. N. Smith, 1990. "A Method for Testing Whether Model Predictions Fall Within a Prescribed Factor of True values, with an Application to Pesticide Leaching", Ecological Modelling, 51, 59-72.

Pennel, K. D., A. G. Hornsby, R. E. Jessup and P. S. C. Rao, 1990, " Evaluation of Five Simulation Models for Predicting Aldicrab and Bromide Behavior Under Field Conditions ", Water Resources Research, 26(11), 2679-2693.

Press W. H., Flannery B. P., S. A. Teusolsy and W. T. Vetterling, 1986, Numerical Recipes, Cambridge College Press, New York, NY.

Rawls, W. J. et al., 1982, "Estimation of Soil Water Properties" Transactions of ASAE, 25(3), 1316-1320.

Reckhow, K. H., J. T. Clements and R. C. Dodd, 1990, "Statistical Evaluation of Mechanistic Water-Quality Models", Journal of Environmental Engineering, 116(2), 250-268.

Reckhow, K. H. and S. C. Chapra, 1983, "Confirmation of Water Quality Models", Ecological Modelling, 20, 113-133.

Rogowski, A. S., 1972, "Watershed Physics: Soil Variability Criteria", Water Resources Research, 8(4), 1015-1023.

Shaeffer, L. D., 1980, "A Model Evaluation Methodology Applicable to Environmental Assessment Models", Ecological Modelling, 8, 275-295.

Sharma, M. L. and A. S. Rogowski, 1983, " Hydrological Characterization of Watersheds ", Proceedings of the Natural Resources Modeling symposium, Pingre Park, CO, Oct. 16-21, 291-296.

Sharpley, A. N., and J. R. Williams, 1990, EPIC - Erosion/Productivity Impact Calculator: Model Documentation USDA Technical Bulletin No. 1768.

Soil Conservation Service, 1972, Hydrology, Section 4, National engineering Handbook, Soil Conservation Service, USDA, Washington, DC.

Stevens E. W., 1993, A Method to Predict the Accuracy of a First Order Approximation of Model Output Variance, Ph. D. Dissertation, Oklahoma State University, Stillwater, OK.

Stockton, J. G. and A. W. Walrick, 1971, "Spatial Variability of Unsaturated Hydraulic Conductivity", Soil Sci. Soc. Amer. J. 36, 847-849.

Thomann, R. V., 1982, "Verification of water Quality Models" Proceedings of the American Society of Civil Engineers, 108(EE5), 923-940.

Tiscareno-Lopez, M., V. L. Lopes, J. J. Stone and L. J. Lane, 1993, "Sensitivity Analysis of the WEPP Watershed Model for Rangeland Applications", Transactions of the ASAE, 36(6), 1659-1672.

US Dept. of Agriculture (unknown), Soil Survey Washington County, Arkansas, USDA, Soil Conservation Service, Washinton County, AR.

Vauclin, M., S. R. Vieira, G. Vachaud and D. R. Nielson, 1983, "Use of Co-Kriging with Limited Field Soil Observations", Soil Sci. Soc. Amer. J., 47, 175-184.

Vicens, G. J., I. Rodrigueze-Iturbe and J. C. Schaake, Jr., 1975," A Bayesian Framework for the use of Regional Information in Hydrology ", Water Resources Research, 11(3), 405-414.

Williams, J. R., C. A. Jones and P. T. Dyke, 1984, "A Modeling Approach to Determining the Relationship Between Erosion and Soil Productivity", Transactions of the ASAE, 129-144.

Wischmeier, W. H., and D. D. Smith, 1978, "Predicting Rainfall Erosion Losses-A Guide to Conservation Planning", USDA, Agriculture Handbook No. 537.

Young R. A., D. D. Bosch and W. P. Andeerson, 1994, "Agricultural Non Point Source Pollution Model, AGNPS user's guide ", Model documentation, Minnesota Pollution Control Agency, St. Paul, MN.

Young, R. A., C. A. Onstad, D. D. Bosch and W. P. Anderson, 1989, "AGNPS: A Nonpoint-Source Pollution Model for Evaluating Agricultural Watersheds", Journal of Soil and Water Conservation, March-April, 44(2), 168-173.

Zacharias, S., C. D. Heatwole and W. Coakley, 1993, "Comparision of Quantitative Techniques used for Pesticide Model Validation", presented at the ASAE International Winter Meeting as paper no. 932506, Dec. 14-17, 1993, Chicago, IL.

Zacharias, S., and C. Heatwole, 1993, " Predicting Tillage Treatment Effects on Pesticide Transport: A Validation Study ", presented at the ASAE International Winter meeting as paper no. 932592, Dec. 14-17, 1993, Chicago, IL.

Zacharias, S., C. Heatwole, T. Dillaha and S. Mostaghimi, 1992, " Evaluation of GLEAMS and PRZM for Predicting Pesticide Leaching Under Field Conditions ", presented at the ASAE International Winter Meeting as paper no. 922541, Dec. 15-18, 1992, Nashville, TN.

APPENDIX A

EPIC INPUT PARAMETERS

No. of year of simulation duration	4
Beginning year of simulation	90
Beginning month of simulation	1
Beginning day of simulation	1
Weather input code	12
No of times random no generator cycles	0
Potential ET equation	1
Peak rate estimate code	0
Soil profile code	0
Automatic heat scheduling code	0
Watershed drainage area	1.46 ha
Curve no.	79
Distance from outlet to most distant point on wtsd.	0.194 m
Average channel slope	0.04 m /m
Channel roughness factor	0.24
Surface roughness factor	0.24
Energy rainfall adjustment factor	1.0
Latitude of watershed	36.6
Average watershed elevation	460
Water content of snow on ground at start of sim.	0
Average concentration of N in rainfall	1.0
No of years of cultivation before simulation	50
CO_2 concentration in atmosphere	330 ppm
CNO_3 concentration irrigation water	0
Channel depth	0 m
Slope length	194 m
Slope steepness	0.04 m/m
Erosion control practice factor	1.0
Equation for water erosion	3
No of years of max. monthly 0.5 hr rainfall record	8.0
Field length	0.0
Field width	0.0
Clockwise angle of field length from north	0.0

Standing crop residue	0.0
Parameter of modified exp dist of wind	0.5
Soil particle diameter	0.0
wind erosion factor	0.0
Soil albedo	0.15
Depth from surface to the bottom of the soil layer	0.01, 0.15, 0.23, 0.61, 0.89
Bulk density of the soil layer (t/m^3)	1.45 (all layers)
Wilting point	0.093, 0.093, 0.118, 0.160, 0.136
Field capacity	0.242, 0.242, 0.259, 0.289, 0.284
Sand content (%)	56.3, 56.3, 45.8, 38.5, 55.1
Silt content (%)	36.0, 35.6, 39.3, 35.8, 26.5
organic N concentration	297, 297, 250, 240, 50
Soil Ph	6.2, 6.2, 5.6, 5.0, 4.8
Sum of bases	2.6, 2.6, 3.4, 3.0, 0.8, 0.0
Organic carbon	1.0, 1.0, 0.21, 0.15, 0.1
Calcium carbonate	0.0 (all layers0
Cation exchange capacity	3.1, 3.1, 4.6, 8.9, 6.1
Coarse fragment content	0.0 (all layers)
Nitrate concentration	10, 10, 5, 5, 5
Labile P concentration	393, 393, 10, 10, 30
Crop residue	0.034, 0.434, 0.445, 0.513, 0.001
Bulk density dry	1.55 (all layers)
P sorption ratio	0.0 (all layers)
Saturated conductivity	0.0 (all layers)
Crop rotation duration	4
Irrigation code	1
Liming code	1

APPENDIX B

RELATIVE SENSITIVITY VALUES FOR EPIC

OUTPUT CODES

Q	Runoff, mm
MUST	Sediment, tons
YON	Nitrogen loss in sediment, Kg/ha
YON3	Nitrogen loss in runoff, Kg/ha
YAP	Phosphourus loss in sediment, g/ha

Parameter	Q	Parameter	MUST	Parameter	YON	Parameter	YNO3	Parameter	YAP
CN2	5.19	CN2	5.29	CN2	11.38	CN2	4.30	CN2	4.26
FC	0.28	S	1.80	BD	3.44	S	1.68	S	1.74
S	0.19	PEC	1.11	FC	0.57	PEC	1.05	PEC	0.97
U	0.11	SIL	0.52	S	0.48	SIL	0.47	WN	0.97
Z	0.09	SPLG	0.39	U	0.19	SPLG	0.37	SIL	0.58
BD	0.09	FC	0.29	Z	0.19	FC	0.26	SPLG	0.39
CO2	0.08	CBN	0.18	CO2	0.10	CBN	0.16	BD	0.19
WN	0.03	U	0.12	RTN	0.10	WN	0.10	CBN	0.19
RTN	0.03	Z	0.10	WN	0.10	CO2	0.08	FC	0.19
STD	0.02	BD	0.10	AP	0.00	Z	0.08	U	0.19
FFC	0.02	CHN	0.10	BDD	0.00	YWI	0.05	Z	0.19
WSA	0.00	CO2	0.08	CBN	0.00	CEC	0.03	AP	0.00
CHL	0.00	CHS	0.04	CEC	0.00	FFC	0.03	BDD	0.00
CHS	0.00	WN	0.03	CHD	0.00	RTN	0.03	CEC	0.00
CHN	0.00	RTN	0.03	CHL	0.00	AP	0.00	CHD	0.00
SN	0.00	YWI	0.03	CHN	0.00	BD	0.00	CHL	0.00
ELEV	0.00	FFC	0.02	CHS	0.00	BDD	0.00	CHN	0.00
SNO	0.00	CEC	0.02	DIAM	0.00	CHD	0.00	CHS	0.00
RCN	0.00	STD	0.01	ELEV	0.00	CHL	0.00	CO2	0.00
CHD	0.00	WSA	0.00	FFC	0.00	CHN	0.00	DIAM	0.00
SPLG	0.00	CHL	0.00	FL	0.00	CHS	0.00	ELEV	0.00
PEC	0.00	SN	0.00	FW	0.00	DIAM	0.00	FFC	0.00
YWI	0.00	ELEV	0.00	PEC	0.00	ELEV	0.00	FL	0.00
FL	0.00	SNO	0.00	PH	0.00	FL	0.00	FW	0.00
FW	0.00	RCN	0.00	RCN	0.00	FW	0.00	PH	0.00
DIAM	0.00	CHD	0.00	RFTT	0.00	PH	0.00	RCN	0.00
SALB	0.00	FL	0.00	RSD	0.00	RCN	0.00	RFTT	0.00
ZQT	0.00	FW	0.00	SALB	0.00	RFTT	0.00	RSD	0.00
WTMN	0.00	DIAM	0.00	SAN	0.00	RSD	0.00	SALB	0.00
WTBX	0.00	SALB	0.00	SC	0.00	SALB	0.00	SAN	0.00
WTBL	0.00	ZQT	0.00	SIL	0.00	SAN	0.00	SC	0.00
RFTT	0.00	WTMN	0.00	SMB	0.00	SC	0.00	SMB	0.00
SAN	0.00	WTBX	0.00	SN	0.00	SMB	0.00	SN	0.00
SIL	0.00	WTBL	0.00	SNO	0.00	SN	0.00	SNO	0.00
PH	0.00	RFTT	0.00	SPLG	0.00	SNO	0.00	STD	0.00
SMB	0.00	SAN	0.00	STD	0.00	STD	0.00	RTN	0.00
CBN	0.00	PH	0.00	WNO3	0.00	U	0.00	WNO3	0.00
CEC	0.00	SMB	0.00	WSA	0.00	WNO3	0.00	WSA	0.00
WNO3	0.00	WNO3	0.00	WTBL	0.00	WSA	0.00	WTBL	0.00
AP	0.00	AP	0.00	WTBX	0.00	WTBL	0.00	WTBX	0.00
RSD	0.00	RSD	0.00	WTMN	0.00	WTBX	0.00	WTMN	0.00
BDD	0.00	BDD	0.00	YWI	0.00	WTMN	0.00	YWI	0.00
SC	0.00	SC	0.00	ZQT	0.00	ZQT	0.00	ZQT	0.00

For input parameter details EPIC users manual can be consulted.

APPENDIX C

Input parameters and changes in the input parameters for AGNPS

Parameters	% changes	Values
Area of each cell, Acres	1%	3.61
Prcipitation, inches	1%	3.74
Nit. conc. in rainfall, ppm	1%	0.8
Energy intensity value	1%	85.08
Duration, hours	1%	24
K coefficient	1%	484
Flow direction	1%	5
SCS curve number	1%	70
Land slope, %	1%	4
Slope length, ft	1%	636
Overland Manning's	1%	0.24
K-factor	4%	0.24
C-factor	4%	0.012
P-factor	4%	0.9
Surf cond. constant	1%	0.22
COD factor	1%	60
Soil N, lb N/lb soil	10%	0.001
Soil P, lb P/lb soil	10%	0.0005
Pore water N conc., ppm	1%	5
Pore water P conc., ppm	1%	2
N extr. coef. for runoff	1%	0.05
P extr. coef. for runoff	1%	0.025
N extr. coef. for leaching	1%	0.25
P extr. coef. for leaching	1%	0.25
% Org matter in soil	1%	20
The other parameters		
Storm type (I, IA, II, III)		2
Slope shape		1
Soil Texture #		3

APPENDIX D

AGNPS SENSITIVITY ANALYSIS RESULTS (RELATIVE SENSITIVITY)

Output	Runoff	Sed	Nit-sed	Nit_runoff	Phop-sed
Input					
SCS # 70	5.172414	2.083333	1.190476	11.84211	0
Land slope 4.0	0	4.166667	3.174603	0	3.174603
Slope length 63	0	0	0	0	0
K-factor 4%	0	1.041667	0.892857	0	1.190476
C-factor 4%	0	1.041667	0.892857	0	1.190476
P-factor 4%	0	1.041667	0.892857	0	1.190476
Soil N 10%	0	0	0.952381	0	0
N extr. runoff	0	0	0	0.657895	0
N extr leach 1%	0	0	0	3.947368	0

APPENDIX E

COMPUTER PROGRAM FOR THE GENERATION OF RANDOM NUMBERS FOR AGNPS MODEL

```
c     This program generates the random numbers for
C     curve #, kcp and N parameters and plugs those values in the  input file
C     for the AGNPS.

      Integer slength,curve,cell1,div1,cell2,div2,dir,cn,shape
      Integer cod, orgmat
      Character*80 data, dumm
      Real sval,mann,kfact,cfact,pfact,surfcon
      Real slope,slrnor,kval,cval,pval,nitval,nrval,nlval
      Real soil,sonit,sophop,poren,porep
      Real nruoff,prunoff,nleach,pleach

      Open (1, file = "wa.dat", status = "old")
      Open (2, file = "wa_sim.dat", status = "unknown")
      Open (7, file = "scratch")
      open (3, file = '1a_all15.dat', status = 'unknown')

      call gettim(ihr,imin,isec,i100th)
      call seed(i100th*i100th)

      Call lognorm(1.343, 0.4722, sval)

      Call lognorm(1.343, 0.2935, slrnor)

      Call lognorm(-7.02, 0.4722, nitval)

      Call lognorm(-3.107, 0.4722, nrval)

      Call lognorm(-1.497, 0.4722, nlval)

      Call kcp(0.18, 0.24, 0.36, kval)

      Call kcp(0.006, 0.012, 0.018, cval)
```

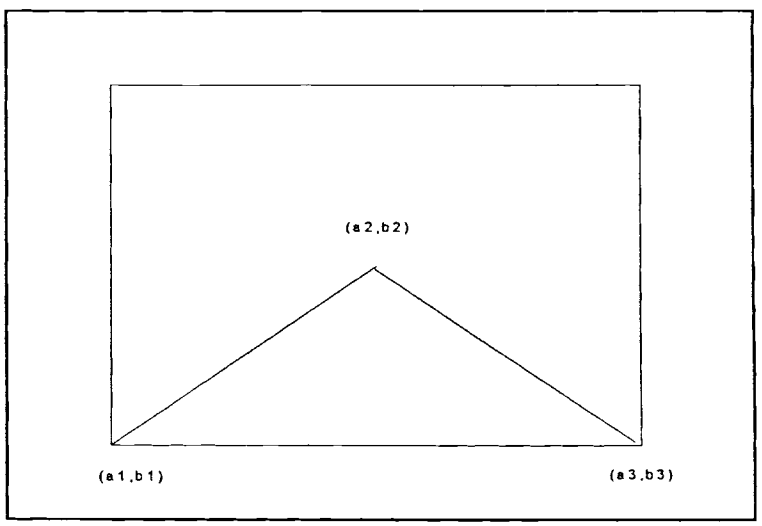
```
      Call p(0.8, 1.0, 1.0, pval)

c     The curve number is equal to the 1000/ (s+10)

      curve = 1000/ (sval+10)


      idc = 0
      do 705 mi=1,10000
        read(3,702,end=706) dumm
        idc=idc+1
702       format(a80)
        write(7,702) dumm
705     continue
706     continue
        rewind (7)
        rewind (3)
        do 780 mi=1,idc
          read(7,702) dumm
          write(3,702) dumm
780     continue

      write (3, 50)curve,slrnor,kval,cval,pval,nitval,nrval,nlval

50  format(i2,3x,f3.1,3x,f4.2,3x,f6.4,3x,f4.2,3x,
     +f6.4,3x,f5.3,3x,f5.3)

      Do 10 i = 1, 6
        Read (1, 60) data
        Write(2, 60) data
10    continue

      Read (1, 61) cell1, div1, cell2, div2, dir, cn, slope,          shape
      write(2, 61) cell1, div1, cell2, div2,          dir,curve,slrnor,shape

      Read (1, 62) slength,mann,kfact,cfact,pfact,surfcon,cod
      write(2, 62)slength,mann,kval,cval,pval,surfcon,cod

      Read (1, 60) data
      write(2, 60) data

      Read (1, 63)soil,sonit,sophop,poren,porep
      Write(2, 63)soil,nitval,sophop,poren,porep
```

```
      Read (1, 64)nruoff,prunoff,nleach,pleach,orgmat
      write(2, 64)nrval,prunoff,nlval,pleach,orgmat

      Do 20 j = 1, 10
        Read (1, 60, end=90) data
        write(2, 60) data
20    continue


60    Format (a80)
61    format(t8,i1,t14,a3,t24,i1,t30,a3,t40,i1,t47,i2,t54,f3.1,t64,i1)
62    Format(t14,i3,t20,f5.3,t29,f4.2,t35,f6.4,t45,f4.2,t53,f4.2,t63,i2)
63    Format (a6,t11,f6.4,t19,f6.4,t29,f4.2,t37,f4.2)
64    Format (t12,f5.3,t20,f5.3,t28,f5.3,t36,f5.3,t47,i2)

90    stop
      End


      Subroutine lognorm(avval, stddev, finval)
      Real s, r1, r2, avval, stddev, rnn, rnor, finval

      s = 2
      do while ( s .ge. 1 )
         call random(ranval)
         r1 = 2*ranval - 1
         call random(ranval)
         r2 = 2*ranval - 1
         s  = r1*r1+r2*r2
      end do

      rnn = r1*sqrt(-2.*log(s)/s)
      rnor = avval + rnn * stddev

C     The random value rnor would be converted to the
c     lognormal distribution by using exp function

      finval = exp(rnor)

      end


      Subroutine kcp(a1, a2, a3, val)
```

```
Real a1, a2, a3, val,ranval

call random(ranval)
If (ranval .le. 0.5) then
    val = a1 + sqrt((a3-a1)*(a2-a1)*ranval)
else
    val = a3 - sqrt((a3-a2)*(a3-a1)*(1-ranval))
endif
end

Subroutine p(a1, a2, a3, pval)

Real a1, a2, a3, pval,ranval

call random(ranval)
pval = a1 + sqrt((a3-a1)*(a2-a1)*ranval)
    end
```

APPENDIX F

EQUATIONS FOR VARIANCE OF TRIANGULARLY DISTRIBUTED PARAMETERS



b2 = 2 / (a3 - a1)
b1 = 0
b3 = 0

$$\mathrm{Var}(x) = E(x^2) - E^2(x) \qquad (1)$$

where E(x) is given by

$$E(x) = \int_{-\infty}^{\infty} x p_x dx \qquad (2)$$

For line 1 p(x) corresponds to

$$p_1(x) = b2.\ x/\ (a2 - a1) + (-a1b2)/(a2-a1)$$

For line 2 p(x) corresponds to

$$p_2(x) = -b2.\ x/(a3-a2) + a3b2/(a3-b2)$$

$E(x^2)$ becomes

$$E(x^2) = \int_{a1}^{a2} x^2\,[b2.\ x\ /\ (a2\ -a1) + (-a1b2)/\ (a2\ -a1)]\ dx\ +$$

$$\int_{a2}^{a3} x^2[(-b2.x)/\ (a3-a2) + a3b2\ /\ (a3\ -\ a2)\ ]\ dx$$

In E(x), x takes the place of x^2 ,

Substituting these equations in (1)

$$\begin{aligned}Var(x) = {} & b2\ (a2^4 - a1^4)/4.(a2 - a1) - a1b2\ (a2^3-a1^3)/\ 3.(a2-a1) \\ & - b2\ (a3^4 - a2^{\,4})\ /\ 4.(a3 - a2) + a3b2\ (a3^3-a2^3)\ /\ 3.\ (a3 - a2) \\ & - \{\ b2\ (a2^3 - a1^3)\ /\ 3.\ (a2 - a1) - b2a1\ (a2^2 - a1^2)\ /\ 2.(a2-a1) \\ & \quad - b2\ (a3^3 - a2^3)/\ 3(a3-a2) + a3b2\ (a3^2 - a2^2)/\ 2.(a3-a2)\}^2\end{aligned}$$

APPENDIX G

THE OBSERVED DATA FROM WA FIELD

Month	Date	Year	Q mm	No3 -N Kg / Ha	P- runoff Kg/ Ha	Tot- P Kg/Ha	Org- N Kg/ Ha	Sediment Kg
10	24	91	1.88	0.066	0.06	0.046	0.045	0.378
10	26	91	31.14	0.828	0.732	0.63	1.053	96.483
10	28	91	16.39	0.621	0.385	0.163	0.53	4.846
10	30	91	0.28	0	0	0	0	0
10	31	91	19.4	0.75	0.427	0.348	0.357	2.818
11	17	91	15.45	0.791	0.404	0.325	0.465	0.776
11	19	91	1.26	0.055	0.023	0.019	0.044	0.101
12	12	91	0.27	0.008	0.003	0.003	0.006	0.238
6	6	92	15.81	0.392	0.511	0.401	3.768	3.192
7	5	92	0.67	0.011	0.014	0.02	0.019	0.425
7	30	92	28.78	0.132	0.368	0.636	1.01	131.794
8	5	92	24.31	0.037	0.425	0.422	0.392	3.44
8	11	92	0.1	0.001	0.002	0.002	0.003	0.014
11	11	92	8.84	0.046	0.183	0.205	0.121	1.352
11	21	92	40.92	0.128	0.698	0.686	0.464	0
12	9	92	1.79	0.005	0.024	0.027	0.021	0.358
12	14	92	67.85	0.088	0.619	0.686	0.418	15.73
12	16	92	0.45	0	0	0	0	0
1	4	93	1.58	0.004	0.014	0.018	0.024	0.741
1	9	93	2.5	0	0	0	0	0
4	14	93	17.56	2.442	0.163	0.179	0.235	1.842
		Total	*297.23*	*6.405*	*5.055*	*4.816*	*8.975*	*264.528*

Q	Runoff
No3 - N	Nitrogen loss in runoff
P - runoff	Phosphorus loss in runoff
Org -N	Nitrogen loss in sediment

Bold lettered outputs correspond to AGNPS observed output.
Bold italic coresponds to the total outputs used in EPIC.

VITA

Sandeep Prabhu

Candidate for the Degree of

Master of Science

Thesis : APPLICATION OF STOCHASTIC MODEL EVALUATION PROTOCOL ON EPIC AND AGNPS.

Major Field : Biosystems Engineering

Biographical :

Personal data : Born in Mangalore, India, on July 1, 1969, the son of Vatsala and Vasudev Prabhu.

Education : Graduated from Canara Pre University College, Mangalore, India in May 1987; received Bachelor of Engineering degree in Industrial and Production Engineering degree from University of Mysore, August 1991; Completed the requirements for the Master of degree at Oklahoma State University, Stillwater, Oklahoma in May 1995.

Experience : Management trainee panchmal Industries, Mangalore, India, from September 1991 to June 1992; Research Assistant, Department of Biosystems and Agricultural Engineering, Oklahoma State University, January 1993 to present.

Professional Memberships: American Society of Agricultural Engineers, Alpha Epsilon